

Spectral and Fractal Analysis of Digital Images for Evaluating Defects in Bridges

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Abstract—The paper proposes a novel approach to the detection of changes in the pattern of defect in a bridge based on dimensionless metrics derived from the texture and fractal analysis of digital images. Currently, the change detection is manually through visual inspection by comparing the current inspection report to the previous ones. However, such approach of making decisions has been identified with several limitations as follows: the process is time-consuming and it is based on inspectors' personal experience. In past years, digital images have been used in identifying changes among digital images acquired at different times using image differentiation methods. But, such approach requires image registration to be performed first before evaluating the changes. Also, the previous approach of change detection is not suitable for computer automated process because the extracted parameters are based on Euclidian geometry. The proposed method of spectral analysis translates digital images from spatial domain to Fourier domain and finds their one dimensional signatures to quantify the defects characteristics. Similarly, the fractal analysis describes the surface disorder of defects by finding fractal dimension (FD) using Box Counting Modeling algorithm. The proposed method eliminates the drawbacks of the traditional approach and generates unique dimensionless metrics which are suitable for an automated application.

Keywords *Components; Change Detection; Spectral Analysis; Fractal Analysis; Digital Images; Visual Inspection; Concrete Bridges.*

I. INTRODUCTION

A large number of reinforced concrete bridges built during the construction boom of 1950s and 1960s in North America are structurally deficient due to increased traffic, aging of construction materials, and several environmental effects. In Canada, more than 40% bridges are older than 50 years, and need immediate actions to ensure that these bridges are still satisfying the current code requirements and are safe for operations [1]. In general, routine bridge inspection is carried out in every two years to collect condition of bridges in the form of text, images, and drawings based on inspection manuals. Thus, the quality of inspection process and reporting are extremely important for predicting future behavior of bridges accurately. Routine inspection is generally carried through visual inspection which is an arm's length inspection

of all portions of a structure using some fundamental measuring methods and tools [2]. The task performed during routine inspection can be broadly classified in two sub-tasks. The first one collects the measurements and observations needed to determine the physical and functional condition of bridges and the second one identifies what changes had happened since the last inspection (Change Detection) so that immediate recommendation can be made to upgrade structures conditions[2]. However, visual inspection suffers from several limitations arising from the qualitative nature of the information and the subjectivity associated with the method [3].

Several attempts have been made in recent years to enhance the quality of visual inspection. One of promising attempts is the application of digital image processing for routine bridge inspection. Bridge inspection manuals guide bridge inspectors to collect several digital images during visual inspection. However, in current practices, these images are not utilized for defects quantification purpose. This paper proposes the methodology of change detection based on non-dimensional metrics obtained from spectral and fractal analysis of the digital images of the bridge defects. The traditional methods for the quantification of surface defects in concrete elements are based on the length, width, and area of the objects. Such defects quantification techniques are not able to capture the non Euclidean geometry properties such as texture and color of surface defects and do not provide a unique metric suitable for an automated system.

II. BACKGROUND

2.1 Change Detection

The change detection process has many engineering applications. For examples, people used this technique to monitors earth's surface such as the changes due to construction, deforestation, floods, forest fires and other kinds of activities [4]. High resolution 3D scanning techniques were used to measure internal damages and crack growth in a small mortar cylinder at different levels of deformation and loadings [5]. Underwater surveillance video frames from remotely operated underwater vehicles were used to track interesting or mundane objects which helped in sorting interesting objects

[6]. In recent years, the concept of change detection through digital images has been extensively used for medical diagnosis. This technique also has a great application to find subtle changes between MRI (Magnetic Resonance Imaging) scans for assessing the evolution of a disease over time [7].

Temporal change information with comparison and analysis among multi-temporal digital images could be achieved through Change Detection [8]. The approach answers some of the fundamental questions such as, 1) how fast the changes are taking places; and 2) what are the trends of the changes [9]. However, there are a number of limitations for a successful application of the change detection techniques in the engineering fields. This includes the lack of *a priori* information about the shapes of the changed areas, the absence of a reference background, differences in lighting conditions, atmospheric conditions, sensor calibrations, change in sensing technology, ground moisture, and the alignment of multi-temporal images (image registration) [10, 11].

