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Density based Traffic Monitoring system in Haze and FOG Conditions

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ABSTRACT

The problem of traffic congestion has increased now-a-day's due to the rapid growth of population in major cities. Overwhelming number of vehicles and insufficient roads are the major causes of traffic congestion. This needs new technologies to be adopted, and a better approach for effective traffic management. In the literature, researchers use conventional methods such as IR sensor, wireless sensor, and Fuzzy logic to measure the traffic density. The main limitations of such conventional methods are that they require personal monitoring of the traffic and ineffective to work in foggy weather. The main aim of this work is to develop a real-time adaptive density-based traffic management system that can quantify number of vehicles on roads under foggy weather conditions. The proposed system involves video acquisition, frame extraction, fog removal and vehicle counting. At first, the video is captured by camera and split into number of frames using frame extraction process. The Dark channel prior (DCP) algorithm is used to remove the fog from each frame and the background subtraction method and certain morphological operations are used to count the number of vehicles in real-time. Based on the vehicle count, the system specifies the time required to clear the traffic. This could facilitate ease traffic flow, save time, and even operate in foggy weather conditions, which is an improvement from the conventional timer-based operations of traffic signals.

Key words : FOG, Haze, Image, DCP, Airlight, Atmospheric Light, Vehicle.

1. INTRODUCTION

Now a day the utilization of automobiles is increasing every day which is causing more traffic congestion. The traffic congestion is a significant problem in Urban and Metro Politian areas. Due to increase in population in these areas causes to increase in vehicular density, traffic related problems. These problems leads to delayed services increase in transportation costs and fuel consumption. Due to the using of conventional traffic light systems at most of the traffic junctions, which are working based on fixed time concept leads to clumsy traffic flow.

Figure 1: Traffic image in Haze condition

For example if we consider two lines where one is having more vehicular density and another is having less vehicular density but both got same time of green signal where it is loss of time for one line. By considering this problem if we provide signal based on the vehicle density, we can avoid the loss of time and clumsy traffic flow. In the automatic light systems video cameras are used to record traffic information continuously. We can analyze traffic videos to detection and tracking of vehicles for traffic flow analysis by using different methods like Mixture of Gaussian (MOG), Code Book (CB) and Modified Code Book (MCB) [1], Tracking learning Detection (TLD) [2], Struck: Structured Output Tracking with Kernels [3] and High-Speed Tracking with Kernelized Correlation Filters [4] to count the number of vehicles passed per given time [5,6].

A vehicle detection approach was presented by Cao and his colleagues [7] in which vehicles are detected in static images using color and edge. In their work, the vehicles were fist extracted from the background only based on color and corner, edge maps, and wavelet coefficient by a cascade multichannel classifier to verify possible candidates. Another automatic vehicle system classification was presented by Ilyas et al. [1] that operate based on pixel-wise relations in a region. They used edge detection to calculate local features of the image and color conversion to segment the vehicle. Also, they used a Dynamic Bayesian Network for their classification. Vehicle detection based on high vertical symmetry was developed by Litzenberger et al. [2] to facilitate vehicle detection on a video stream. Also, Sun and his colleagues [4] proposed a new method to detect vehicles based on feature extraction and classification process. They used the Gabor filter to extract features and used support vector machine for classification. Meshram and his colleague in [5] fist constructed an initial background image according to the real-time situation of traffic environment and then segmented the current frame into a foreground region and background region accurately using the combined method of interface difference and subtraction method. Their method can detect moving vehicles fast and accurately in complex traffic situations. Also, [6] used the connected component labeling technique for complex conditions. Since reliable vehicle detection and tracking are a critical problem for most of the existing methods, we decided to present a new system to count vehicles even in dusty weather, vibrating camera, occlusion, and background noise. These conditions are hard to deal with, and not many works have been published working in such situation. Zhang et al. [14] proposed a video-based vehicle detection and classification system for vehicle counting, operating under 3 different conditions: normal weather, heavy shadow in the images, and light rain with slight camera vibration. Even though their results are quite promising, their system cannot handle longitudinal vehicle occlusions, severe camera vibrations, and headlight reflection problems. Ikoma et al. [13] proposed a method for car tracking based on bicycle specific motions in vertical vibration and angular variation via prediction and likelihood models, using particle filter for state estimation. The method was tested only under normal weather condition observing that the estimation was limited as the lighting conditions were reduced. Finally, Afolabi et al. [9] used monocular cameras, mounted on moving vehicles such as quadcopters or similar unmanned aerial vehicles (UAVs). These cameras are subjected to vibration due to the constant movement experienced by these vehicles and consequently the captured images are often distorted. Their approach used the Hough transform for ground line detection under normal weather conditions and concentrated on reducing the effect of the camera vibration. Our approach outperforms this point thanks to the implementation of our particle filter.

