# Straightening Curved Traffic Lanes in Video 

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#### Abstract

Video based vehicle sensing from uncalibrated cameras provides useful traffic information to modern Intelligent Transportation Systems (ITS). This requires vehicle tracking and Turning Movement Counts (TMCs). Traffic scenes contain vehicle motion constrained along possibly curved traffic lanes which can be normalized into straight lines. A simple interpolation scheme is presented which projects to image sequences where vehicles always appear to move straight horizontally for simplified vehicle tracking.


## 1 Introduction

There is an increasing demand for video based sensing of vehicle traffic for use by ITS to reduce congestion and decrease delays [1]. These applications require vehicle tracking to estimate detailed traffic parameters including speed, delay, and TMCs [2]. Uncalibrated cameras are required for cost effective mass deployment of video sensors in an ITS [3].

Tracking vehicles in traffic is simplified compared to the general multiple target tracking problem as vehicles are constrained to move along 1 -dimensional lanes [3, 4]. It is desirable to capture any general traffic video and project it into a new video with vehicles traveling horizontally at a constant speed.

## 2 Method

Two curves, $\mathbf{f}_{0}$, and $\mathbf{f}_{1}$ lie along a lane edge. See Fig. 1. The main idea is to linearly interpolate between these two curves.


Fig. 1: Two curves along lane edge. Edge finding may be used; here, they are Catmull-Rom splines with manually placed control points.

For each new frame, a new image is constructed by mapping a curvilinear coordinate space aligned along the lane in the source image to a rectilinear space in the target image. A simple transformation, $\mathbf{T}: \mathbb{R}^{2} \rightarrow \mathbb{R}^{2}$ is constructed which transforms points in parametric lane coordinates, $u \in[0,1]$ along the lane, and $v \in[0,1]$ across the lane to points from the source image. A straight lane projected image, $R$ is constructed from the source traffic image, $I$.

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\begin{gather*}
\mathbf{T}(u, v)=v \mathbf{f}_{0}(u)+(1-v) \mathbf{f}_{1}(u)  \tag{1}\\
R(u, v)=I(\mathbf{T}(u, v)) \tag{2}
\end{gather*}
$$



Fig. 2: Linear interpolation between two splines.

## 3 Discussion

Reparameterizations of $u$ and $v$ may be used to approximately correct for perspective; here $u$ is dynamically reparameterized depending on apparent lane widths $\left|\mathbf{f}_{1}(u)-\mathbf{f}_{0}(u)\right|$.


Fig. 3: (Top) Traffic video. (Bottom) Straightened image for left turn. Some extrapolation is necessary to capture entire vehicles.

This method straightens only lane surfaces. Since vehicles do not lie entirely on the lane surface, there is some moderate distortion in vehicle appearance. See Fig. 3. This is best addressed by using vehicle detection features that are robust to these distortions.

In order to properly handle occlusion of vehicles across lanes, a projected image including all adjacent lanes and gaps between lanes is required. Since not all traffic lanes are parallel, constructing one multi-lane image requires several simultaneous lane projections stacked together. Care must be taken in order to maintain continuity across lanes in the resulting image. Fig. 4 shows how $C^{0}$ continuity was achieved by sharing edge splines between adjacent lanes. Fig. 5 shows results. A spline surface over all lanes can be used for $C^{1}$ and higher continuity across lanes.


Fig. 4: Stacking projections for multiple lanes and gaps. Splines $\mathbf{f}_{1}$, $\mathbf{f}_{2}, \mathbf{f}_{3}$, and $\mathbf{f}_{4}$ are shared between adjacent lanes or gaps.


Fig. 5: (Left) Image with two nonparallel lanes. (Right) Projected image with both lanes normalized simultaneously.

## References

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