2.4 Fractal Damage Characteristics

Fractal geometry has the ability to model irregular shapes and to measure fractal dimension more accurately than dividing the region into regular geometry [12]. Recently, fractal theory has been extensively used in many engineering fields and the application has been also tested on the analysis of concrete structures [13, 14]. For example, fracture surfaces of rock were measured by fractal dimension which basically characterize the topology of rock surfaces [15].

Carpinteri et al. [16] also used fractal analysis for evaluation of damages in concrete elements. They found that single fractal dimension did not adequately describe a crack network since two crack domains having the same fractal dimension may have significantly different properties. This emphasizes that apart from the fractal features, other feature attributes need to be considered in defining the system properly. Fadi [17] developed a framework to automate the detection, localization, and characterization of subsurface defects inside bridge decks based on ground penetrating radar (GPR) images. The developed algorithms were based on a fractal-based feature extraction method to detect defective regions on a concrete surface, estimate the depth of defects, and classify them.

Irregular shapes can be quantified by fractal theory such as quantification of shape of moving clouds [18], in which a box-counting algorithm was used for calculating the fractal dimension of moving clouds. In that case, the average fractal dimension of clouds at an elevation of 7 km above ground level was found to be 1.5 ± 0.1 .

2.2 Defects modeling based on Photos

While software have been developed for the design of structural components, very little attention has been given on how to model defects in concrete elements based on defect parameters such as extent, severity and intensity of defects. The simplest way to describe the geometry of defects is to measure the defects at the time of inspection. But that is a time consuming and costly task. Therefore, modeling of defects

from images for condition assessment of structural components provides a more attractive alternative. .

A photographic documentation can be used to estimate the measurement of defects [19]. In [19], the authors developed a tool for modeling concrete surface defects from photographs. The presented system was equipped with an advanced graphical editor which enabled fast creation of a 3D model of a damaged component and presents graphical representation of results.

Moselhi and Shehab - Eldeen [20] proposed models for automating detection and identification of defects in sewer pipelines. They considered various sewer defects (cracks, joint displacement etc.) and those defects were represented by feature vectors area, perimeter, major axis length, minor axis length, and elongation for defects discrimination and classification.

McRobbie [21] reported that images of structures could be collected and processed (manually or automatically) to identify defects. He used various image processing techniques to segment defects and the attributes of defects considered were area, eccentricity, extent, orientation, major axis length, and minor axis length.

A system called “micro to macro on any objects” was developed as a new bridge inspection methodology which collected high resolution images of defects as well as the element containing defects [22]. They suggested that in order to compare the history of components, the acquired images needed to maintain their same position and image resolution. However, even a commercial camera equipped with GPS, the exact location of camera position and direction of shooting is not possible to achieve.

2.3 Measuring Shapes

Dryden [23] defines “shape” as all the geometric information that remains when location, scale, and rotational effects are filtered out from an object. However, describing images with a few numbers is a challenging task [24].

Traditionally, man-made objects can be easily classified after finding area, length, and perimeter based on Euclidean geometry. These 2D features are well developed for image interpretation and can be calculated using mathematical modeling [25]. However, these features are not suitable for natural defects occurring in bridges because of the irregular size and wide range of variability in texture patterns. Also, there is a problem in working with a large number of individual images which have been photographed at different locations [22]. It is not possible to work with individual images in finding their locations and image scale. This paper discusses the features which are invariant to translation, rotation, and scale manipulation in describing objects.

Loncaric [26] explained that finding few numeric values for describing shape is an important goal for computer vision approach. However, the selection of the best set of few numerical descriptors that will provide adequate information and show correlation with human intuition is a complex subject. The choice of descriptors depends on a particular application. However, for this work, the methods which

produce a few set of shape numbers and are invariant to image manipulations are selected for change detection.

III. METHODOLOGY

A new approach of feature extraction which can adequately quantify the changes in the condition states and are suitable for computer automated processes has been proposed based on the spectral and fractal analysis as described in Fig. 1. The proposed method requires detailed images (the minimum image resolution should be 1 pixel/mm) for defects analysis. To achieve high resolution images, the approach uses two cameras one mounted over another. The first camera will capture the scene including the surrounding details, and the second camera will capture detailed defect images from the same location.

