Learning class specific edges for vanishing point estimation

Olga Barinova, Anna Kuzmishkina, Alexander Vezhnvets, Vladimir Vezhnevets
Department of Computational Mathematics and Cybernetics
Moscow State University, Moscow, Russia
{obarinova, akuzmishkina, avezhnevets, dmoroz}@graphics.csmsu.ru

Abstract

Vanishing point estimation is useful for a variety of computer vision tasks. Recent efforts in building large city models showed that the structural regularities of man-made environments, such as presence of sets of parallel and orthogonal lines and planes can be exploited towards 3D reconstruction of the buildings using the information about vanishing points and vanishing lines. Recent research into recognizing object classes showed the effectiveness of learning class-specific edges in object detection and recognition tasks. Because class-specific edge detection provides a low-level analysis of the image it may be integrated into any edge-based vanishing points estimation strategy without significant change in the high-level algorithms. In this paper we illustrate an application of learning class-specific edges to vanishing point estimation task. We modify algorithm proposed by Kosecka & Zhang and show that its performance is considerably improved by integrating class-specific edge filtering. The performance of our modified vanishing point estimation method, along with original method, are evaluated and compared.

Keywords: *Vanishing points, Edge detection, Machine Learning.*

1. INTRODUCTION

Due to the effects of perspective projection, the line segments parallel in the 3D world intersect in the image. Depending on the orientation of the lines the intersection point can be finite or infinite and is referred to as vanishing point.

The knowledge of environment geometry is effectively exploited in the task of building large city models. Particularly, in architectural environments vanishing points provide independent geometrical constraints which can be exploited in several ways: from the camera self-calibration and a dimensional analysis of the object to its partial 3D reconstruction. In this paper the task of vanishing points estimation in structured man-made environments is considered assuming uncalibrated cameras.

The starting point common to all vanishing points estimation techniques is the edge detection. Resulting edge maps are usually very noisy and contain lots of edges arising from internal discontinuities, and background clutter which are not relevant to any vanishing point. Noisy edges can be harmful for vanishing point estimation algorithm and should better be pruned out.

Figure 1 illustrates this idea. At the fig. 1 noisy edges were pruned out manually and then vanishing points detection algorithm proposed in [1] was applied. Such procedure results in quite good vanishing points detection for vast majority of pictures.

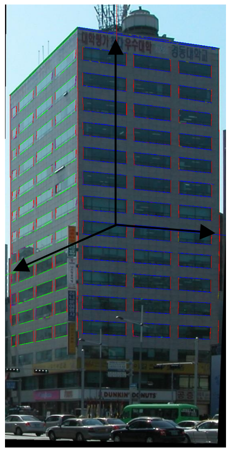

Figure 1: Result of applying vanishing point detection algorithm to manually labeled lines (solid colored lines connect center of the picture with vanishing points)

Our objective is to learn a classifier based on local information around an edge than apply it to edge filtering. In this paper we consider integration of class-specific edge filtering into vanishing points estimation algorithm proposed in [1].

This paper is organized as follows. In the next section the related work in fields of vanishing point estimation and learning class-specific edges is described. Then we introduce our class-specific edge filtering approach (subsection 3.1), and experimental results on it (subsection 3.2). In section 4 our modification of EM initialization (subsection 4.1) integration of class-specific edge filtering into vanishing point estimation algorithm [1] (subsection 4.2) are described. In section 5 we present experimental results on our vanishing point estimation algorithm. Finally, some conclusions are given.

2. RELATED WORK

The subproblems related to our approach fall into two categories: vanishing points estimation and learning class-specific edges.

Traditional approaches for vanishing points detection suggest the edge detection, followed by edge chaining and line fitting. In [1] the simultaneous grouping and estimation stage are formulated using Expectation Maximization (EM) algorithm and applied for the case of uncalibrated camera. We also consider the case of uncalibrated camera and focus on building up an approach proposed in [1].

