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Hough Transforms to Detect and Classify Road Cracks

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***Abstrac* - A system for road crack detection and characterization is proposed here to minimize the human subjectivity as in the customary overviews routines. There are three tasks addressed here .The first task is crack detection for which Hough transformation used. This based on learning from samples images, where a subset of the available image database is selected and used for supervised training of the system. The second task deals with crack type characterization, for which SVM classifier is used, to characterize the detected cracks as to which type of crack it is. As the third task a methodology for the assignment of crack severity levels is introduced, computing an estimate for the average width of each detected crack. Experimental crack detection and characterization results are presented based on images captured during a visual road pavement surface survey over Indian highways.**

Index Terms— crack characterization, crack severity level, road crack detection, segmentation, supervised learning.

I. INTRODUCTION

A road crack is the separation of road surface into two, or more, pieces under the action of stress. Detecting and classifying these cracks can be essential for optimal road maintenance. It is important for us to identify cracks and distinguish these from other surface variations. Road distresses disturb and adversely affect the traffic flow and traffic safety leading to poor performance of the road. They also cause an increase in fuel costs, result in time delay and prove troublesome for every road user. Identification of the road cracks at an early stage is essential as preventive road maintenance and effective remedial measures can be applied before the problem becomes too severe and the pavement fails. Also, the distresses are a nuisance to the road users and may prove hazardous if neglected for a long period as their condition worsens with time. Proper, timely and selective road maintenance thus becomes an important principle which lengthens the life of the pavement and also reduces the cost of maintenance. Crack detection and characterization systems are being developed for fast and reliable pavement surface defect analysis, instead of slow traditional human inspection procedures This strategy additionally helps the improvement of a more secure review system, especially when checking rapid streets like expressways.

Here a supervised two-step pattern recognition system is presented. First is the detection of image blocks containing crack pixels is addressed. Then, cracks are characterized into three types as specified by the Portuguese Distress Catalog, and a classifier is being used to classify the different crack types present in a given image. Later on the mean width of the crack is estimated for a crack severity level assignment. The 2-D features that are extracted for crack detection are mean and standard deviation which are simple but effective features.

II. LITERAT URE REVIEW

Up till now, some studies about the automatic crack detection have been done. Several methods using neural networks, SVM and digital image processing have been proposed. In some cases, the quality of the images may also have an effect on the obtained output. Other methods for crack detection include various techniques such as wavelet-based transform, fuzzy set theory, SVM and GLCM features.

In publication [1] automatic crack detection and classification system is proposed to both speed up and reduce the subjectivity of the process. After the pavement images are captured by a digital camera, regions corresponding to cracks are detected over the acquired images by local segmentation and then represented by a matrix of square tiles. Since the crack pattern can be represented by the distribution of the crack tiles, standard deviations for both vertical and horizontal histograms are calculated to map the cracks onto a 2D features. Details on image characteristics or the type of sensor used to capture them are not provided.

In [2] the authors here have proposed a novel, fast and self-adaptive image processing method for the extraction and connection of break points of cracks in pavement images. The algorithm first finds the initial point of a crack and then determines the crack's classification into transverse, longitudinal and alligator types. Different search algorithms are used for different types of cracks. Then the algorithm traces along the crack pixels to find the break point and then connect the identified crack point to the nearest break point in the particular search area.. The connection algorithm used may not be very effective in maximizing the accuracy of crack identification.

In summary, most of the automatic crack detection strategies reported in the literature are performing a pixel-based analysis of road pavement surface images, producing global image analysis results, to indicate the type of distress detected in that image. Usually, just a qualitative analysis of the results is done.

So in this paper performing (fast) block-based crack detection instead of pixel based is implemented. This is capable of identifying the presence of multiple cracks in a given image and providing a detailed quantitative evaluation of the results obtained, highlighting which blocks in each image contain cracks, identifying the type of each detected crack, and assigning it a severity level.

III. SUPERVISED CRACK DETECTION

The proposed framework to detect and characterize cracks found on the road pavement surfaces are based on block-based image analysis approach. The image database considered here for the experimental work consists of 84 images. These images are converted to gray-level images of fixed size with pixel intensities ranging from 0 (black) to 255 (white). The images should be captured by a good digital camera at sunlight with its optical axis perpendicular to the road surface and its lateral edges parallel to the road axis. We need to avoid the shades of trees, flyovers, bridges and other obstacles while capturing. Each pixel of the image corresponds to a road area of about 1 mm^2.

