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Day and Night-Time Drive Analysis using Stereo Vision for Naturalistic Driving Studies

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Abstract— In order to understand dangerous situations in the driving environment, naturalistic driving studies (NDS) are conducted by collecting and analyzing data from sensors looking inside and outside of the car. Manually processing the overwhelming amounts of data that are generated in such studies is very comprehensive. We propose a method for automatic data reduction for NDS based on stereo vision vehicle detection and tracking during day- and nighttime. The developed system can automatically register five NDS events, mainly related to intersections, from an existing NDS dictionary. We propose a new drive event which takes advantage of the extra dimension provided by stereo vision.In total, six drive events are selected on the basis of them being problematic to detect automatically using conventional monocular computer vision approaches. The proposed system is evaluated on day- and nighttime data, resulting in drive analysis report. The proposed system reach an overall precision of 0.78 and an overall recall of 0.72.

I. INTRODUCTION & MOTIVATION

In 2011 a total of 253,108,389 vehicles were registered in the USA [1], with this many vehicles on the road, crashes are going to happen. In order to analyze the causes of crashes, a lot of research has been done in naturalistic driving studies (NDS). NDS are the study of data from everyday driving, where a wide range of data are collected and analyzed. The purpose is to provide insight into the patterns and behaviors of drivers leading up to and during near-crashes and crashes. [2] defines the scope of understanding vehicular traffic behavior from video as being able to analyze and recognize moving behavioral patterns and being able to describe them using natural language.

The two most notable NDS are the 100-car study [3] and the Strategic Highway Research Program(SHRP) [4], [5], which try to determine patterns and factors impacting the driver's behavior on the road. Discovering these patterns and factors could provide an indication of what sometimes leads to crashes. The previously mentioned 100-car study is based on data captured from 2 million miles on the road, corresponding to nearly 4,300 hours of data, captured from 240 different drivers in the span of 1 year. In the more recent SHRP study, nearly 3,100 drivers have been collecting data from six different places in the USA during the 3-year study. The information is collected with a variety of sensors, providing data such as speed, GPS-position, vehicle dynamics, and video footage covering 360°around
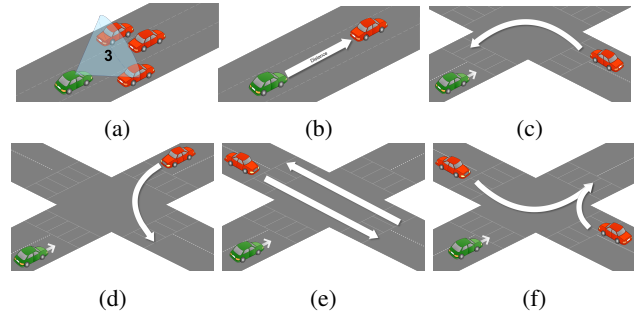
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Fig. 1: Automatically detectable data and events. Green is ego-vehicle, red is other vehicles. **(a)** Avg. vehicles in front of ego-vehicle **(b)** Distance to rear-end of front vehicle. **(c)** Vehicle turn to opposite direction. **(d)** Vehicle turn left across path. **(e)** Vehicle drive straight across path. **(f)** Vehicle turn to same direction.

the vehicle. All this data is not straightforward to analyze. In [6] the NDS data is categorized into:

- Low-level: sensor data e.g. position from GPS.
- Mid-level: drive events e.g. lane changes or traffic density information.
- High-level: high level semantics e.g. driver behavior or driving styles.

In [7], [8], data reduction for NDS is carried out manually by trained personnel, e.g. hand-labeling a sequence of video footage. The hand-labeling of events must be consistent, therefore a dictionary, such as the one found in [9] is used. This NDS dictionary was adapted in SHRP. If processing of the collected data could be automated, it would allow for more comprehensive studies. 61% of daytime and 38% of night time crashes involve multiple vehicles [10], therefore NDS events based on detection and tracking of other vehicles are essential. Since a disproportionate number of crashes happen at night [11], it is important to also to detect vehicles during nighttime. Intersection are especially prone to crashes, since vehicles need to cross paths. To the best of the authors' knowledge, non of the current published work in the area of data reduction for NDS, utilize stereo vision for automatic drive analysis. [12] detects objects' 3D location and orientation in intersection traffic scenes using scene information from stereo images. However, it is not used for NDS, nor evaluated on nighttime data. In [13], the symmetry and color rear-lamp pairs are utilized for detection and tracking. A similar approach is used in [14], where