Different vehicle monitoring systems have been developed that use video in intelligent traffic systems. In this area, we must focus on two challenging parts of moving vehicle segmentation and recount cancellation strategy in different conditions such as cluttered background, dusty weather, and haze (fog, mist, dust, and other atmospheric phenomena) conditions. The main recession of outer images is due to haze, which affects image by color and contrast. Haze or Fog is nothing, but it is a collection of water droplets, it causes absorption and scattering. Scattering is having two phenomena attenuation and airlight and the resulting light coming towards the camera or the observer from the scene gets attenuated due to scattering through water droplets which reduces the quality of outdoor scene, visibility of the images, deforms visual perception, limits contrast. Visibility degradation due to bad weather is one of the biggest causes of road fatal injuries across the world. Diminishing the contrast due to scattering is termed as attenuation. The whiteness effect in the scene towards the observer or the camera is known as airlight. It is observed that attenuation and airlight are the functions of the distance between camera and scene. Hence depth map estimation is required for restoring true scene. World Health Organization (WHO) declared; one person is killed every 25 s due to road injuries. With the advancement of technology, many single image fog removal methods have been proposed. Fattal[10] proposed a method based on Independent Component Analysis (ICA) to estimate transmission map where restoration was based on color information and hence cannot be applied to the gray image and dense fog because dense fog is colorless. Tarel and Hautier [11] proposed a fast visibility restoration method based on linear operations but requires many parameters for adjustment. He et al. [12] proposed a very simple but effective single-image haze removal method using DCP and refined by soft matting. DCP is a kind of statistics of outdoor haze-free images that contain some pixels whose intensity is very low in at least one channel. Using this prior technique, direct estimation of airlight map is possible and high quality haze-free image is recovered but fails when the brightness of scene object is very close to the atmospheric light.The de-hazing Image improves the quality of an image in computer vision applications, like object detection and tracking, de-hazing improves the visual quality of images in computer vision applications, such as object detection and object tracking; however, haze removal is a challenging problem because of the significant difference between the haze and the unknown scene depth. Due to this several attempts have been made in devices by various computer vision algorithms to remove fog from images.

Fog removal algorithms [7,8] estimate the depth information under various assumptions as discussed for the Dark Channel Prior (DCP) technique [7]. In this work, Dark Channel Prior (DCP) is used as a base line for the proposed fog removal algorithm. Initially, the transmission map is defined using the DCP technique; subsequently, the transmission map is refined with the aid of a Simplified Dark Channel Prior (SDCP) using a set of filters consisting of the Proposed Adaptive Filter and an edge-preserving filter. Next, the refined transmission map is used to modify the scene radiance as the fog is removed.

Although, the Dark Channel Prior is an efficient method to remove fog and enhance image Contrast, it suffers from lengthy execution time, computational complexity and large memory requirement. The fog removal method proposed here, is fast and has negligible image degradation when used as input for the subsequent stage of car detection. Once the process of fog removal is complete, an edge detection algorithm is performed on the video, which is followed by a simplified car detection algorithm. The resultant image is clear with distinctively visible and detectable edges. The next step is to apply the proposed and simplified car detection algorithm. In this thesis, the main idea behind the car detection algorithm is to detect the vehicles and removes the fog or haze then it will count the vehicles.

