PROBABILISTIC DETECTION AND GROUPING OF HIGHWAY LANE MARKS

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Abstract

Most automated traffic surveillance systems use inductive loops to estimate traffic conditions such as traffic density. The main drawbacks of this technology are the high installation and maintenance costs. Alternatively, video cameras infrastructures are used to perform visual (i.e. human) monitoring. Such infrastructures could be used to perform more complex tasks such as vehicles tracking and classification as well as low-cost automatic traffic density estimation and motion analysis.

One of the challenges in using highway camera data for traffic analysis is that the external parameters of each camera (pan/tilt/zoom) may be changed several times a day by the operator, precluding pre-calibration. Thus successful deployment of computer vision traffic analysis algorithms depends upon reliable algorithms for automatic camera calibration.

The work presented here is focused on the automatic detection and grouping of highway structure for the purpose of camera calibration and image rectification of straight and curved highways.

We focus on the detection and grouping of lane markings into curvilinear chains. Unlike existing Hough-based methods to extract lines and estimate vanishing points, our method is based on a probabilistic approach where the lane marks are detected locally by means of cross-correlating a set of hypothesized lane mark templates with the input image. Our detector produces a set of lane mark hypotheses including location, length and orientation. The problem of extracting lane marks chains from the set of detections is formulated as a graph problem in which the edges are lane mark hypotheses and the possible connections between them. Grouping cues such as proximity and good continuation are used to compute likelihood ratios which are used as weights for the connection edges. A greedy algorithm is used to compute a bipartite sub-graph, and the Hungarian algorithm is used to compute the most probable lane mark chains.

Lane Mark Detection

Let *Ho* and *H1* be the hypotheses that an area of the image looks like (or does not look like) a lane mark on the road, and let *D* be an image patch being analyzed. Assuming an error with a normal distribution and that the elements of *D* are statistically independent, we compute the likelihood ratio as follows:

$$\lambda = \frac{p(H_0 \mid D)}{p(H_1 \mid D)} = \frac{\prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma_o}} \exp\left[\frac{-(d_i - h_{0i})^2}{2\sigma_0^2}\right]}{\prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma_1}} \exp\left[\frac{-(d_i - h_{1i})^2}{2\sigma_1^2}\right]}.$$

Taking the logarithm, we obtain our objective function:

$$\lambda_{\log} \propto \frac{1}{\sigma^2} = \left[\sum_{i=1}^{N} d_i\left(h_{0i} - h_{1i}\right) - \frac{1}{2}\sum_{i=1}^{N}\left(h_{1i}^2 - h_{0i}^2\right)\right].$$

We seek to maximize this function in order to detect areas of the input image that look like lane marks.

Templates.

37 highway images were hand-labelled to generate a set of average templates: 16 angles x 12 vertical regions.

The detector produces both, true and false detections. We use a spatial Greedy inhibition mechanism that eliminates weak detections within a rectangular neighbourhood of the strongest detections. The detections are refined with a nonlinear optimization stage .

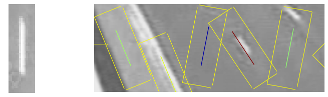

Figure 1. Left: An average template. Right: Inhibition mechanism

The output of the detector is a set $T = \{\vec{t}_1, \ldots \vec{t}_K\}$ of *K* detections which includes location, angle, length and Log-likelihood response.