the proposed system is limited to only consider scenarios where vehicles are fully visible. The same paper provides a brief overview of how monocular vehicle detection has trouble dealing with variations in lighting, weather, changing vehicle shape, and color. The most notable issue with these approaches is that the detection is highly depended on both rear-lamps being visible. Stereo vision is used in [15] to track a vehicle after detecting it using monocular vision. The purpose of introducing stereo vision is to make their system more robust to occlusion. This is also discussed in [16], where the introduction of 3D shows promising results and alleviate some occlusion issues. Most vehicle detection is done in the monocular domain, as e.g in [17] where lane detection is included for localizing and tracking the vehicles and in [18] where parts of vehicles are detected and tracking, the same paper remarks that detecting the turning vehicles in intersection is especially challenging. Monocular systems which aspire to detect vehicle from all possible viewpoints and under changing light conditions, requires a large amount of varied training data.

In this paper, we introduce a stereo vision system for automatic NDS data reduction on both day- and nighttime data. This enables detection and tracking of vehicles in scenarios that would be problematic for monocular detectors. The proposed system will handle a handful of NDS events, which especially benefit from the extra dimension in stereo vision. The treated NDS events are illustrated in Figure 1.

The contributions made in this paper are:
- Using stereo vision for automatic data reduction for NDS on both day- and nighttime data, with focus on intersections (Figure 1c, 1d, 1e, 1f).
- Using stereo vision for determining the average number of vehicles in front of the ego-vehicle. (Figure 1a).
- Introducing a new NDS event: Average distance to vehicles directly in front of the ego-vehicle. (Figure 1b).

The rest of the paper is organized as follows: In Section II, related work in the area of data reduction for NDS is presented followed by an overview of recent work on stereo vision for obstacle detection on roads. An overview of the developed system and the drive semantics that we wish to label automatically are presented in Section III. In section IV the methods which constitute the system are presented. The results are discussed in Section V, followed by concluding remarks in Section VI.

II. RELATED WORK

Before developing a stereo vision system to be used for generating a drive analysis report, we briefly present some of the recent research published with regards to automatic NDS data reduction. Furthermore, we introduce some of the recent and most notable work in the field of object detection with stereo vision. This is limited only consider stereo vision with the purpose of either improving the disparity with regard to object detection in traffic scenes and work that utilizes stereo vision for vehicle detection.

In [19], the statistics of near-crashes and crashes are used to identify factors related to driver associated risks, such as age, experience, gender, and demographic. Similar studies are conducted in [20], where results show that near-crash and crash percentage among teenagers were 75 % lower in the presence of adult passengers and 96 % higher among teenagers with risky friends. In [21] NDS are used to quantify distracting activities from e.g. a mobile phone, that results in loss of concentration. Results show that a driver in average is engaged in a distracting activity every 6 minutes, which could results in a near-crash or crash.

The process for manual data reduction for NDS is quite comprehensive and time consuming, it is therefore desirable to automate it by e.g. applying computer vision to understand the traffic scene. An example of one such study is seen in [6], where monocular computer vision and information from the CAN bus is used to automatically detect 23 drive events, including lane position, vehicle localization within lanes, vehicle speed, traffic density, and road curvature. In [22], a system is developed for automatic labeling driver behavior events with regards to overtaking and receding vehicle detection. This type of system is categorized as Looking-In and Looking-Out(LiLo), which is discussed in depth in [23]. LiLo fits well with using multiple inputs to understand the driver's behavior. An example of Li is [24] where driver behavior with respect to hand activity is evaluated.

In [25], a review of the research conducted since 2005 in both monocular and stereo vision with respect to vision-based vehicle detection is presented. Before 2005, [26] conducted a review of on-road vehicle detection. Most of the research published with regard to vehicle detection is evaluating the methods on data, representing a limited part of the challenges. In [27] the accurate and efficient Semi-Global Matching(SGM) is introduced. SGM make use of epipolar geometry, and in most cases a set of rectified stereo images. Horizontal lines in the images are used as a scan lines, matches are then found with a 1D disparity search. A match for a pixel in the left image is found in the right image by searching through the corresponding horizontal line and locating the most similar block to a reference block around the original pixel in the left image. The offset between these pixels is known as the disparity, which is directly related to the distance to the corresponding object. In the same paper, the LR-RL-consistency check is proposed for reducing noise in the calculated disparity image.