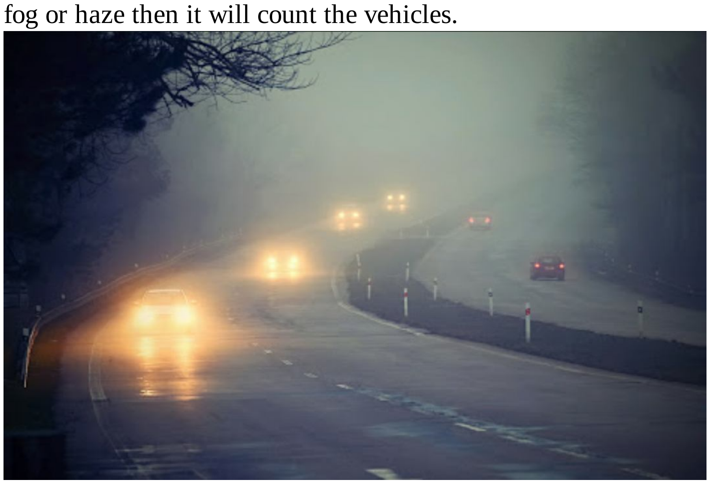

Figure 2: vehicles in Haze

In strict assumptions had to be made to detect the wheels, e.g., they must be of the same size, exist on the same horizontal line, and not at the top of the image with an approximate width and height of a car. The height was assumed to be about two-third and the width was assumed to be about three-fifth of the distance between the two wheels. It is important to state that this method cannot detect cars with oval shaped roof.

2. PROPOSED METHOD

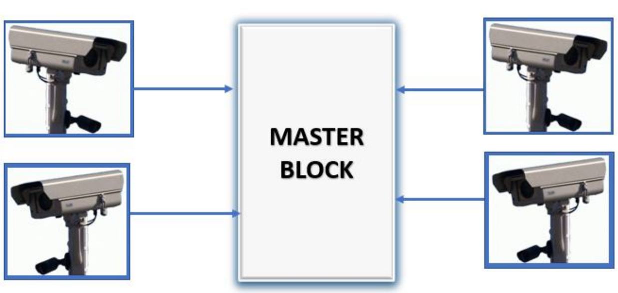

Figure 4: Block diagram of the proposed method

There are four cameras placed in such away that they are facing four different directions so that we can capture the traffic 360 degrees around them. They are capable of capturing the video frames parallelly. Further they are connected to the master block which is the logical and control unit of the whole system. We can referee the number of objects i.e vehicles as the density of each video frame. Depending on the density of each video frame the level of signal can be sent by the master block which is proportional to the density. This system is designed especially for the conditions such as Haze, FOG, dew so that we can track the traffic accurately. According to the system it is already predefined in the master block that delay in timer of traffic signals can be decided which is proportional to the density of the traffic. The series of process that takes place in the master block can be explained with the help of flow chart.

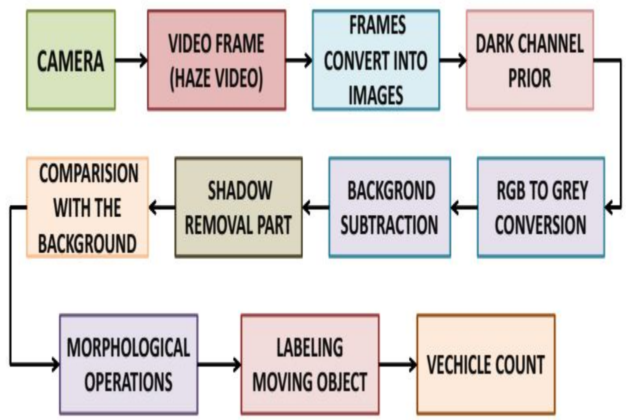

Figure 5: Steps of the proposed method

2.1 Dark Channel Prior

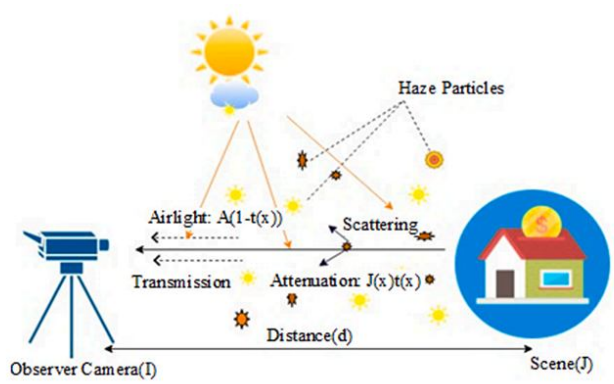

Figure 4: Formation of Hazy Image

The degradation of image quality in haze weather is mainly caused by the light scattering. Atmospheric scattering model [16] describes the physical properties of light transmitted, hazy image obtained by the imaging equipment can be represented as:

$$I(x) = J(x)t(x) + A(1 - t(x)) \qquad (2.1)$$

Where I is the observed hazy image, J is the scene radiance, A is the global atmospheric light that represents the ambient light in the atmosphere, and t(x) is the transmission of the reflected light, which is determined by the distance d(x) between the scene point and the cameras.