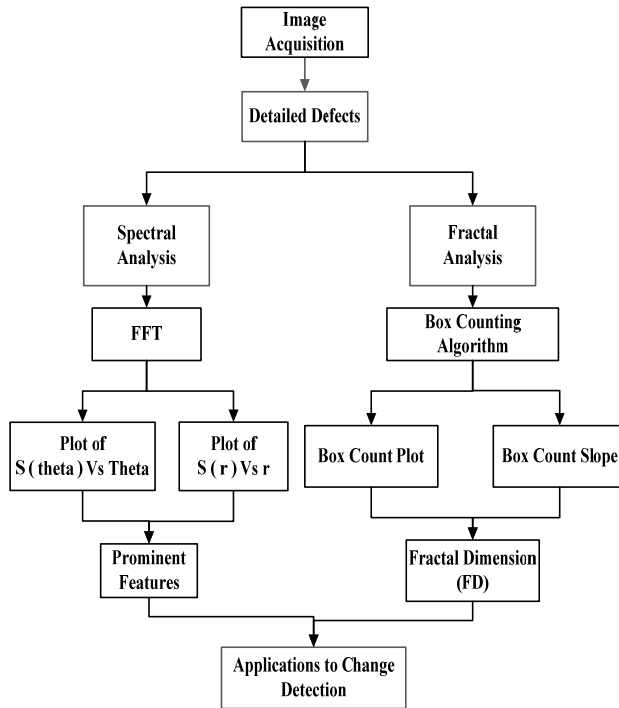


Fig. 1: Methodology

3.1 The proposed Spectral Analysis

Fig. 1 illustrates the work flow diagram for the change detection procedure in spectral domain. Spectral descriptors can provide quantitative information of images taken at different times to classify and rank them. For this operation, we need to convert the original images into frequency domain by Fast Fourier Transform (FFT). The resulting spectrum reveals information about the principal direction of textures contained in the images. Also, the location of the fundamental peaks provides information about the fundamental periods associated with the texture of the given images. This method is useful for discriminating between the periodic and non-periodic texture patterns, and for quantifying the differences among the periodic patterns. For

convenience, Fourier Spectrum is expressed in polar coordinates. This procedure yields a function $S(r, \theta)$ called the spectrum function, where r and θ are the spatial variables in polar coordinate system [27].

A global description of the change can be obtained by integrating (summing for discrete variables) these functions as shown in (1) and (2), [27]:

$$S(r) = \sum_{\theta=0}^{\pi} S_{\theta}(r) \quad (1)$$

$$S(\theta) = \sum_{r=1}^{R_0} S_r(\theta) \quad (2)$$

where R_0 is the distance from the origin. The typical descriptors include the location of the highest value, the mean and variance of both the amplitude and axial variations, and the distance between the mean and the highest value of the function. The application of this method has been demonstrated in later in the paper (i.e., Section IV).

3.2 The Fractal Analysis

The concept of fractal was first introduced by Mandelbrot [12] to describe the irregular structures of many natural objects and phenomena. Euclidean geometry is well suited for describing man-made objects, whereas fractal geometry is well suited for objects whose shapes are dependent on several environmental factors. The chaotic and turbulent characteristics of nature such as the shape of cloud, the length of coast lines, and the spatial distribution of celestial bodies are well explained by Mandelbrot using the concept of fractal dimension. For detail information about fractal dimension can be found in literature [28].

IV. EXPERIMENTS AND RESULTS

Models for this work were developed in a Window Vista Enterprise 32 bit operating System. The desktop consists of Intel® Core™ 2 Duo CPU, E6550 @ 2.33 GHz. The methodology for spectral and fractal application algorithms was implemented in MATLAB R2012a [29]. A commercially available SONY-DSC T5 digital camera of 5.1 mega pixels with 3x optical zoom has been used here for image acquisition of defects. The object-detection techniques (in this case, threshold-based) have a great influence on the quantification of defects and the percentage of deterioration in an image from initial time (T1) to final time (T2). To make this operation more distinct, the images were analyzed separately and the results were demonstrated in Fig. 2. Figure 2(a) presents an original image taken at time T2 and the binary image obtained by global image threshold using Otsu's method [30]. After this operation, the threshold image was labeled with different color as shown in Figure 2(b) and the number of pixels contained in each object were counted and displayed. This operation was performed to account for the defects present on concrete surface in the form of texture irregularities. The results are summarized in Table 1. For example the table lists object pixels 246 at time T1 and 2300 at time T2 with threshold 0.5. These values are used to evaluate change in defects with time.

