Lane Detection and Tracking by Monocular Vision System in Road Vehicle

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***Abstract*— In this paper, we address the problem of lane detection and lane tracking system by a single camera CCD, installed on-broad of a vehicle for driving assistance or autonomous vehicle control in road environments. A lane detection algorithm based on Support Vector Machines (SVM) classifier for marked or unmarked roads is proposed and Catmull Rom splines based lane model combined with a simple Kalman filter for the tracking algorithm. The results of the experiment are evaluated on a number of road scenes images, and show the performance of our proposed approach.**

Keywords- Lane detection; Lane tracking; Support Vector Machine; Catmull Rom splines; Machine vision; Kalman filter.

I. INTRODUCTION

Advanced Driver Assistance Systems (ADAS) essentially focus on intelligent vehicles which, through some form of sensor, can understand the environment around them to assist the human driver in vehicle operations (driver assistance) or fully control the vehicle (automation). For examples of ADAS are Adaptive Cruise Control (ACC), for automatically maintaining a safe time gap with a preceding vehicle, and Lane Departure Warning (LDW), for warning the driver in case the vehicle starts to leave the lane inadvertently. The major characteristic of ADAS is the requirement of observing and understanding key aspects of the vehicle's environment in real-time. A robust detection and tracking via on board camera of lane markings and boundaries is an important component of the driver assistance and warning system, which provides information on lane and boundaries structure [2], [3] and [4].

It is important to obtain robust information about road boundaries. Variety of methodologies and concept has been proposed by utilising various computer vision and image processing techniques for vision based road boundary detection and Tracking systems [17], [18] and [19]. However, several conditions can decisively degrade the performance of lane detection techniques: shadows, climate, occlusion, etc…

Conventionally, there are two classes of approaches used in lane detection and tracking in an images sequence: the feature-based approach and the model-based approach. In feature-based technique, tracking is performed by combining the low level features such as painted line or edges or road boundaries. However this technique may suffer from occlusion or noise or in critical shadows conditions. The model-based technique attempt to determine mathematical models for road boundaries, like straight line, parabolic or spline curve of the tracking road [10]. The processing of detecting lanes is approached as processing of calculating those model parameters. This way, the model-based technique is much more robust against noise and missing data compared with the feature-based technique.

Motivated by the above problems, we presents in this paper our proposed lane boundaries detection and tracking algorithm, which firstly segments the images into two classes of regions (Road, Not-Road) based on an Support Vector Machine (SVM) learning, secondly modelling the curves of lane boundaries by a Catmull Rom splines technique to define the initial contours of the road, finally a Kalman filter is used to track the lane boundaries over time in an images sequences.

II. EXTRACTION OF ROAD AREA

A fundamental stage in computer vision system is to generate a compact and a representative description of an image, more exploitable than the whole of the pixels; it acts of the segmentation of images. It allows the extraction of the principal areas of the scene by using one or more homogeneity criteria (Color, Texture, Form …) and connexity space.

The segmentation of image color can be done starting from an unspecified representation of the color: therefore, the first stage of any method of color segmentation will consist in transforming the image of space RGB in selected space (L*a*b, YCbCr, HSV ...). The choice of the color space for the segmentation of an image is not easy and it is sometimes dependant on the type of application and very particular factors.

A segmentation category method of images is based on a classification algorithm. The main idea of the classification algorithm is to classify the road image into two classes: Road and Not-Road, obtaining a binary image as show in Fig. 1, based on the theory learning using the color and coordination as the features. Feature is one of most important ingredients for building a good classification system.

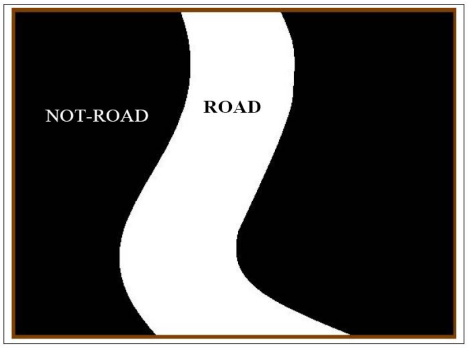

Figure 1. Classification by SVM of a road image.