$$t(x) = e^{\wedge} - \beta d(x) \quad (2.2)$$

Where d is imaging distance, and β is the scattering coefficient of the atmosphere. Since the visible light with different wavelength scatter in the same proportion under homogeneous atmosphere conditions, so β commonly assumed to be a constant. The first term J(x)t(x) represents the direct attenuation model. Due to the effect of atmospheric particles' scattering and absorption, part of the reflected light from the surface of object suffers from scattering or absorption, and the intensity of rest exponentially decreases with the increase of imaging distance. The second term A(1-t(x)) represents the air light model. Because of atmospheric particles scattering, the color of the scene has been shifted. With the imaging of spreading distance, the atmospheric light intensity increases gradually.

In clear weather conditions, we have $\beta \approx 0$, and thus $I \approx J$. However, β becomes non-negligible for hazy images. The first term of $J(x)t(x)$ (*the direct attenuation*), decreases as the scene depth increases. In contrast, the second term of $A(1-t(x))$ (*the airlight*), increases as the scene depth increases. Since the goal of image dehazing is to recover J from I, once A and t are estimated from I, J can be arithmetically obtained as

$$J(x)=((I(x)-A)/t(x))+A \quad (2.3)$$

Dark channel prior algorithm is built on the supposition of the images which do not contain haze of outdoor. According to this assumption there are few pixels whose intensity value is very less or close to zero. These pixels are known as dark pixels. Dark channel is built on this observation. $Jdark$ is dark channel for image J where $Jdark$ is as:

$$J^{dark}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in (r,g,b)} J^{c}(y) \right) \quad (2.4)$$

where $\Omega(x)$is a patch centred at x, $J^c$is the color channel intensity. Dark Channel of an image is generally obtained using two minimum operators.

2.1.1 Atmospheric Light Estimation

The direct equation to evaluate the atmospheric light, $\hat{A}$is as follows

$$\hat{A} = \hat{I}\,(\mathrm{argmaxx}(I^{dark}(x))) \quad (2.5)$$

However, this method cannot estimate the atmospheric light correctly when image contains bright objects. Therefore pixels with top 0.1 percent of values of dark channel are carefully chosen as haze opaque. After selecting, the highest intensity pixel value among the selected is the value of $\hat{A}$ which is nothing but atmospheric light. The entropy value is given below which is taken directly as:

$$E(x) = \sum_{i=0}^{N} (p_x(i) * log_2(p_x(i))) \quad (2.6)$$

2.1.2 Transmission Map Estimation

After the construction of dark channel and estimation of atmospheric light, the next step is estimation of transmission map $\tilde{t}(x)$. To find the transmission map equation is modified as below:

$$\tilde{t}(x) = 1 \min_{y \in \Omega(x)} \left(\min_{c} \frac{I^c(y)}{A^c} \right)$$

$$\tilde{t}(x) \min_{y \in \Omega(x)} \left(\min_{c} \frac{I^c(y)}{A^c} \right) \quad (2.7)$$

It is mentioned that image may not look naturally when entire haze is removed as mentioned above. Therefore we need to retain small amount of haze. To achieve this a constant $\omega_0\,(0 < \omega_0 < 1)$is used and the equation is modified as follows:

$$\tilde{t}(x) = 1 - \omega_0 \min_{y \in \Omega(x)} \left(\min_{c} \frac{I^c(y)}{A^c} \right) \quad (2.8)$$

When the transmission map is not estimated properly or it is under estimated then problem arises. To avoid it we simply add a constant ρ. Now the transmission map equation becomes as follows:

$$\tilde{t}(x) = 1 - \min_{y \in \Omega(x)} \left(\min_{c} \frac{I^c(y)}{A^c} \right) + \rho \quad (2.9)$$

2.1.3 Transmission map refinement

Incorrect estimation for the transmission map can lead to some problems such as false textures and blocking artifacts. In particular, the block-min process decreases the apparent resolution of the dark channel, resulting in blurry transmission maps. For this reason, many methods have been developed to further sharpen the transmission map.

