Vanishing Point Detection with Direct and Transposed Fast Hough Transform inside the neural network

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Abstract

In this paper, we suggest a new neural network architecture for vanishing point detection in images. The key element is the use of the direct and transposed Fast Hough Transforms separated by convolutional layer blocks with activation functions. It allows us to get the answer in the coordinates of the input image at the output of the network and thus to calculate the coordinates of the vanishing point by simply selecting the maximum. The use of integral operators enables the neural network to rely on global rectilinear features in the image, and so it is ideal for detecting vanishing points. To demonstrate the effectiveness of the proposed architecture, we use a set of images from a DVR and show its superiority over existing methods. Note, in addition, that the proposed neural network architecture essentially repeats the process of direct and back projection used, for example, in computed tomography.

Keywords: Fast Hough Transform, vanishing points, deep learning, convolutional neural networks.

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Introduction

The vanishing point (VP) is the intersection point of 2D projections of straight lines that are parallel in 3D space. In the field of computer vision, the problem of VP detection regularly arises in a great number of applications. It includes an analysis of both 2D and 3D scenes using images obtained by various types of cameras. In the 2D case, for example, we encounter all kinds of flat objects, such as documents with text (ID cards, bank cards, scanned pages, etc.). The current solution, in this case, begins with searching for the rectangle of the object [1] followed by straightening [2] for further recognition. The problem is that it is not always possible to find the rectangle because it may be beyond the edges of the image, merged with the background or obscured by other objects. There is an alternative group of methods that solve this problem using VP detection. In the case of a 3D scene, the detection of vanishing points is necessary to find objects, to assess their orientation or the orientation of the camera [3]. An example is shown in Figure 1. The vanishing point there (V in Figure) is the intersection point of the road edges. Similar images are used in this paper for VP detection.

![Fig.1. Vanishing point](image)

The classical approach to VP detection is presented in the work of Stephen Barnard [4]. The author uses a Gaussian sphere located in the optical center of the camera. Each point in the image corresponds to a point on the sphere, which is regarded as a radius vector. In this way, we can get mappings of infinitely distant points into a finite space and process them using conventional methods. In this case, the radius vector of an infinitely distant point will have the zero coordinate \( z \). To find vanishing points, it is necessary to find the intersection points of all the lines in the image, and then to combine them into clusters. All the lines belonging to the same cluster represent a bunch of parallel straight lines in a certain perspective. For example, in [5], the authors propose to find the baselines of a text and the inclination angle of the characters using clusters of points on the Gaussian sphere. The main problem of the method...
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is that the detection of straight lines is not so simple in images of natural scenes.

Another approach to VP detection is based on finding the intersection point of lines in the image. The following model is used to describe it: Let \( P = p_1, i = 1 \ldots n \) be straight lines on flat images representing parallel lines in space. The line \( p_i \) is described by a linear equation:

\[
p_i = \{(x, y) | ax + by = c_i\}
\]

Thus, the vanishing point \( V(x, y) \) is an approximate solution to the system of linear equations (1) because there may not be an exact solution (when, for example, there are more than two straight lines and there is no unique intersection point). To find the VP using this model, we need to find straight lines in the image. A standard approach to finding them is to use the Hough Transform (HT). The paper [6] demonstrates various possible applications of such algorithms.

In [7], the author uses this algorithm to detect three vanishing points, but he notes that his method works only when applied to good synthetic data. The authors of [8] search for the VP successively applying two Hough transforms, but this method is very unstable to noise and the presence of outliers. A specific application of the Hough Transform for camera calibration is presented in [9]. The authors do not use information about camera parameters, but instead, transform the image of a chessboard because it contains a set of contrasting orthogonal lines that are easy to detect.

Recent papers show that artificial neural networks began to be used in VP detection. For example, [10] contains a solution to the problem of finding a vanishing point in images of road views using convolutional/fully connected neural network architectures with a large number of learning parameters (AlexNet, VGG). It also can be seen there that the method shows a low quality of work on images other than images from the training sample. Another application of convolutional neural networks in a similar problem is proposed in [11]. The authors trained the network to detect the horizon lines in the image. However, the use of these architectures for such tasks contains one serious problem: in the general case, the problem of the vanishing point detection cannot be solved only on local features, as it is done in fully convolutional networks, and the application of fully connected layers to the whole picture typically adds a huge number of learning parameters and significantly increases the amount of data required for training.

In this paper, we propose the architecture of a neural network, which is a combination of convolutional layers, of the Fast Hough Transform (FHT), and of a transposed HT, which will enable the neural network to use not only local (as is the case with fully convolutional neural networks), but also global features. The interpretation of the network response will be reduced to a simple choice of the maximum owing to the use of the transposed HT. The effectiveness of the proposed approach will be demonstrated based on the task of the VP detection on road images taken from DVRs.

1. The proposed approach

The simplified idea of using a combination of the FHT and the transposed HT is shown in Figure 2. As an example, we took image 2a containing three lines with a common intersection point and a fourth line lying separately. Image 2b is the result of applying the FHT; it shows four blurry points, one for each straight line in the original image. The result of applying the transposed HT for a set of mostly horizontal lines to image 2b is shown in image 2c. The brightest point corresponds to the line on which the most points of the image 2b lie.