The task of class-specific edge detection is formulated as statistical inference in [4]. Proposed statistical edge detection is data driven, unlike standard methods for edge detection which are model based. Pre-segmented images are used to learn the probability distributions of filter responses conditioned on whether they are evaluated on or off an edge. Edge detection is formulated as a discrimination task specified by a likelihood ratio test on the filter responses.

In [3] an approach to separating class-specific boundary edges from other image edges is proposed. Class-specific edge detection task is formulated as classification of edges obtained by standard edge detector. The authors show that it is easy to modify existing applications to use class-specific edges, which offers the potential for improved performance across a range of applications.

In this paper we integrate class-specific edge filtering [3] into the vanishing point estimation algorithm described in [1], for which we also propose effective initialization scheme.

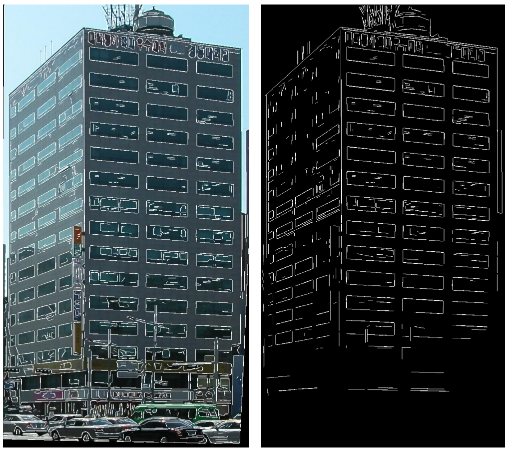

Figure 2: Left to right: line detection (white lines) and class-specific edge filtering result on a picture from the test set.

3. CLASS-SPECIFIC EDGE FILTERING

3.1 Learning class-specific edges

In the task of vanishing point estimation it is known beforehand that edges relevant to vanishing points form line segments.

Line fitting stage in our experiments follows an approach described in [1]. This algorithm, given an edge detection output, groups edge pixels into line segments. Example of line detection is shown in fig. 2.

Our edge classification approach resembles the one proposed in [3]. We also classify edges obtained by standard edge detector (Canny edge detector in our experiments). In contrast to [3] where edge pixels classification is proposed we propose line segments classification. Line segment classification is more advantageous than pixel classification in vanishing point estimation task because it allows calculating more informative features for classification. Line segments here can be viewed as an analog to superpixels [8], which are widely used in computer vision tasks.

Pictures for training were manually labeled. Line segments relevant to vanishing points were labeled as good; other ones were labeled as bad.

The features for classification can be divided into three groups: color cues, geometric cues and gradient cues.

Geometric cues of a given line segment include coordinates of segment ends, its direction and length, and the percent of line segments which are almost collinear to the given one. Coordinates of line ends are very informative because most bad lines usually lie at the bottom of picture. The percent of almost collinear lines is used, because lines relevant to the same vanishing point usually have close directions.

Color cues include first four central statistical moments calculated over the area around line segment. Color features help to prune out edges of noisy objects like trees, cars etc.

We also used mean value of gradient along the line segment. This feature gives the information about edge strength.

List of features is shown in a table 1.

Feature description	Num.
Geometric cues	
Coordinates of line segment ends	4
Line segment direction	1
Line segment length	1
Percent of almost collinear lines	1
Color cues	
Central statistical moments around line segment	4
Gradient cues	
Mean value of gradient along the line segment	1

Table 1: List of features

3.2 Experiments on learning class-specific edges

Training set in our experiments contained 20 pictures and test set contained 6 pictures. All these pictures were manually labeled.

We used boosted decision trees [6] as a classifier. Average percent of good lines classified as bad ones on test pictures (error of first kind) is 14%. Average percent of bad lines classified as good ones on test pictures (error of second kind) is 13%.

Result of raw line detection and classification result are shown in figure 2

4. VANISHING POINT ESTIMATION USING CLASS-SPECIFIC EDGES

In this section we will describe integration of our class-specific edge filtering into vanishing point estimation method proposed in [1] and describe our modification of its initialization method.