It is especially mentioned that many dehazing methods differ in the way of smoothing the transmission map. Table lists post-filtering methods used to improve the accuracy of the transmission map. Some filtering methods, such as the Gaussian and bilateral filters, use only transmission maps, whereas the other methods, such as soft matting, cross-bilateral filter, and guided filter, exploit a hazy color image as a guidance signal. Each method and its performance are analyzed in the following subsections.

2.1.4 Soft matting

We found that the Gaussian and bilateral filters are effective for removing false color textures in the transmission map. However, the transmission map should have a similar level of sharpness

to the color image for dehazing, which is impossible if the color image is not used in the transmission map refinement. To this end, the original DCP-based dehazing algorithm adopted the soft matting to refine the transmission map. From the observation that the degradation model is similar to the matting equation, the refined transmission map ^t is obtained by minimizing the energy function. It is equivalent to that of the sparse linear equation.

As can be seen, blurry edges in the transmission maps have been sharpened due to the use of color images. It should be noted here that the bilateral filter was also applied to the result of the soft matting to further refine the transmission map. To evaluate the performance of the soft matting only, the bilateral filter is not applied. Different values of λ and patch sizes were

used to find out the dependency of the performance of the soft

matting on the parameters. A large value of λ was preferred when a small local patch was used because the transmission map before the refinement tended to be inherently similar to the hazy image.

When the local patch of the size 15 × 15 was used, a proper value of λ (=2 × 10− 4 in our experiment)showed the best performance.

2.1.5 Image dehazing

The haze-free image can be easily obtained from the degradation model after estimating the airlight and transmission map which can be expressed as

$$J(x) = (I(x) - A / (\max(t(x), t0))) + A \qquad (2.10)$$

The background subtraction method is used for detecting the objects. This is done by comparing the two different frames with the matrix distance differences. In most of the background subtraction techniques it is observed that the video sequence is the static background. The background subtraction methods some of them which are developed by the researches are the Kernel Density Estimation (KDE), Gaussian Mixture Model (GMM) etc. The results of these two methods are good but not in real time. The background subtraction method has mainly three stages i.e., background modelling, foreground detection and preprocessing. The preprocessing stage, it involves the simple image processing in the input video and also it involves the image resizing, conversion and other processings. The next step is Foreground Detection, at this stage the foreground extraction process from the background. It is so simple and can be explained in equation (1)

$$h(x,y) = f(x,y) - g(x,y) \qquad (2.11)$$

Where □(x, y) is background subtraction result, f(x, y) is image frame, and g(x, y) is background modelling.

One way to extract objects from the background is to select this model through a threshold value of T.The image at the point g(x, y) at the value f(x, y) ≥ T is called the object (foreground), while the other is called the background. The equation of the thresholding value can be written as follows

$$g(x,y) = \begin{matrix} 1, if\ f(x,y) \leq T \\ 0, if\ f(x,y) < T \end{matrix} \qquad (2.12)$$

For multi thresholding condition the equation is as follows, Where T1 and T2 is thresholding value.

$$g(x,y) = \begin{matrix} 0, if\ (x,y) > T2 \\ 1, if\ (x,y) \leq T2 \\ 0, if (x,y) \leq T1 \end{matrix} \qquad (2.13)$$

Vehicle detection was managed with stages of pre-processing, background subtraction, gray scale to binary conversion and morphology operation as in the below figure.

(a) (b) (c)

(d) (e) (f)

Figure 5: Vehicle detection for counting (a) and (b) Original Image, (c) and (d) Conversion from RGB to Grayscale, (e) Background subtraction from (c) and (d), (f) Multi- thresholding with $\boldsymbol{T}1$ = 143and$\boldsymbol{T}2$ = 200

Background subtraction:

Background subtraction is a method for isolating out closer view components from the background and is finished by creating a frontal area veil. This method is utilized for recognizing progressively moving items from static cameras. Background subtraction strategy is significant for object following.