Recently, particular attention has been dedicated to Support Vector Machines as a classification method or statistical learning tool that was initially developed by Vapnik in 1979 and later developed to a more complex concept of structural risk minimization (SRM) [12]. SVMs have often been found to provide better classification results that other widely used pattern recognition methods, such as the maximum likelihood and neural network classifiers. Thus, SVMs are very attractive for the classification of images.

The SVM approach seeks to find the optimal separating hyperplane between classes by focusing on the training cases that are placed at the edge of the class descriptors. These training cases are called support vectors. A complete formulation of Support Vector Machines can be found at a number of publications [11], [12] and [13]. Here, the basic principles will be presented and then their implementation and application to Road Based Image Extraction will be evaluated.

A. SVM Algorithm

Let us consider a supervised binary classification problem. If the training data are represented by $D=\{x_i, y_i\}_{i=1}^{k}$, where $x_i \in R^n$ is an input vector and $y_i \in \{\pm 1\}$ is an output class label vector. In this paper, x_i is consisted the three components of a color image, after transformation of spaces: RGB space towards YCbCr space followed by a transformation into HSV space, and $y_i=+1$ for class Road area and $y_i=-1$ for class Not-Road.

Suppose the two classes are linearly separable. This means that it is possible to find at least one hyperplane defined by a vector w with a bias b, which can separate the classes:

$$g(x)=w\bullet x+b=0. \tag{1}$$

To find such a hyperplane, $w \in R^n$ and $b \in R$ should be estimated in a way that $y_i(w\bullet x_i+b)\geq +1$ for $y_i=+1$ (class Road) and $y_i(w\bullet x_i+b)\leq -1$ for $y_i=-1$ (class Not-Road). These two, can be combined to provide (2):

$$y_i(w\bullet x_i+b)-1\geq 0. \tag{2}$$

Many hyperplanes could be fitted to separate the two classes but there is only one optimal hyperplane that is expected to generalize better than other hyperplanes, Fig. 2. The goal is to search for the hyperplane that leaves the maximum margin between classes. To be able to find the optimal hyperplane, the support vectors must be defined. The support vectors lie on two hyperplanes which are parallel to the optimal and are given by:

$$w\bullet x_i+b=\pm 1. \tag{3}$$

If a simple rescale of the hyperplane parameters w and b takes place, the margin can be expressed as $\frac{2}{\|w\|}$. The optimal hyperplane can be found by solving the following optimization problem:

$$\text{Minimize} \quad \frac{1}{2}\|w\|^2. \tag{4}$$

$$\text{Subject to} \quad y_i(w\bullet x_i+b)\geq 1. \quad i=1,2,\ldots k.$$

Using a Lagrangian formulation, the above problem can be translated to:

$$\text{Maximize} \quad \sum_{i=1}^{k}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{k}y_i y_j\alpha_i\alpha_j\langle x_i, y_j\rangle. \tag{5}$$

$$\text{Subject to} \quad \sum_{i=1}^{k}y_i\alpha_i=0. \text{ and } \alpha_i\geq 0.$$

Where α_i are the Lagrange multipliers associated with constraints in (5).

Under this formulation, the optimal hyperplane discriminant function becomes:

$$g(x)=\sum_{i\in S}\alpha_i y_i\langle x_i x\rangle+b. \tag{6}$$

Where S is a subset of training samples, that correspond to nonzero Lagrange multipliers. These training samples are called support vectors.

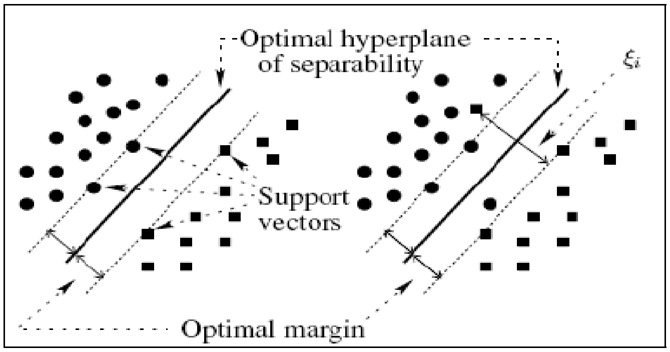

Figure 2. Left: The case of linear separable classes. Right: The case of non linear separable classes. ξ measures the error of the hyperplane fitting.