4.1 Initialization of vanishing points coordinates

EM algorithm, used in [1] is known to be very sensitive to initialization. Hence it is very important that the algorithm is correctly initialized.

In [1] the initialization stage is based on the observation that lines that belong to a particular vanishing direction have similar orientation in the image. The peaks of histogram of line segment orientations are detected by first computing the curvature of the histogram, followed by a search for zero crossings, which separate the dominant peaks.

This approach is prone to loosing some important low-grade histogram peaks, which is harmful for the following EM stage. As long as the number of vanishing directions doesn't increase during EM phase of the algorithm, loss of histogram peaks leads to loss of vanishing directions.

To avoid this effect we use mean shift clustering [9] of line directions at the initial stage of vanishing point detection. Mean shift is a procedure for searching probability density maximums, which are histogram peaks for one-dimensional case.

While being very sensitive to noise and resulting in many clusters on raw edge data, mean shift clustering gives good results after applying class-specific edge filtering. Moreover it provides automatic determination of clusters number.

4.2 Integrating class-specific edge filtering into EM algorithm

The grouping stage and vanishing point estimation stage are held simultaneously and are addressed as a problem of probabilistic inference with an unknown model in [1]. The coordinates of vanishing points as well as the probabilities of individual line segments belonging to a particular vanishing direction are estimated by Expectation Maximization algorithm (EM).

Algorithm proposed in [1] exploits the fact that posterior distribution of the vanishing points given line segments can be expressed using Bayes rule in terms of the conditional distribution and prior probability of the vanishing points:

$$p(v_k \mid l_i) = \frac{p(l_i \mid v_k)\, p(v_k)}{p(l_i)},$$

where $p(l_i \mid v_k)$ is the likelihood of the line segment belonging to a particular vanishing point with coordinates v_k, $p(v_k \mid l_i)$ is the probability of vanishing point coordinates v_k in condition of line segment l_i, $p(v_k)$ is the prior of vanishing point coordinates v_k, and $p(l_i)$ is the prior for line segment l_i to be relevant to any vanishing point.

Class-specific edge filtering provides probabilities for line segments to belong to some real vanishing point (being good in our terms). These probabilities obtained from boosting (exploiting fact that boosting is logistic regression) [6] are treated as priors for line segments to be relevant to any vanishing point $p(l_i)$ and are integrated into EM-algorithm.

In experiments described in this paper we first pruned out line segments classified as bad and then used probabilistic output for the rest ones as priors for line segment.

Algorithm proposed in [1] also provides a scheme for calculating priors of detected vanishing points $p(v_k)$. In our experiments when more then three vanishing directions are detected, the three with the largest priors are retained.

5. EXPERIMENTAL RESULTS

There is no common quality measure for vanishing points detection methods. Performance evaluation techniques proposed in the literature are usually dependant on application of vanishing point coordinates. In [5] the goal of vanishing point application is to find 3D orientations of structures in the scene, so orientation error is used as an error metric.

In this paper we performed only qualitative evaluation of algorithm performance. Figures 3, 4, 5 show experimental comparison of original vanishing point estimation method, proposed in [1] and our modification of it. Solid colored lines connect center of the picture with determined vanishing points. The lines are colored according to the vanishing point they belong to. More results in high resolution will be available at web site of the project [10].

In figure 3 original method grouped lines relevant to together with noisy ones which can lead to errors in vanishing points coordinates' determination (should be viewed in color). In figures 4 and 5 original method detected wrong vanishing points, while our modification of vanishing point estimation method detected all vanishing points correctly.