The images are later on segmented for processing purposes. So no overlapping 75 × 75 pixel blocks are made, as this size is not too less or not to big and represents a good compromise between computational performance and accuracy of the detection. After the segmentation for each of the cracked blocks two feature matrices are computed: 1) the mean matrix (M_m), with each block's average intensity, and 2) the standard deviation matrix (STD_m), with the corresponding standard deviation (*std*) values. In the crack detection task, a training stage is implemented, where images are selected from image database and are used for training the system, these images compose the training set (TrS), whereas the remaining database Images are used for testing, composing the test set ($TstS$), to provide a quantitative measure of the crack detection quality. The entire flow of the proposed scheme is represented in fig.2.

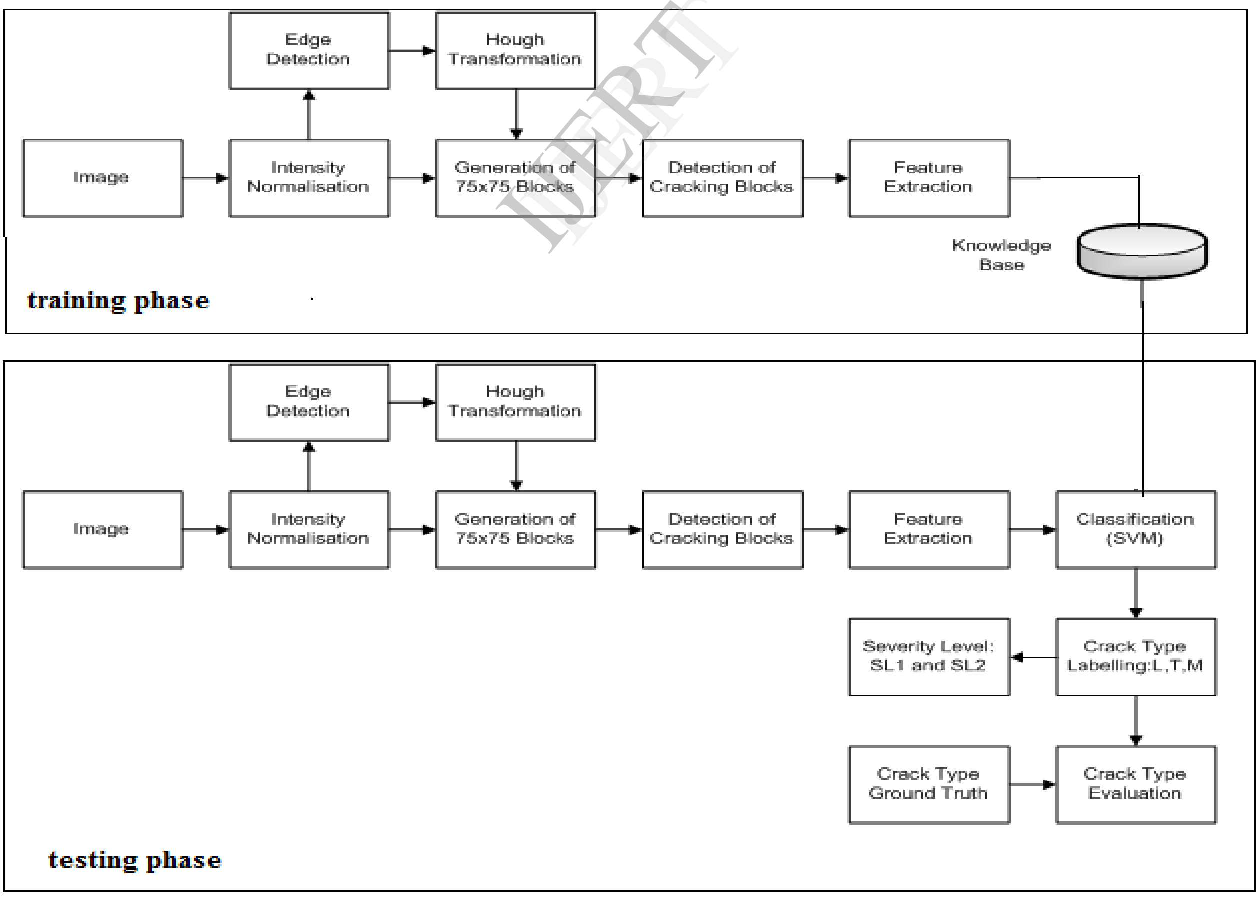

Fig.1 Block diagram of the proposed system

A. *Preprocessing*

The images of the roads that are captured may comprise of dust and sand or some other particles that may obstruct our processing. so it critical that we eliminate all these and concentrate mainly on the road surface. So preprocessing the images before actual process is necessary.

Intensity Normalization: Preprocessing begins with pixel intensity normalization, which is autonomously applied to each image. This deals with the nonuniform background illumination, which is mainly due to the type of sensor used for image capture. The objective is to obtain the same average pixel intensity for blocks which do not have cracks, whereas the remaining (crack) blocks keep a lower average intensity due to the presence of darker crack pixels. To handle this problem consists of applying a saturation function, such that pixels with intensities higher than a proposed crack certain threshold are replaced by the threshold value. These results in slightly darker images, without losing information regarding the presence of cracks, as notably, the "*std*" feature becomes more discriminative [5]. This also makes the visibility of the road cracks clear.

Feature Extraction: This detection step relies on two simple but effective features: the mean and the standard deviation values of pixel-normalized intensities within an image block. Because of different individual average intensities, which would influence negatively the classification results a feature space normalization procedure is proposed.

B .*Crack Detection*

After completely training the classifier with training images the test stage begins. For each *TstS* image, the estimated decision boundaries are superimposed to the computed 2-D feature points to identify the image blocks without crack pixels or with crack pixels. Detection results are stored using binary matrices with "1s" and "0s"