In most cases, classes are not linearly separable, and the constrain (2) cannot be satisfied. In order to handle such cases, a cost function can be formulated to combine maximization of margin and minimization of error criteria, using a set of variables called slack variables ξ, see *Fig. 2*. This cost function is defined as:

$$\text{Minimize } J(w,b,\xi) = \frac{1}{2}\left\|w^2\right\| + C\sum_{i=1}^{k}\xi_i. \tag{7}$$

$$\text{Subject to } y_i(w \bullet x_i + b) \geq 1 - \xi_i. \quad \text{i=1,2,…k.}$$

To generalize the above method to non-linear discriminant functions, the Support Vector Machine maps the input vector x into a high-dimensional feature space and then constructs the optimal separating hyperplane in that space. One would consider that mapping into a high dimensional feature space would add extra complexity to the problem. But, according to the Mercer's theorem [12] and [13], the inner product of the vectors in the mapping space, can be expressed as a function of the inner products of the corresponding vectors in the original space.

The inner product operation has an equivalent representation:

$$\phi(x)\phi(z) = K(x,z). \tag{8}$$

Where $K(x,z)$ is called a kernel function. If a kernel function K can be found, this function can be used for training without knowing the explicit form of ϕ . The dual optimization problem is now formed as:

$$\text{Maximize} \sum_{i=1}^{k}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{k} y_i y_j \alpha_i \alpha_j K(x_i, x_j). \tag{9}$$

$$\text{Subject to } \sum_{i=1}^{k} y_i \alpha_i = 0. \text{ and } \alpha_i \geq 0.$$

By choosing different kernel functions, the SVM can emulate some well known classifiers:

- Linear kernel:

$$K(x_i, x_j) = x_i . x_j .$$

- Polynomial of degree d:

$$K(x_i, x_j) = (1 + x_i . x_j)^d .$$

- Gaussian radial bias function (RBF):

$$K(x_i, x_j) = \exp - \frac{\left|x_i - x_j\right|^2}{\sigma^2}.$$

The resulting classifier, we will get the decision function:

$$g(x) = sign(\sum_{i \in S} \alpha_i y_i K(x_i, x) + b). \tag{10}$$

Now, we can be applied this decision function $g(x)$, to other road images to extract the two classes, Road area and Not-Road area (obtaining a binary image), it is the good generalization ability of the SVM.

III. EXTRACTION OF LANE BOUNDARIES MODEL

The simplest geometrical model which can be used to represent the two road boundaries or the way (the central center line of highway) is the straight line. But in order, to if required take account the curve of the road, it is necessary to introduce at least an additional parameter into the model [5], [6] and [7]. As Catmull Rom splines can form arbitrary shapes by control points, it can describe a wider range of lane structures than other lane models such as straight and parabolic model, developed for computer graphics purpose [10]. It is initial use was in design of curves and surfaces, and has recently been used in several applications.

The local interpolating spline Catmull Rom splines are a family of cubic interpolating splines, have C1 continuity, local control, and interpolation, but do not lie within the convex hull of their control points. Formulated such that the tangent at each point P_i is calculated using the previous and next point on the spline. Consider a single Catmull Rom segment $P(t)$. Let us suppose that we seek to define the segment of spline Catmull Rom which passes by the two control points (P_{i-1}, P_i) and which we know the tangents with the segment in these points, see Fig. 3. We know that since it is cubic, it can be expressed by the polynomial form [9]:

$$P(t) = a + bt + ct^2 + dt^3. \quad t \in [0,1] \tag{11}$$

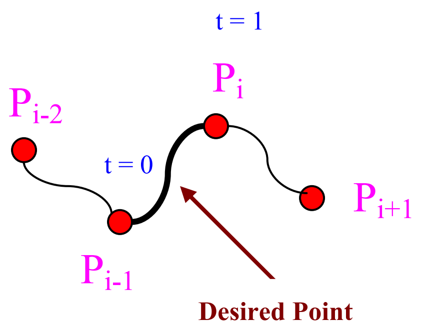

Figure 3. A Catmull Rom splines interpolating the two control points (Pi-1 , Pi).