![Fig.2. Hough Transform for vanishing point](image-url)
convolutional layer will correspond to the vanishing point in the original image.

2. Basic units

Neural network layers

An artificial neural network is an information processing paradigm built from the model of biological neural network functioning. It was first introduced in 1943 by Warren McCulloch and Walter Pitts [15]. The network is based on a set of connected units called artificial neurons. The neurons are combined into layers of various types, which can perform different kinds of transformations of input data.

The neural networks with convolutional layers (convolutional neural networks) have been used since 1980 [16]; they have been developing rapidly since then and are currently one of the most popular and powerful image analysis tools. The input and output data of convolutional neural networks are images. A convolutional layer consists of a set of filters, each of which has its kernel. The filters are applied to different image areas spaced with a predetermined interval, for which reason convolutional layers are much less likely to be overfitted than fully connected ones, which ensures a better generalizing ability. The main drawback of convolutional neural networks is their high consumption of computational time resources, but numerous methods have already been developed to solve this problem from concurrent recognition on the GPU and CPU using fixed-point arithmetic [17] to the tensor decomposition of filters [18].

Fast Hough Transform

The Hough transform is a linear transform [19] that associates each straight line in the input image with a point in the output image. The result is the space \( H \subset \mathbb{R}^2 \). The point \((s, \alpha) \in H\) contains the sum of the pixel intensities of the input image \( I \) along a line \( l \) where \( s \) is the distance from the line to the origin and \( \alpha \) is the angle between the line and the positive direction of the abscissa axis on \( l \). That is,

\[
I(s, \alpha) = \{(x, y) \mid s = x \cos \alpha + y \sin \alpha\}.
\]

The Hough transform as a neural network layer

To train a neural network to detect lines and vanishing points, it is necessary to calculate the FHT inside the neural network. Our first implementation was based on the idea that both the classical and fast Hough transform can be calculated using an untrainable fully connected layer with pre-calculated weights. This approach makes it possible to use standard training tools without any changes. The main disadvantage of this method is that it requires \( O(n^2) \) memory, where \( n \) is the length of the input vector. Another problem is that the weight matrix contains many zero values, which indicates unnecessary time costs.

For this reason, the next step was the implementation of a new FHT layer, which simply calculates the transformation inside the neural network. Since learning layers are located before the FHT layer, it was necessary to implement the backpropagation of the gradient for it. We used the FHT for forward propagation and equation (5) for backpropagation, which corresponds to the transposed Hough Transform. The equation was obtained numerically.

\[
I_{ht}(x, y) = \sum_{(s, \alpha) \in \{(x, y)\}} H(s, \alpha),
\]

where \( I_{ht} \) is the transposed Hough transform and \( \{(s, \alpha) \mid s = x \cos \alpha + y \sin \alpha\} \) is the set of Hough-
parameters of all lines passing through the point \((x, y)\) in the space of the image.

3. Experiments

We used data from [10] for a numerical experiment. This dataset consists of frames of records from DVRs of cars, buses, or trucks found on YouTube and made in traveling around America. The frame size was 300×300 pixels. There were 9972 images in total, which were randomly divided into a training sample (8974 images) and a test sample (998 images). Examples of the images are shown in Figure 3. To estimate the error, we used the method also proposed by the author of the dataset. Each image was covered with 10×10, 20×20, and 30×30 grids, and the answer was considered correct if the resultant vanishing point fell into a cell with the correct answer.

At first, we tried to use the proposed AlexNet architecture but later realized that the declared quality can be achieved with a simpler architecture of the neural network. The convolutional network architecture consisted of four convolutional layers and one fully connected layer. And the input images had to be resized to 227×227 pixels as required by the original architecture. The main difference between our base architecture and AlexNet is that it has a smaller number of convolution kernels and just one fully connected layer.

The detailed description of the basic architecture is presented in Table 1. The network with a new architecture was trained after training the core network. The innovation was training through the layers of the direct and transposed HFT, which we added between the layers of convolutions. Moreover, we removed the fully connected layer and searched instead for the pixel with the maximum brightness value in the output image because the image remained in the original coordinates after the application of the direct and transposed HFT. The description of the proposed architecture is presented in Table 2. Padding layers were used before applying the FHT and transposed HT to compensate for the reduction in image size due to the use of convolutional layers without padding. Thus, just a “frame” of zero values around the picture was created in these layers.

The total number of learning coefficients in the basic architecture was 170967, 516576, and 1092576 for grids of 10×10, 20×20, and 30×30, respectively, while the new network had 25309 learning coefficients regardless of the grid size. It should be noted that we used a heavily modified version of cuda-convnet for training the networks [24]. In the proposed architecture, a hyperbolic tangent was chosen as an activation function for convolutional layers and the function (6) for layers following the direct and transposed FHT.

\[
rf[a, b] = \frac{x^a}{b + |x^a|} \quad (6)
\]

It was found empirically that this kind of function qualitatively improves the network convergence. We assume that the presence of an inflection point at zero plays the role of an amplifier of local extrema on Hough images, but this issue requires additional research.