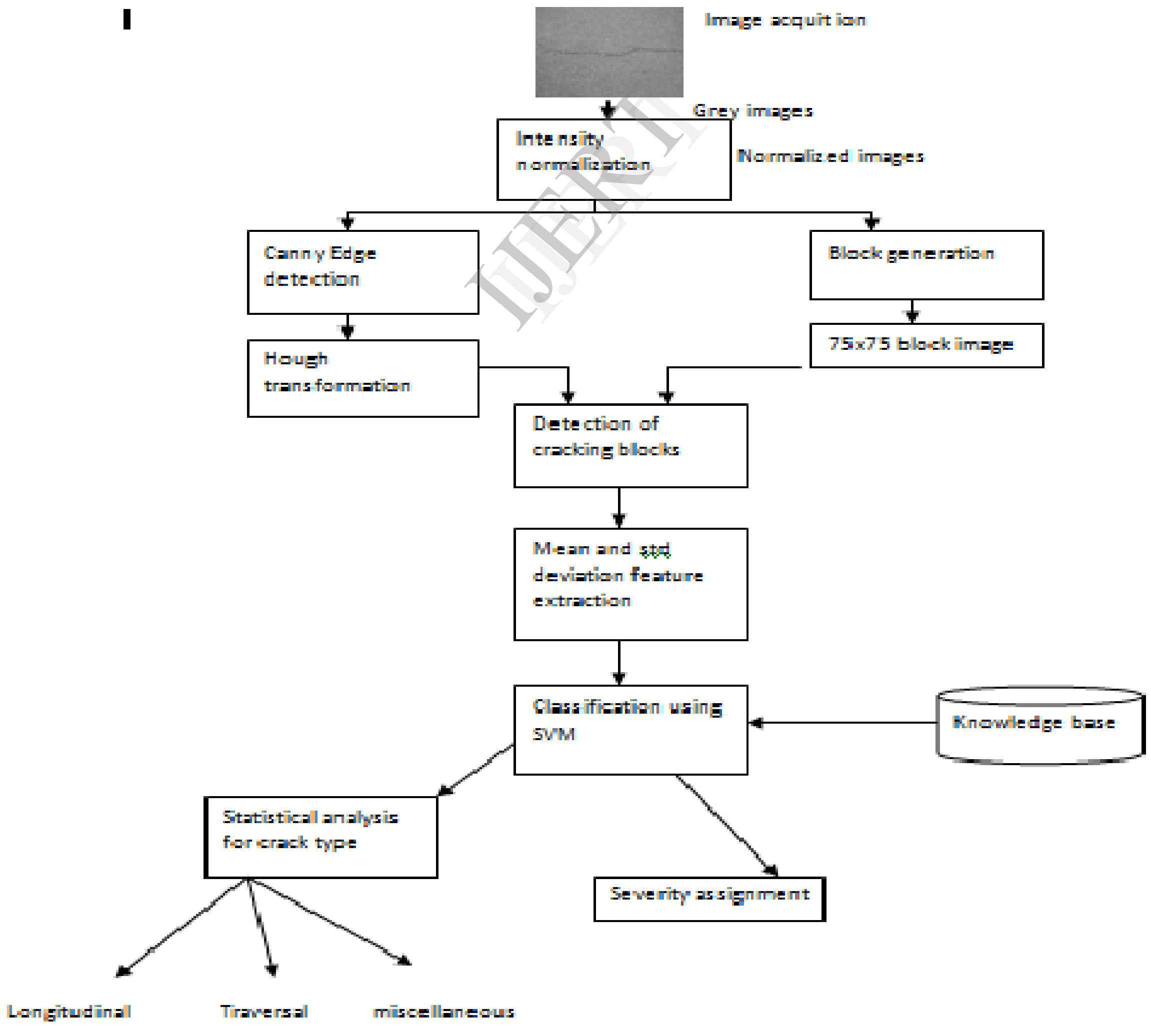

Fig. 2 Flow diagram of proposed scheme

The linear Hough transform algorithm is used here to detect edges which are described by $r = x\cos\theta + y\sin\theta$. For each pixel at *(x,y)* and its neighborhood, the Hough transform algorithm determines if there is enough evidence of a straight line at that pixel. If so, it will calculate the parameters (r,θ) of that line, and then look for the accumulator's bin that the parameters fall into, and increment the value of that bin. So by this we can detect the presence of cracks.

Before we do the crack detection an additional step may be considered remove isolated small crack blocks. This is required here because oil spots are often found in pavement surfaces, which appear as isolated clusters of dark pixels that could be erroneously detected as crack pixels, resulting in false-positive detections.