And: $P^{'}(t) = b + 2ct + 3dt^2$.

We need to express some constraints, and we find the following relations:

$$\begin{aligned} P_{i-1} &= P(0) = a. \\ P_i &= P(1) = a + b + c + d. \\ P_{i-1}^{'} &= P^{'}(0) = b. \\ P_i^{'} &= P^{'}(1) = b + 2c + 3d. \end{aligned} \tag{12}$$

With: $P_i^{'} = \dfrac{P_{i+1} - P_{i-1}}{2}$; $P_{i-1}^{'} = \dfrac{P_{i-2} - P_i}{2}$.

Now, we can combine these constraints with (11) to get the following form basis matrix:

$$P(t) = (1 \quad t \quad t^2 \quad t^3).M.\begin{pmatrix} P_{i-2} \\ P_{i-1} \\ P_i \\ P_{i+1} \end{pmatrix}. \quad t \in [0,1] \tag{13}$$

Where:

$$M = (\frac{1}{2}).\begin{pmatrix} 0 & 2 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 2 & -5 & 4 & -1 \\ -1 & 3 & -3 & 1 \end{pmatrix}.$$

This matrix representation actually defines a cubic curve, which represents the portion of the local curve between two successive control points. While a spline segment is defined using four control points, a spline may have any number of additional control points. This results in a continuous chain of segments, each defined by the two control points that form the end points of the segments, plus an additional control point on either side of the end points. Because a segment requires control points to the outside of the segment endpoints, the segments at the extreme ends of the spline cannot be calculated [8].

Before modelling the lane boundaries of road by the Catmull Rom splines, we sample the binary image obtained by SVM, in such way to obtain points, called the control points. The splines passing through this control points. In our case, the boundary edges of lane can be regarded as the spline model's control points. The algorithm for the extraction of the control points is described as follow Fig. 4.

Given a set of n control points, with $n \geq 4$, a Catmull Rom splines interpolates all the points, has C1 continuity, and offers local control, meaning that a change in the position of a control point does not require to recomputed the whole curve.

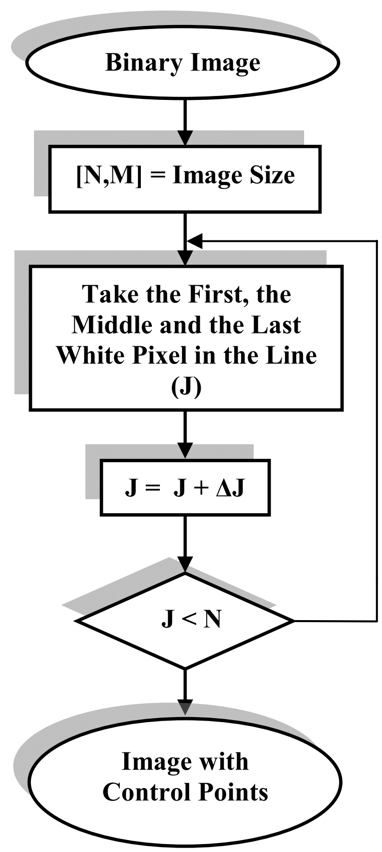

Figure 4. Control points extraction algorithm.

IV. LANE TRACKING

This section explains the components of tracking system that have been implemented for road tracking application. A distinction can be made between the problems of lane detection and tracking. Lane detection involves determining the location of lane boundaries in a single image without strong prior knowledge regarding the lane position. Lane tracking involves determining the location of lane boundaries in a sequence of consecutive images, using about the lane location in previous images in the sequence to constrain the probable lane detection in the current image [17] and [18]. We have developed a road tracking algorithm based on a combination of Catmull Rom splines modelling and a standard Kalman filter for tracking the road model in video sequence. The system and measurement equations as well as the Kalman update equations at time k-1 are shown below [15].