In [28], [29], the so-called v-disparity is generated and used for separating objects from the ground/road surface. The v-disparity examines the vertical coordinates in a (u,v) image coordinate system and is constructed using a disparity map from, e.g. the SGM algorithm. What is especially histograms are calculated for each row in the disparity. Significant surfaces in the disparity map will then show up as lines in the v-disparity.

In [30], 6D-vision is introduced, where features are found in the left monocular image and then located in 3D by
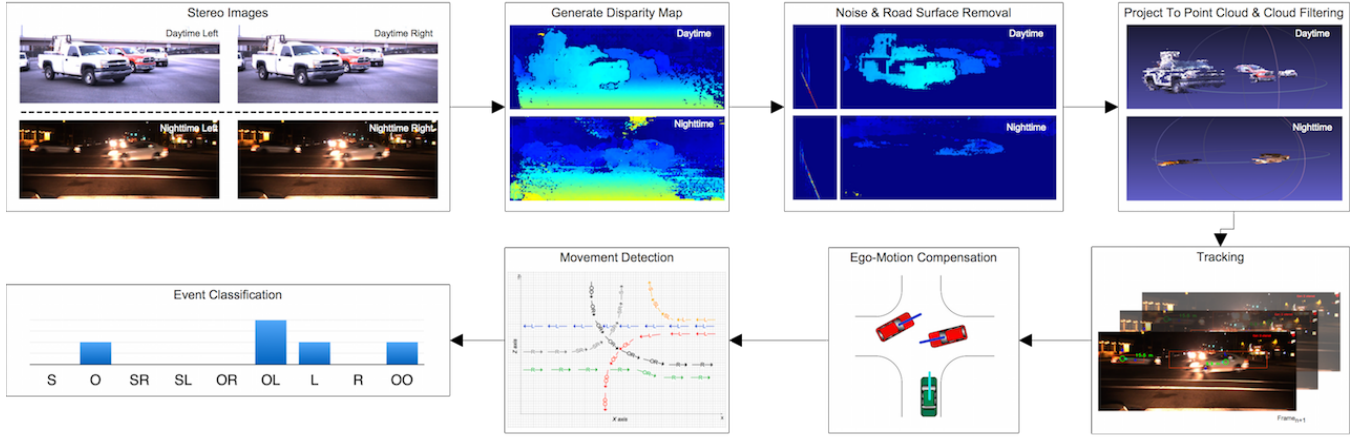
Fig. 2: Flow diagram of the developed system, illustrated with both day- and nighttime data.

using the stereo images. For each feature point, a Kalman filter is used to estimate a 6D vector consisting of the 3D position and 3D motion vector. [30] is able to do ego-motion compensation by identifying the static 6D points. The predicted static world points are then compared to the remaining points to isolate the ego-motion. In [31], this work is continued and by using 6D-vision, tracked feature points are represented as stixels, which is a vertical areas of equal disparity. The tracked objects are being classified using prior knowledge of vehicle shapes. Alternatively, objects can be classified using clustering in the disparity map, as seen in [28]. In [32], [33], temporal and scene priors from good conditions are used with the purpose of improving the disparity map in adverse weather conditions, such as night, rain, and snow. Using these priors, the object detection rate improves on a database of 3000 frames including bad weather while reducing the false positive rate.

III. SYSTEM OVERVIEW

The flow of the system is shown in Figure 2. A Bumblebee XB3 stereo camera is used to acquire stereo image pairs with a capture speed of 16 FPS in an resolution of 1280x960. These images are rectified using the factory calibration. A disparity map is generated and noisy pixels are removed. The road surface is removed using the detected line in a corresponding v-disparity. The remaining pixels are considered vehicle candidate pixels. These pixels are projected into 3D world coordinates and outliers are removed. Clusters are found by grouping points that are close neighbors. Each sufficiently big cluster is regarded as a detected vehicle. The clusters' center points are used for nearest neighbor tracking between frames and for determining the distances from ego-vehicle to detected vehicles. Before the detected vehicles' movement between frames is determined, their movement is adjusted according to the ego-vehicles motion. Finally, the vehicles are tracked, and NDS event are detected and logged in a drive analysis report.