IV. CRACK TYPE LABELING AND SEVERITY LEVELS

Crack Type Labeling

Crack type labeling begins with the application of a connected component algorithm to the crack detection results. Here we use standard deviations of the column (feature one) and row (feature two) coordinates of each crack connected component. The cracks are classified as

1) longitudinal crack (class *cL*),
2) transversal crack (class *cT*),
3) miscellaneous crack (class *cM*),

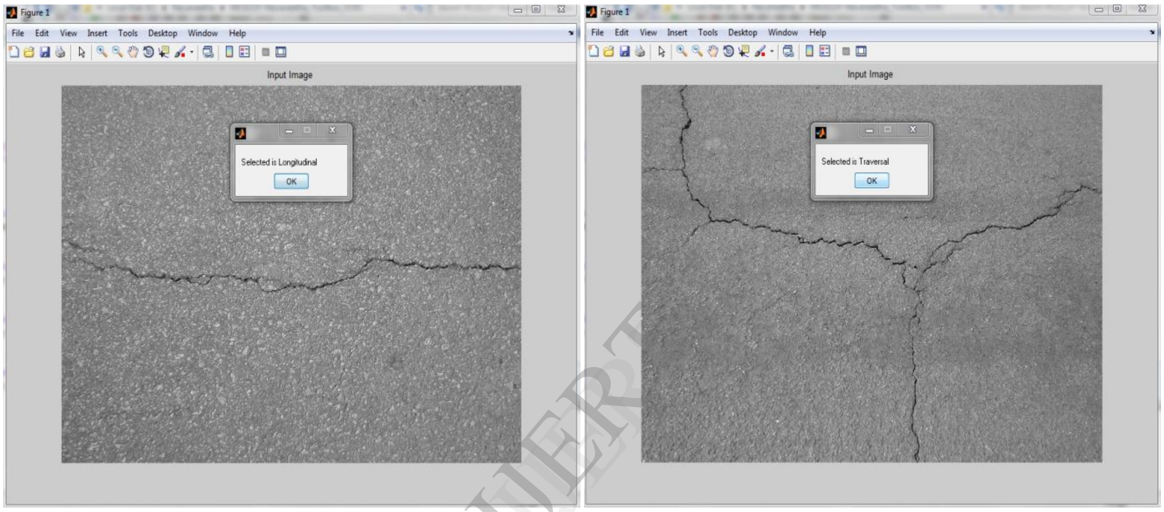

Fig 3 a) longitudinal crack b) traversal crack

Severity levels assignment

Severity levels assignment defines two levels of severity for cracks mainly related to their width :

level 1, for closed cracks with less than 2 mm width;
level 2, for open cracks with more than 2 mm width