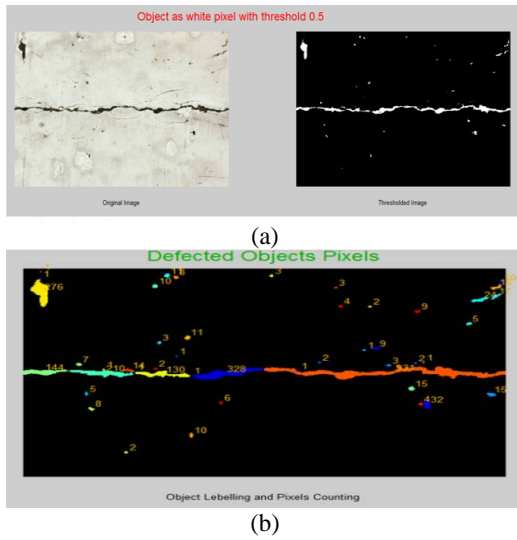


Fig. 2 – (a) image at Time T2 at threshold 0.5, (b) Object labelling and area in pixels

Table 1 - Change Analysis based on image registration

| Image Size | Threshold(T*) | Threshold(T*) |
|------------------|---------------|---------------|
| | (0.5) | (0.8) |
| Image at Time T1 | 298 x 448 | 298 x 448 |
| Image at Time T2 | 246 | 1532 |
| % Defects at T1 | 2300 | 14853 |
| % Defects at T2 | 0.18 | 1.15 |
| % Change | 1.72 | 11.13 |
| | 1.54 | 9.98 |

$T^* = \text{Threshold}$

4.1 Change Detection by Spectral Analysis

The same images were analyzed in frequency domain as illustrated in the work flow diagram shown in Fig. 3. Figure 3(a) showed the Fast Fourier Transform (FFT) of the image taken at time T2 and its 3D visualization. Figure 3(c) showed the result of the whole process of transforming FFT image to a one-dimensional (1D) representation in the form of energy distribution in the radial direction and angular plot of texture variations. These plots provided quantitative values of information contained in both images and could be adopted for comparison between them. Here, the mean values of radial and angular plots were of interest to detect the degree of change as summarized in Table 2. For example, the table lists unique number of 1386 obtained from radial plot as a mean value at time T1. These numbers are used to compute change in defects over times.

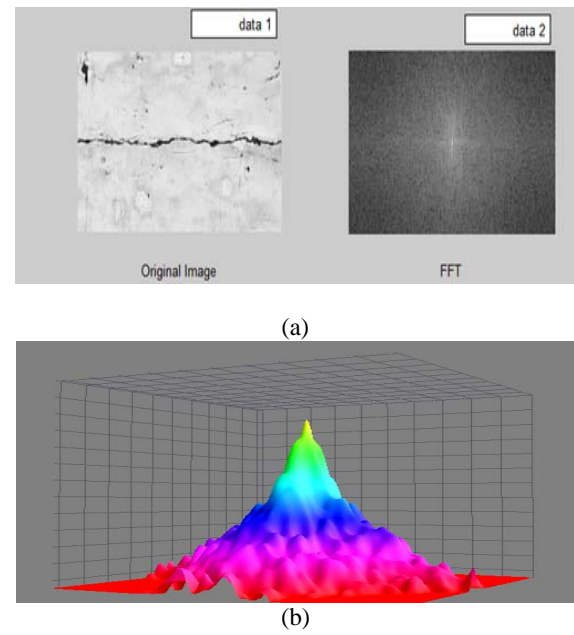


Fig. 3 – (a) Original Image at time T2 and FFT, (b) FFT in 3D visualization

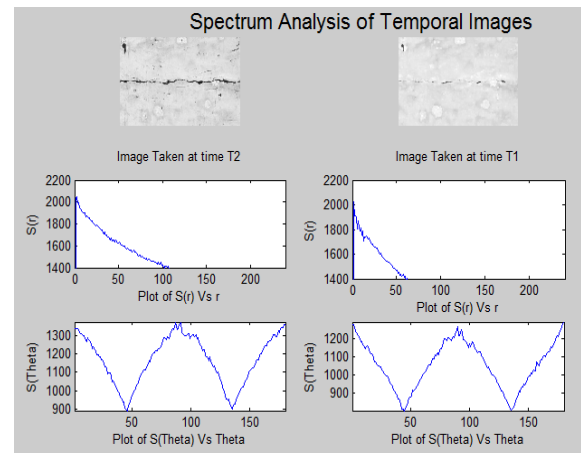


Fig. 3 – (c) Spectral analysis of image at Time T1 and T2 (radial and angular profiles)