Table 1. Base architecture

| # | Type       | Parameters                  | Activation function |
|---|------------|-----------------------------|---------------------|
| 1 | Convolutional | 32 filters 11×11, no padding, stride 4×4 | relu                |
| 2 | Convolutional | 32 filters 5×5, padding 2×2, stride 1×1 | relu                |
| 3 | Convolutional | 32 filters 3×3, padding 1×1, stride 1×1 | relu                |
| 4 | Convolutional | 32 filters 3×3, padding 1×1, stride 1×1 | relu                |
| 5 | Fully-connected | - | -                   |
| 6 | Softmax        | - | -                   |

Table 2. Improved architecture

| # | Type       | Parameters                  | Activation function |
|---|------------|-----------------------------|---------------------|
| 1 | Convolutional | 12 filters 5×5, no padding, stride 1×1 | tanh                |
| 2 | Convolutional | 12 filters 5×5, no padding, stride 3×3 | tanh                |
| 3 | Convolutional | 12 filters 3×3, no padding, stride 1×1 | tanh                |
| 4 | Convolutional | 12 filters 3×3, no padding, stride 1×1 | tanh                |
| 5 | Padding     | 6×6 | -                   |
| 6 | FHT         | - | -                   |
| 7 | Convolutional | 12 filters 5×5, no padding, stride 1×1 | tanh                |
| 8 | Convolutional | 12 filters 5×5, no padding, stride 1×1 | tanh                |
| 9 | Convolutional | 12 filters 5×5, no padding, stride 1×1 | tanh                |
| 10 | Padding      | 6×6 | -                   |
| 11 | Transposed HT | rf[3,1] | -                   |
| 12 | Convolutional | 12 filters 5×5, no padding, stride 1×1 | tanh                |
| 13 | Convolutional | 12 filters 5×5, no padding, stride 1×1 | tanh                |
| 14 | Convolutional | 12 filters 5×5, no padding, stride 1×1 | rf[2,1]             |

4. Results

As a result of this study, an improved algorithm of training the convolutional neural network through the Hough transform layers was implemented. Although this type of layer can be expressed with fully connected and theoretically there is no need to invent anything, the matrix of this layer will consist of \(n^2\) units, where \(n = w\times h\times c\) is the length of the input vector. Therefore, the weight matrix will have 4×10^9 units for an image of 100×100×20 in size (relatively small for a convolutional neural network). The approach thus implemented makes it possible to calculate direct and back passages through the HT layers without using this type of matrix.
Figure 4 shows examples of the operation of the proposed algorithm and visualizes the purpose of the FHT layer. Since the intermediate outputs of the network are multichannel, we selected for illustrations the channels that we thought to be the most illustrative. 4a shows the original image, 4b is the image obtained after the first block of convolutions, 4c is the output of the fast Hough transform layer, 4d is the output of the FHT after the second block of convolutions, 4e is the output of the layer of the transposed FHT, and 4f is the image obtained at the output of the network - a bright spot at the assumed location of the vanishing point. It can be seen that by using the proposed method it is possible to train convolutional layers to select suitable straight lines and boundaries and to solve the problem after that.

It is important to note that the FHT layer has no learning coefficients, so it does not complicate the network architecture in terms of the number of weights. All operations on this layer are predetermined and do not change in the process of training.

Finally, it is necessary to estimate the contribution of the FHT layer to the computational complexity of the algorithm. The number of the required operations is about $c^2 \log(s)$, where $c$ is the number of image channels, and $s$ is the linear image size. The convolutional layer needs about $c^2 f^2 m$ operations, where $f$ is the linear size of the filter and $m$ is the number of filters. The ratio of the computational complexities of the convolutional and FHT layers is $\frac{f^2 m}{\log(s)}$. Hence, the contribution is small and practically negligible in the case of deep convolutional networks.

**Conclusion**

In this paper, we suggest a new neural network architecture based on using the direct and transposed Fast Hough Transforms. The effectiveness of the architecture was demonstrated on the task of vanishing point detection in road images. In this case, the main advantage of the proposed method is that it avoids attempts to detect the vanishing point in some position in favor of finding suitable elements in the input image using convolution filters and constructing the resultant VP based on these elements.

The experiments thus conducted have shown that a trained network with the proposed architecture has a significantly higher quality of detection and at the same time a much lower number of trainable parameters. In addition, due to the absence of fully connected layers, the neural network builds its answer regardless of the position and hence is not overfitted on the positions of correct answers in the training sample.

As part of further studies, it is planned to test this approach on other tasks from image segmentation to determining the orientation of objects. Additional research is needed for the use of a special activation function after the layers of the direct and transposed Hough Transform. It is also planned to use other error functions to improve the learning process and convergence, and to investigate under what parametrizations it is possible to calculate the transposed Hough Transform for the logarithmic complexity. Moreover, a more efficient implementation of the method on the CPU and GPU is planned to obtain finally a neural network capable of operation on mobile devices in a reasonable amount of time.

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