IV. METHODS

In this section all of the methods which are used in the proposed system are presented. The section is divided into subsections corresponding to the stages seen in Figure 2.

A. Generate Disparity Map & Noise Removal

Stereo images captured under poor conditions may contain very dark, very bright, or otherwise untextured regions causing noise and artifacts in the disparity map. Besides this, inconsistencies between the image pairs may arise in an uncontrolled environment e.g. because of reflections in the camera lenses. A noisy disparity map is bound to lead to problems later in the system, therefore the disparity map is post-processed in an attempt to reduce the number of noisy pixels. Figure 3 shows an examples of a two noisy disparity image in the left box. In the right box, the two corresponding noise reduced disparity images are seen.
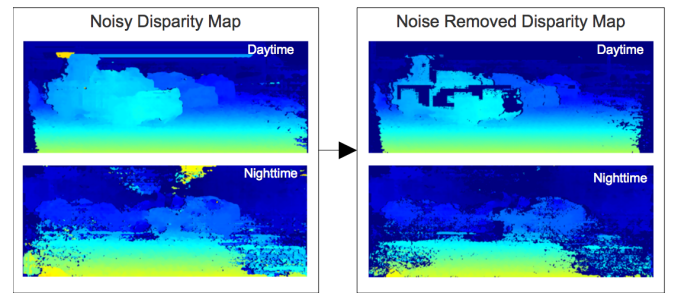
Fig. 3: Examples of raw day and night-time disparity maps and the corresponding noise reduced disparity maps.

1) LR-RL consistency check: By using first left and then right image as reference, when searching for matches in the stereo pair, a so called LR-RL consistency check is done. The LR-RL consistency check is used a little differently compared to the original proposal in [27] and the implementation provided by OpenCV. We wish to keep as many disparity pixels as possible for later stages. In case of a disparity difference in the consistency check, the lowest

value is simply selected as the output pixel, rather than discarding the pixel entirely. The result this modified LR-RL consistency check versus the traditional, with a maximum disparity difference of 5 is seen in Figure 4.

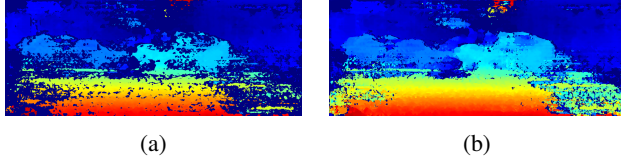(a)   (b)

Fig. 4: (a) Traditional LR-RL consistency check. (b) Proposed LR-RL consistency check.

2) Temporal consistency check: By looking at the value of a pixel in the previous frame and comparing it with the value in the current frame, a significant amount of noise can be removed. This check is based on the assumption that it is uncommon for correctly matched disparity pixels to erratically change value from frame to frame. In case of movement, this check will result in a dark edge around the moving objects in the disparity map.

3) Monocular color check: Large uniform regions are problematic when calculating the disparity map as they may result in artifacts and noise. Especially in night scenes, a large part of the images consist of dark regions. The same is the case in brightly lit scenes. Over and under exposure can be handled to some degree by adjusting the camera accordingly. Regions are removed by searching for pixels with values very close to either of the extremes in the left monocular RGB image. As these pixels are considered as sources of noise, they are simply masked out in the disparity map.

B. Road Surface Removal

The noise reduced disparity map contains disparities for road surface pixels and obstacle pixels. Since the vehicles that must be detected are found among the obstacle pixels, the disparity pixels associated with the road surface must be removed.

1) Road surface detection using v-disparity: The road surface is found by searching for the most significant line in the v-disparity using RANSAC. This method will not work well unless parts of the road surface is visible. In cases where a satisfactory line cannot be found, the last good line is used for road surface removal. Additionally, the line parameters are filtered using a Kalman filter to smooth out faulty road surface estimations. The calculated line is then used as a threshold for determining if pixels belong to objects above the road surface.