Table 2 - Change Detection based on Spectral Analysis

| | Image at T1 | Image at T2 | % Change |
|----------------------|-------------|-------------|----------|
| Mean of Radial Plot | 1386 | 1537 | 10.89 |
| Mean of Angular Plot | 1055 | 1167 | 10.62 |

4.2 Change Detection by Fractal Analysis

To demonstrate the process of change detection using fractal dimensions, crack images were created using fractal

tree algorithms. By changing the number of iterations (n) and affine transformation parameters (translation, rotation, and scaling) to the fractal tree algorithms, it is convenient to generate different simulated cracks as shown in Fig. 4. The generated cracks from n = 1 to 4 were considered as crack propagation from time T1 to T4. These images were used to calculate fractal dimension shown in Fig. 5.

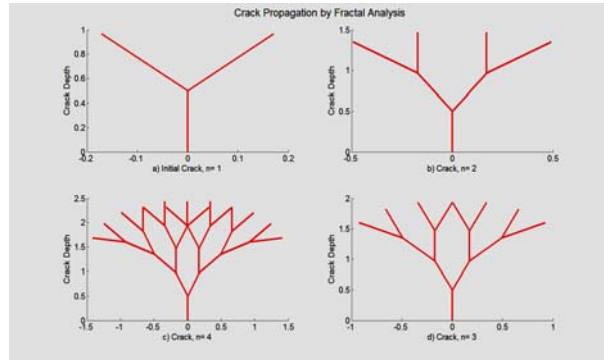


Figure 4 – Fractal images generated by Fractal Tree algorithms simulating cracks from Time T1 to T4

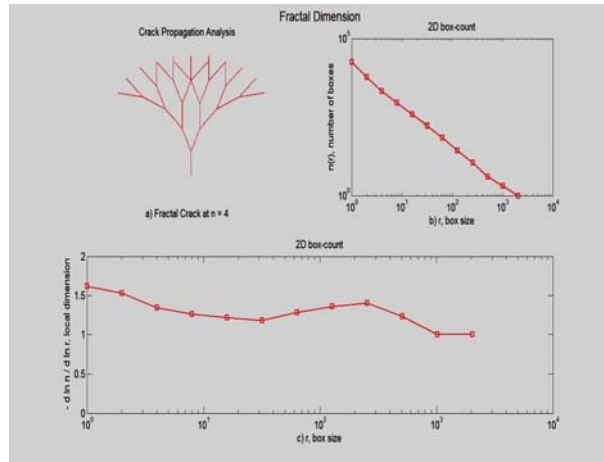


Fig. 5 – Estimation of Fractal Dimension using Box Count Algorithms (FD = 1.1752)

For the purpose of comparing the results from the spectral analysis and the tradition methods, the cracked images were again analyzed individually by finding their length (for crack density – a traditional approach of crack comparison) as shown in Fig. 6, and spectral features (mean of radial and angular plot in frequency domain) as shown in Fig. 7. All the results were summarized in Table 5 showing the comparison of results from fractal analysis, spectral analysis, and traditional approach of crack density. The result showed that the results by spectral and fractal were close to 3%, 8%, and 13% changes among various cracks considered in the experiment, however, the result by traditional approach were not in similar trend since the traditional approach is unable to capture texture information.