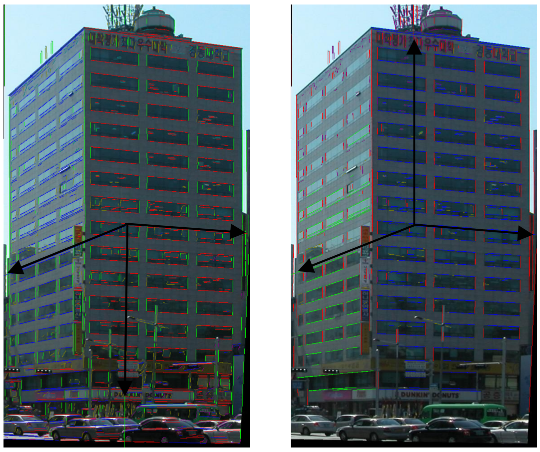

Figure 3 Vanishing points estimation results on a picture from test set: left – result of original method proposed in [1], right – results of our method

6. CONCLUSION

In this paper we modified vanishing point estimation method proposed in [1]. We proposed mean shift initialization for EM algorithm and incorporated class-specific edge filtering into this method. We have demonstrated that using class-specific edges offers the potential for improved performance of vanishing point estimation.

We presented an efficient, completely automated approach for detection of vanishing points from a single view assuming an uncalibrated camera. We account for the specific of man-made environments at all stages of our method.

Figure 4: Vanishing points estimation results on a picture from test set: left– results obtained by method proposed in [1], right– results of our method

7. REFERENCES

[1] J. Kosecka, W. Zhang. *Video Compass, Proceedings of the 7th European Conference on Computer Vision-Part IV Pp: 476-490, 2002*

[2] D.G. Aguilera, J. Gómez Lahoz, J. Finat Codes *A new method for vanishing points detection in 3D reconstruction from a single view, ISPRS Commission V, WG V/2. Mestre (Venice), 2005*

[3] M. Prasad, A. Zisserman, A. Fitzgibbon, M. Pawan Kumar, P. H. S. Torr *Learning Class-specific Edges for Object Detection and Segmentation*

[4] S. Konishi, A. Yuille, J. Coughlan, S Zhu. *Statistical Edge Detection: Learning and Evaluating Edge Cues, IEEE Transactions on Pattern Analysis, pp: 57- 74 2003*

[5] J. A. Shufelt *Performance Evaluation and Analysis of Vanishing Point Detection Techniques, IEEE Transactions on Pattern Analysis and Machine Intelligence, pp: 282 - 288 1999*

[6] Friedman, J. H., Hastie, T. and Tibshirani, R. *Additive logistic regression: a statistical view of boosting. Dept. of* Statistics, Stanford University Technical Report. 1998

[7] M. Antone and S. Teller. *Automatic recovery of relative camera rotations for urban scenes. In IEEE Proceedings of CVPR, 2000.*

[8] X. Ren, J. Malik, *Learning a Classification Model for Segmentation. ICCV '03, volume 1, pages 10-17, Nice 2003.*

[9] Y. Cheng, *Mean Shift, Mode Seeking, and Clustering IEEE Transactions on Pattern Analysis and Machine Intelligence Vol.17 , Pp: 790 - 799 (August 1995)*

[10] *http://research.graphicon.ru/machine-learning/learning-class-specific-edges-for-vanishing-point-estim.html*

Figure 5: Vanishing points estimation results on a picture from test set: left – results obtained by method proposed in [1], right – results of our method

About the authors

Olga Barinova is a Ph.D. student at Moscow State University, Department of Computational Mathematics and Cybernetics at Graphics and Media Lab. Her research interests include machine learning, statistics, computer vision, image processing and adjacent field. olga@graphics.cs.msu.ru.

Anna Kuzmishkina is a student at Moscow State University, Department of Computational Mathematics and Cybernetics at Graphics and Media Lab. Her research interests include machine learning and computer vision. akuz@graphics.cs.msu.ru.

Alexander Vezhnevets is a Ph.D. student at Moscow State University, Department of Computational Mathematics and Cybernetics at Graphics and Media Lab. His research interests include machine learning, statistics, computer vision, image processing and adjacent field. avezhnevets@graphics.cs.msu.ru.

Vladimir Veznevets is a vice head of Graphics and Media Laboratory of Moscow State Lomonosov University, Department of Computational Mathematics and Cybernetics. His research interests include image processing, pattern recognition, computer vision and adjacent fields. dmoroz@graphics.cs.msu.ru