C. Project To Point Cloud & Cloud Filtering

1) Projecting disparity image to 3D point cloud: Using the camera's focal length f(in pixels) and baseline b(in meters), along with the calculated disparity d(in pixels), the actual distance z to objects in the camera's view can be

found. The remaining x and y components of the world co-ordinate are the column and row index of the disparity pixel. Equation (1) shows the relations that make this possible.

$$z = \frac{f \cdot B}{d} \quad x = \frac{col \cdot z}{f} \quad y = \frac{row \cdot z}{f} \tag{1}$$

Only disparity map pixels above a certain threshold are projected to 3D world points. This is due to the exponentially increasing inaccuracy with lower disparity values, which makes it difficult to determine whether point is noise, background, or in fact belong to an object.

D. Vehicle Segmentation in Point Cloud

The acquired point cloud is preprocessed in the following steps in order to clean up the data points for segmentation into clusters constituting vehicles.

1) A pass through filter removes near and distant points. These point degrade performance and can be removed since they are of little interest.
2) Remaining points are downsampled using a voxel grid, insuring an even distribution of points and greatly reduces the number of points, resulting in a reduced processing time.
3) Outlier removal based on mean distance to neighboring points compared to a global mean and standard deviation.

Clusters are found by creating a k-d tree which organizes points according to their distance to neighbors, this enables efficient searches in the 3D point cloud.

E. Vehicle Tracking

In order to understand what other drivers are doing in relation to the ego-vehicle, their vehicles must be tracked. This is done based on the center point of each of the segmented clusters, these center points are filtered using a Kalman filter in order to make the prediction of a match in the following frame more accurate. The best match is found using the euclidean distance between the predicted center point and the segmented center point in the next frame.

F. Visual Ego-Motion Compensation

For compensating for the subject vehicle's ego-motion while e.g. approaching an intersection, we utilize the *LIB-VISO2: C++ Library for Visual Odometry 2* which can calculate the translation and rotation between moving frames captured by stereo camera. For further explanation we refer to [34].

G. NDS Event Detection

For all detected vehicles, individual frame to frame movements are categorized to form a basis for determining which NDS events have occurred. Figure 5 shows the different movements that are detected. Based on the movements, a histogram is created and used for classifying the NDS event type. The arrows symbolizes vectors between vehicle center points and the attached letters indicate the movement type.
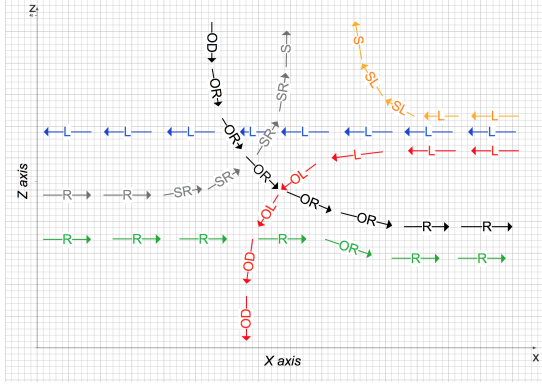
Fig. 5: Movements detected by the system. Every movement is seen from the viewpoint of the ego-vehicle. S (same direction), SR (same direction and towards the right), SL (same direction and towards the left), O (opposite direction), OR (opposite direction and towards the right), OL (opposite direction and towards the left), R (right), L (left).

In addition to the movements seen in Figure 5, a category is created for cases where little or no movement are detected. This category is labeled OO. A movement histogram is created for each vehicle, where a bin corresponds to one type of movement. The histogram is matched to a training histogram for each of the NDS events. Figure 6 shows an example on one such histogram.

Fig. 6: Example of histogram of detected movements.

The following four NDS event are each described by specific training histograms.

- Other vehicle turn left across path.
- Other vehicle turn onto opposite direction.
- Other vehicle drive straight across path.
- Other vehicle turn onto same direction.

Additionally, we quantify the existing NDS event, *Average number of cars in front of ego-vehicle*. The total number of detected vehicles is recorded for each frame throughout the entire video sequence and the average is calculated when the NDS rapport is generated. The purpose is to quantify the traffic scene density, by the average number of vehicles in front for the ego-vehicle. Finally we propose a new NDS event which is the *average distance to the rear end of the vehicle directly in front* of the ego-vehicle. This is meant as a measure of the ego-vehicle driver's aggressiveness.