$$x_{k/k-1} = A.x_{k-1/k-1}. \tag{14}$$

$$P_{k/k-1} = A.P_{k-1/k-1}.A^T + Q. \tag{15}$$

$$K_k = P_{k/k-1}.C^T.(C.P_{K/k-1}.C^T + R)^{-1}. \tag{16}$$

$$Z_{k/k-1} = C.x_{k/k-1}. \tag{17}$$

$$x_k = x_{k/k-1} + K_k.(Z_k - Z_{k/k-1}). \tag{18}$$

$$P_{k/k} = (I - K_k.C).P_{k/k-1}. \tag{19}$$

Where $x = (a,b,c,d)$ is the lane model parameters of the Catmull Rom splines between two control points, who formed our state vector and it is updated by merging the information from the predicted state and the visual measurements corrected by the Kalman gain K. The coefficients of the dynamic model are defined as:

A: the transition matrix where is considered that the identity matrix, because we have a local controllability, which implies that local changes in shape are confined to the Catmull Rom spline parameters local to that change:

$$A = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

C: is the measurement matrix where is considered that the inverse matrix of M:

$$C = M^{-1} = (\frac{1}{2}).\begin{pmatrix} -1 & 3 & -3 & 1 \\ 2 & -5 & 4 & -1 \\ -1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \end{pmatrix}.$$

Q and R: are respectively the process noise covariance matrix and the measurement noise covariance matrix:

$$Q = R = (0.01).\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

V. EXPERIMENTAL RESULTS

We tested the proposed technique on video sequences, grabbed by a "Logitech" webcam installed on broad simulator vehicle « **SCANER II** » as shown in Fig. 5; all sequences were captured with a resolution of 320x240 pixels. These images include straight and curve roads painted or unpainted. Some results of the road detection by SVM algorithm, with a Gaussian kernel function, are shown in Fig. 6. We have using a MATLAB "SVM Toolbox" on an HSV images, to obtain a binary images (Road, Not-Road) with a noisy pixels, we have cleaning and filter it, by the application of the morphology mathematics (Dilatation and Erosion operations) in MATLAB. In Fig. 7 we showed the control point's extraction algorithm, to determine the middle, the left and the right sides of road. To modelling the road boundaries and the middle line of road, we have used two successive control points, by applied the Catmul Rom splines parameters. To track this parameters model along the images sequences is based on the application of simple Kalman method like shown Fig. 8. The experimental results obtained from the implementation of all algorithms developed in this paper, where works very well in the acquired images sequences and they have validate our approach with acceptable results. But the limitation of the proposed technique is regarded for videos acquired at night.

Figure 5. Simulator of vehicle « SCANER II ».

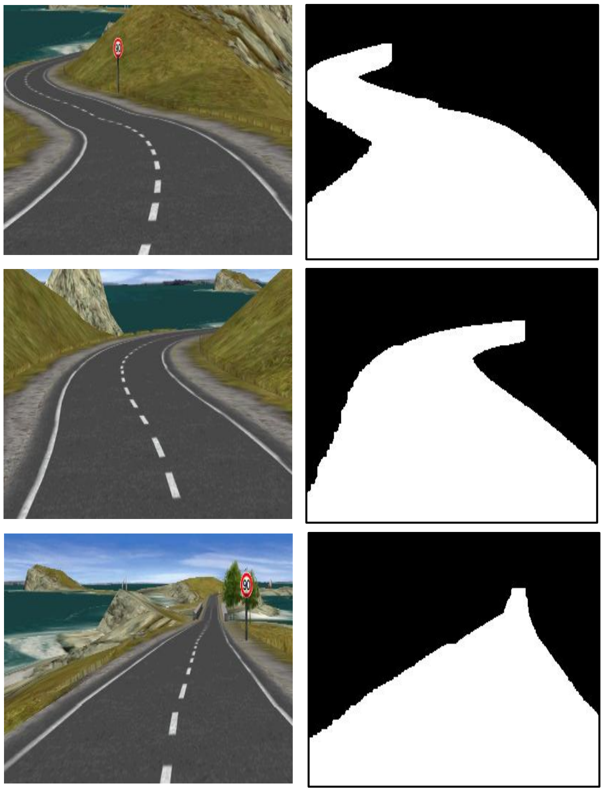

Figure 6. Examples of road detection by SVM method.