Shadows removal:

Shadows are regular marvels that show up in pictures because of the conflicting light of the scene being caught. As of late, the requirement for removal of shadows from pictures and recordings has picked up wide consideration because of the evil impacts of shadows on numerous PC vision assignments.

Comparison with the background: In this step we are comparing with the shadow removal image with ground truth image for finding the objects.

Morphological Operations

Morphology is a wide arrangement of picture processing activities that process pictures dependent on shapes. In a morphological activity, every pixel in the picture is changed dependent on the estimation of different pixels in its area. By picking the size and state of the area, you can build a morphological activity that is touchy to explicit shapes in the info picture.

The morphological operations are used and works on the basis of set theory. The main objective of this operation is to remove the unwanted pixels or to remove the imperfections of an image. It consists of four types of operations, they are as follows dilation, erosion, opening and closing. Here in these we are using the two operations they are dilation and erosion. The dilation is used to fill the holes and gaps i.e., the missing pixels are filled in the continuous object. In short, the dilation is nothing but adding the pixels to the boundary elements. The erosion is opposite to the operation of dilation. It reduces the size and boundary pixels. It removes those structures which are lesser in size and it removes the noisy between the two objects. The opening and closing operations are the combination of dilation and erosion.

After completion of all steps label the object and count the vehicles. In this paper we are using only one camera for analysis, removing haze and count the vehicle density. For Traffic signal application place four cameras in each direction.

5. RESULTS

In the below image we can see the images of the vehicles which consists of fog. The first step we are taking the video of the vehicles with fog. Then in the next step we are removing the fog by using the dark channel prior algorithm. In the third step, we are going to eliminate the background part by using the background subtraction method. After eliminating the background part we are getting the foreground part with vehicles. In the final step we are going to detect the vehicles and count the vehicles. Depending on the vehicle count we are going to give the duration.

Figure 6: Result Images of the vehicles with count 1

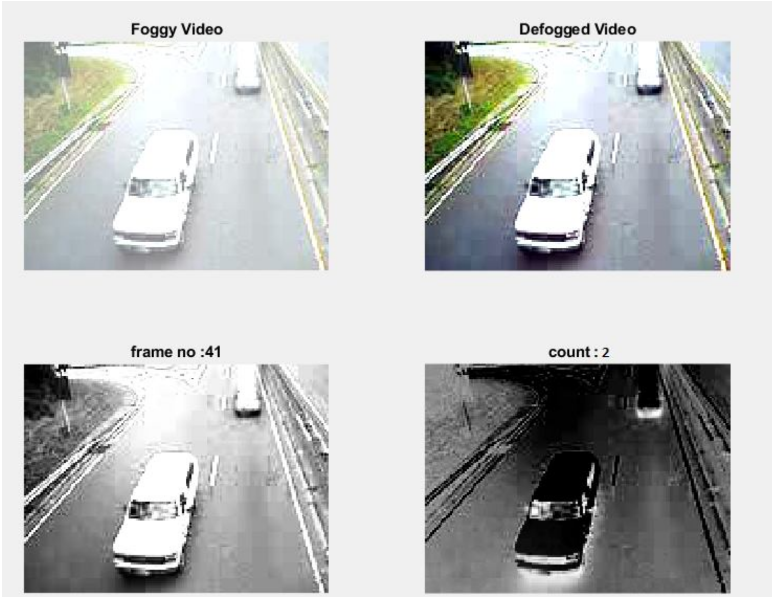

Figure 7: Result Images of the vehicles with count 2

Figure 8: Result Images of the vehicles with count 3

5. CONCLUSION

Here in this paper, we proposed a system which overcomes the limitation of the earlier techniques in controlling the traffic in both normal as well as foggy conditions. In the previous system there are some drawbacks, one of them is that time is being wasted by green light on the empty roads and the other problem is that the previous existing system of the traffic control does not work in the cloudy conditions. By using this technique, we can overcome the problems. This paper says that the image processing is more efficient method in order to control the traffic as compared to the traditional techniques. To control the traffic light the image processing is the better technique. It can reduce the traffic congestion and avoids the time being wasted on empty roads. In future this technique can be used to find the number plate of the vehicles in foggy as well as hazy conditions. This technique is very useful in the application of video surveillance in foggy as well as haze environments.

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