V. RESULTS

The system is evaluated based on 14 day and 12 night video sequences. In each sequence the occurrence of each event, also referred to as the ground truth (GT) is manually hand-labeled. Precision and recall are found using the system output(SO), correctly detected events(TP), incorrectly detected events(FP), and finally missed events(FN). Precision and recall are calculated according to (2).

$$Precision = \frac{TP}{TP + FP} \quad Recall = \frac{TP}{TP + FN} \quad (2)$$

Precision is the ratio of correct event detections compared to the actual number of events. Recall is the ratio of correct event detections compared to the total number of detections.

In Figure 7, an example of the NDS event *left turn across Path* is seen. The blue cross represents the cluster's center of mass, the blue text, next to the blue circle, is the measured distance from ego-vehicle to the vehicle's closest point. The blue text stating, "R" and "OR" next to the green circle, tells that the detected vehicles' movements are determined to be right and opposite right movement, respectively.
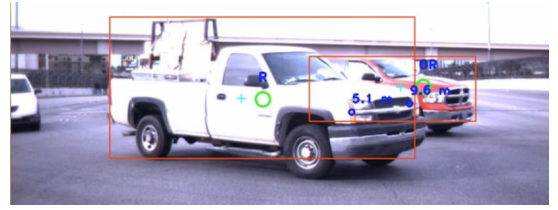

Fig. 7: Partially occluded vehicle detected in a left turn.

In Table I the results are shown. The 12 nighttime video sequences consists of a total of 3933 frames. The 14 daytime videos consists a total of 4992 frames. A result of e.g 35/32 corresponds to 32 manually annotated GT events and 35 system detections. For calculating the precision and recall, each classification done by the system is manually defined as either a TP, FP, or FN. The listed precision and recall numbers are a total from both day- and nighttime data.

TABLE I: Summary of drive analysis from NDS. Results are listed as [SO/GT]. P and R are abbreviations for precision and recall.

Drive Behavior Event	Daytime	Nighttime	P	R
Right - straight across path	35/32	5/19	0.95	0.63
Left - straight across path	45/34	11/33	0.87	0.67
Left turn across path	5/5	20/1	0.75	1
Turn onto opposite dir.	32/37	41/15	0.68	0.93
Short turn onto same dir.	7/5	9/5	0.63	1
Long turn onto same dir.	1/16	1/8	1	0.09
Avg. number of cars	1.67/1.74	1.6/1.3	NA	NA
Avg. distance to car	8.73 m	10.98 m	NA	NA

Table I indicates that the proposed system is able to handle most of the events. However, the system often had difficulties with detecting vehicle far away, especially at night, resulting in poor performance for vehicles turning onto the same direction. The average distance to the vehicle in front of the ego-vehicle was found to be shorter during the daytime, which could indicate people are using a larger safety distance when the visibility is decreased, or it might be a result of lower traffic density in those hours.

Future improvements to the system includes creating a mask using top-hat morphology instead of the monocular

color check for removing big texture-less regions. The color check method removes big parts of black and white vehicles. It was not possible to verify the accuracy of the measured average distance to vehicles, based on the video clips that were used for testing. Finding the ground truth using a laser range finder would be interesting to establish the accuracy of the distance measurements. The ego-motion compensation proved useful, but the estimates were noisy at times. The exact motion of the vehicle can alternatively be extracted from the CAN bus. More significant was the impact from the tracked center points of vehicles, which would shift back and fourth based on the quality of the disparity map. These two issues were the main contributors to wrong event classifications. The varying performance can be attributed to the difficult conditions under which much of the image data was collected. Most false negatives were a result of occlusions or incorrect road surface detection.

VI. CONCLUSION

We presented a system using stereo vision for automatic data reduction in NDS with focus on intersections and distance measurements. The use of stereo vision is considered beneficial, especially in scenarios such as the one seen in Figure 7. The system proved to work in both day and nighttime conditions with a drop in overall performance for the night sequences. Experiments show very promising detection, trajectory, and automatic event classification rates with an overall precision of 0.78 and recall of 0.72.

Future work includes looking at additional NDS events where stereo vision can be utilized and identifying the exact accuracy of the distance measurements achieved with stereo vision.

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