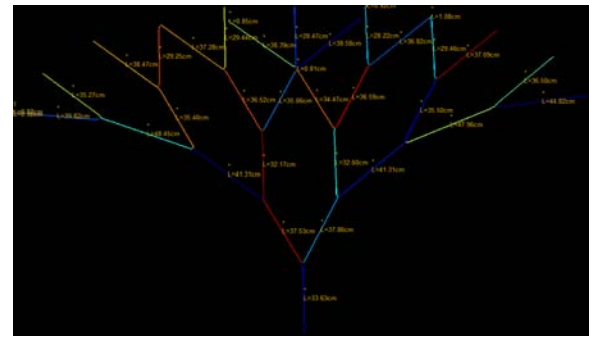


Fig. 6 – Change Detection by Traditional Approach, Total Length: 1100.00 mm

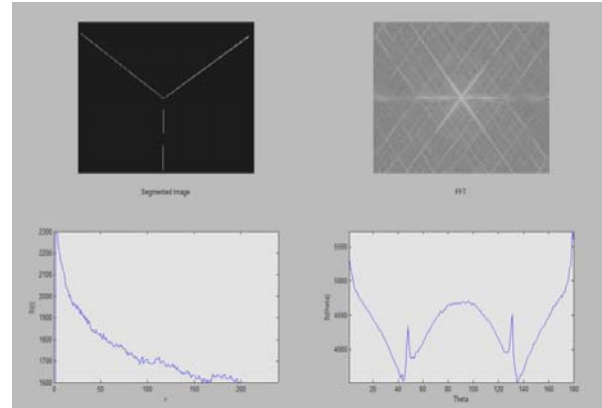


Fig. 7 – Spectral Analysis of Fractal Images

Table 5 - Change Detection based on Spectral Analysis and Fractal Analysis

| Fractal Analysis | Crack # 1 | Crack # 2 | Crack # 3 | Crack # 4 |
|-------------------------|-----------|--------------|--------------|---------------|
| No. of Branch (n) | 1 | 2 | 3 | 4 |
| Fractal Dimension (FD) | 1.13 | 1.18 | 1.22 | 1.28 |
| % Crack Growth | | 3.87 | 8.21 | 13.26 |
| Spectral Analysis | | | | |
| Spectral Mean Values | 1618.00 | 1656.00 | 1743.00 | 1798.00 |
| % Crack Growth | | 2.35 | 7.73 | 11.12 |
| Traditional | | | | |
| Length (mm) | 390.00 | 500.00 | 716.00 | 1105.00 |
| Area (mm ²) | 45135.00 | 45144.00 | 45144.00 | 45144.00 |
| Crack Density (%) | 0.86 | 1.11 | 1.59 | 2.45 |
| % Crack Growth | | 28.31 | 83.95 | 184.15 |

V. CONCLUSION

This Paper demonstrated a novel method of comparing the bridge condition states through digital images acquired at different times (Change Detection) using spectral and fractal image analysis. The results showed that image subtraction method was largely dependent on the established threshold

level, for example, the detected change for the selected representative images taken at time T1 and T2 was 1.54% at threshold 0.5 and 9.98% at threshold 0.8. The change detected using the proposed spectral analysis was found to be 10.62% which neither required threshold value nor required image registration process. The proposed method overcomes the limitations of the existing methods as indicated by Singh [11] that there is a need for exploring the possibility of developing a change detection procedure that requires a less precise registration of images or simply bypass the registration process.

Another approach of change detection was illustrated by using fractal theory using fractal dimension (FD) as a shape descriptor. The temporal cracked images were simulated by generating fractal crack images and FD was obtained by Box Counting Modeling algorithms. Based on this feature, the degree of change in the four temporal cracks from the base crack #1 was found to be 3.87%, 8.21%, and 13.26%. The results were again compared with spectral analysis and crack density approach (a traditional approach). The spectral and fractal analysis showed very close estimate of change with the average values of 3%, 8%, and 12% from the base crack #1. However, the traditional approach of comparing the crack density had very different results showing 28%, 83%, and 184% of change from the base image. The results showed that the traditional approach is not able to capture the non-Euclidean geometric properties. Since the proposed shape descriptors are scale invariants, they are suitable for computer application and the existing method of visual inspection can be enhanced by the proposed approach.

VI. ACKNOWLEDGEMENT

The authors would like to thank Concordia University, Montreal, Canada; and Natural Sciences and Engineering Research Council of Canada (NSERC) for financial supports for this research. The valuable comments and information about condition of bridges in Quebec provided by Mr. Adel Zaki, Chief Engineer (Roads and Bridges), SNC Lavalin Inc. are also gratefully acknowledged. The contribution of all experts participated in this work is also gratefully acknowledged.

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