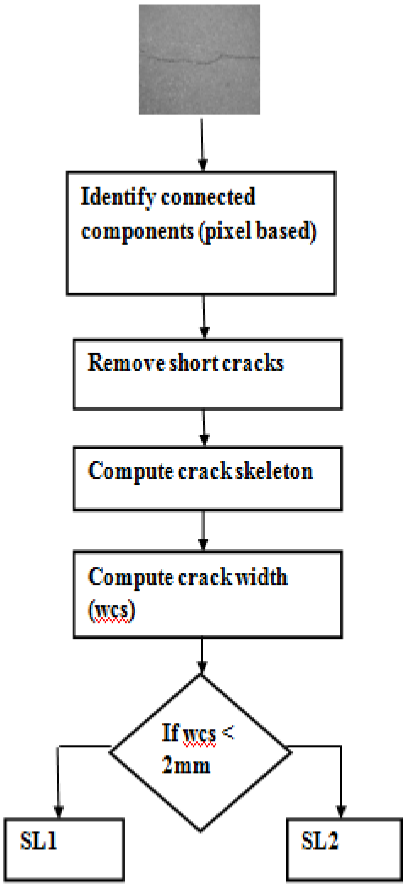

Fig.4 .Flow diagram for the severity level

V. EXPERIMENTAL RESULTS

Performance evaluation of the proposed crack detection and characterization, with severity level assignment strategies, uses images taken during a visual pavement The surface survey of a Portuguese road. The evaluation database contains 56 gray- level images. The Matlab algorithms are being implemented with the support of image processing toolbox. The first evaluation targets the crack detection task, fig 5 (a) and (b) shows the image and its normalized image crack detection involves first detecting the edges using Hough transformation and later detecting the crack blocks. The Hough transformation results are shown in fig .7. This two-step quantitative evaluation procedure proves to be a more robust strategy when compared with the ones commonly found in the literature.