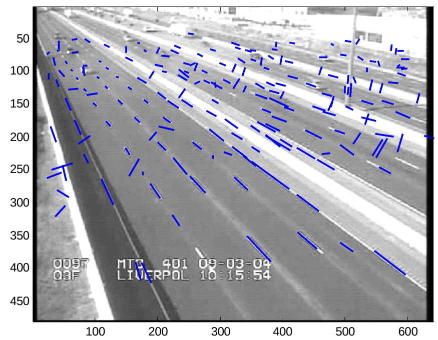

Figure 2. Example of detector's output

Lane Marks Grouping

Formulation as a Graph Problem

Let $G = (V, E)$ be an undirected graph in which *V* represents the set of vertices and *E* represents the corresponding edges. We map the end-points of the *k-th* detected lane mark (segment) to the vertices $u_k, v_k \in V$. We also map the lane marks to the set of edges *E'*:

$$f : T \to E' \qquad \vec{t}_k \to (u_k, v_k)$$

E is comprised of two disjoint subsets: $E = E' \cup E''$, where *E'* represents the detected segments and *E''* represents potential connections between vertices. We construct the graph *G* by creating what we call a locally-connected graph. That is, by generating the set *E'' as:*

$$E'' = \{(u_i, v_j)\}, \forall i \neq j : \|u_i - v_j\| < r$$

where *r* is a radius obtained from lane marks statistics. Figure 4 shows an example of a graph *G*.

We constrain the graph *G* to be bipartite. This enables us to assign the vertices u_k, v_k to the sets V_A and V_B such that $\forall u_k \in V_A, (u_k, v_l) \in E \to v_l \in V_B$. Our goal then is to find the optimal matching $M \subset E''$.

Weights

In order to seek for an optimal matching, we assign weights to the edges *E''* by making use of the *proximity* and *good continuation* grouping cues [1, 2].

$$C = \{\vec{c}_{ij}\}, \forall i \neq j \in E'' \qquad \vec{c}_{ij} = \left[d_{ij}, \alpha_{ij}, \beta_{ij}\right]^T$$

where $\vec{c}_{ij}$ is a cues vector relating the *i-th* and *j-th* edges and $d_{ij}, \alpha_{ij}, \beta_{ij}$ represent distance, parallelism and co-linearity [1].

We maximize the posterior $p(M \mid C) \propto p(C \mid M) p(M)$

Where the likelihood term is expressed as:

$$p(C \mid M) = \prod_{(u,v) \in M} p(C \mid M) \prod_{(u,v) \in E'' \setminus M} p(C \mid M)$$

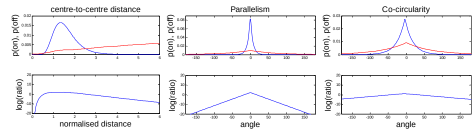

Figure 3. Likelihood distributions for the grouping cues utilized

Results

Figures 4 and 5 show examples of an input graph *G* and the grouped lane marks for one of the highway images .

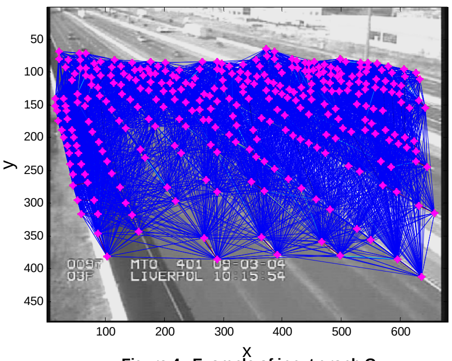

Figure 4. Example of input graph G.

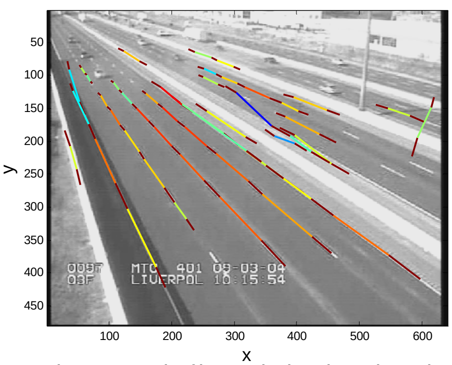

Figure 5. Example of lane marks detection and grouping.

Comments and Conclusions

The proposed method is expected to outperform existing methods, especially on highways with arbitrary curvatures.

Our future work plans involve fitting the extracted chains to conics, determine vanishing points, perform camera calibration, image rectification, motion analysis and structure recovery.

References

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