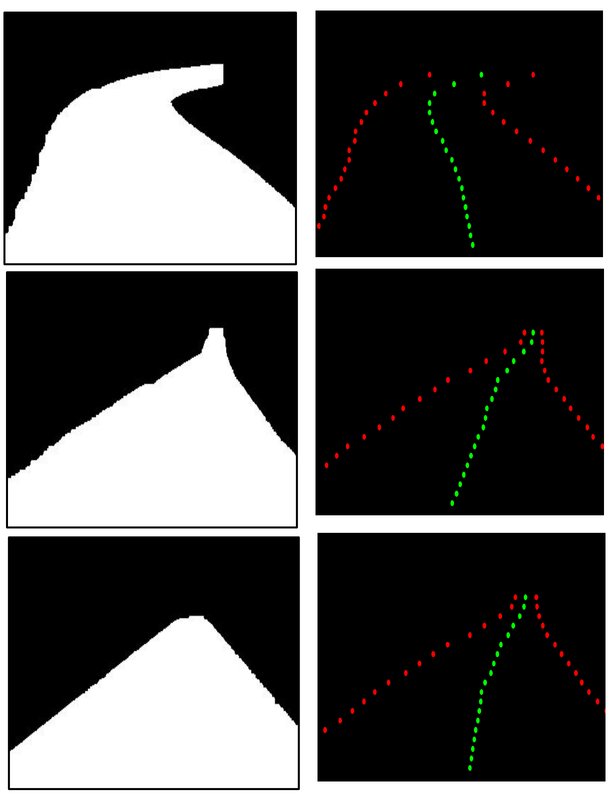

Figure 7. Examples of the extraction control points.

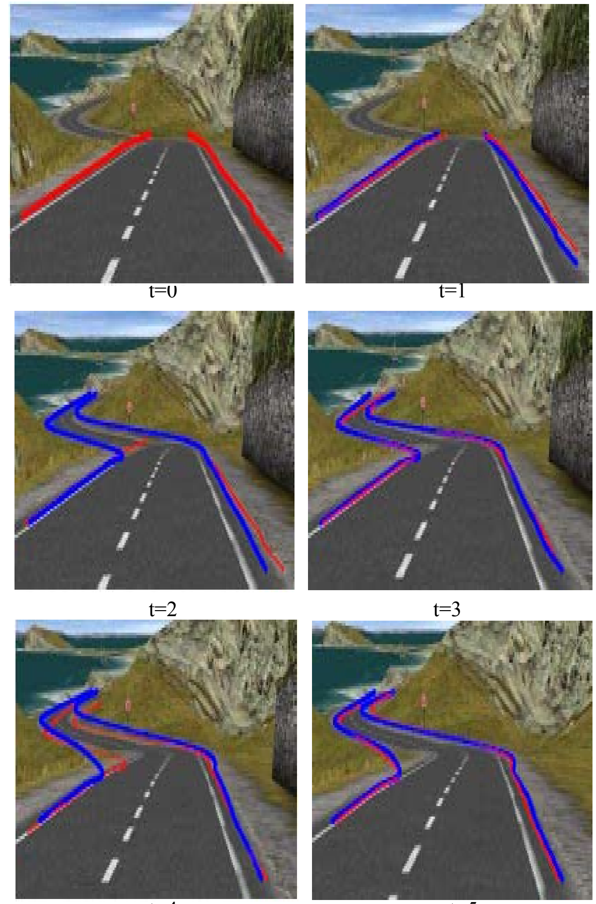

Figure 8. Results of the tracking algorithm.

VI. CONCLUSION

In this paper, we proposed a new lane detection and tracking algorithm, based on video sequence taken from a vehicle driving simulator on highway or rural road. In the lane detection algorithm, color cues were used to conduct image segmentation by SVM method in a binary image. The main advantage it is suitable for both marked and unmarked road and with any road shape. We have interpolating the extracted points control by Cattmul Rom splines modelling. The proprieties of this, like interpolation, smoothness and local control, allows to describe a wider range of lane structures than other lane models such as straight and parabolic models. The results obtained are satisfying, and successfully tracks wider range of road model in an image sequence. However, the robustness of the tracking algorithm can be increased by the uses of the Particle Filtering or Distillation Algorithm, to track the Catmull Rom splines road model along the images sequences, for future works.

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