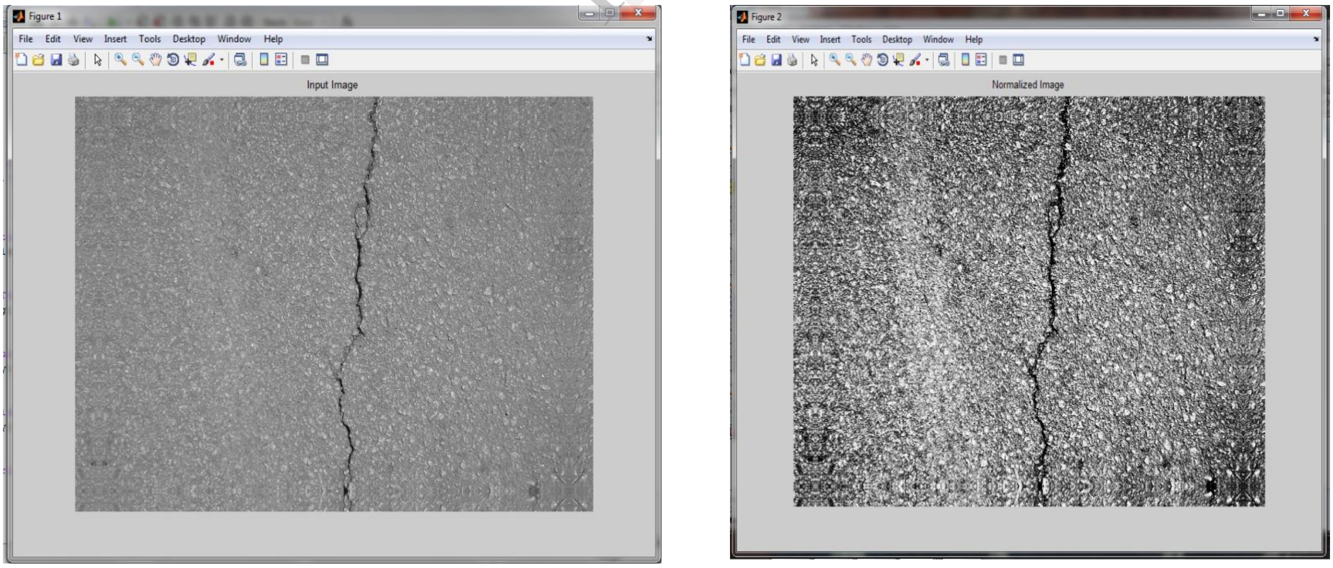

Fig.5 (a) original image (b) Normalized image

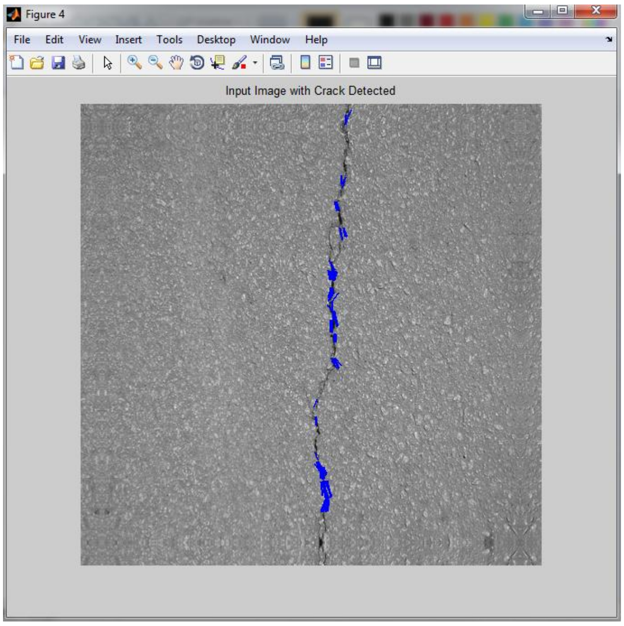

Fig.7 Result of Hough transformation

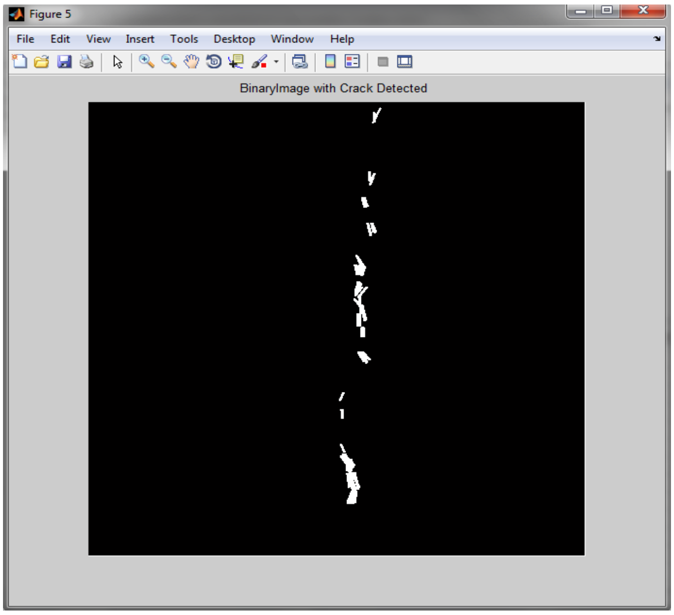

Fig.6 Shows the Presence of Crack

VI. CONCLUSION AND FUTURE ENHANCEMENTS

This paper has proposed a system for crack detection and characterization to help out the civil engineers. CrackIT is able to detect multiple cracks in the same image, taking minimum time to process the images of the database including crack detection, type characterization, and also severity level assignment. Its working is on a Pentium i5-750 processor at 2.6 GHz with 4 GB of RAM.

Crack detection and type characterization results are good, but dealing with very thin cracks which are less than 2 mm width has become a difficult task to deal with. The paper also has not dealt with the depth of the cracks which is also an important factor. This can be worked in as a further improvement.

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