A Fast HOG Descriptor Using Lookup Table and Integral Image

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Abstract

The histogram of oriented gradients (HOG) is a widely used feature descriptor in computer vision for the purpose of object detection. In the paper, a modified HOG descriptor is described, it uses a lookup table and the method of integral image to speed up the detection performance by a factor of $5 \sim 10$. By exploiting the special hardware features of a given platform (e.g. a digital signal processor), further improvement can be made to the HOG descriptor in order to have real-time object detection and tracking.

1. Introduction

The process of using a HOG descriptor to detect object includes feature generation and region scanning. A widely used implementation is given by the OpenCV. It’s implemented in a way for general application purpose based on the OpenCV’s large programming functions libraries. For a image of size $800 \times 600$, it takes 100s ms to process in a common PC (Intel i3/i5/i7 CPU). To speed up the procedure, a lookup table is used to compute the oriented gradients. Afterward the integral image method is used to cache the histogram features, which will be used to predict object bounds and objectness scores at each position. Details of these two modifications will be described in the next two sections.

2. Lookup Table for Gradients Calculation

The first step to generate HOG feature requires the oriented gradients information at every point for a given image. Let $P_c[x][y]$ be the gray value ($0 \sim 255$) for a pixel at position $(x, y)$ of the color channel $c$ ($c = R, G, B$). To find the oriented gradients of the pixel, the gray value changes in both horizontal (x direction) and vertical (y direction) directions should be computed using the current pixel’s previous and next neighboring’s gray values. The differences in x and y directions are denoted as:

$$
\begin{align*}
    dx &= P_c[x + 1][y] - P_c[x - 1][y] \\
    dy &= P_c[x][y + 1] - P_c[x][y - 1]
\end{align*}
$$

Transforming the pair $(dx, dy)$ from Cartesian coordinates to polar coordinates representation yields the magnitude $r$ and orientation angle $\phi$, which are the oriented gradients. Since the $dx$ and the $dy$ are integers ranging from -225 to 255, a lookup table with $511 \times 511$ entries for each pair of $(dx, dy)$ can be constructed and fill with precomputed values. Then for every given input image, its oriented gradients map can be build very fast simply by looking up the pre-built table, without doing any computationally expensive coordinates conversion. One example of calculating the oriented gradients is shown in the Fig[1]. It should be clear that the direct calculations of the magnitude and orientation angle would be much slower than querying a table. Besides, the lookup table needs no more calculation once it’s constructed at the very beginning.

Additionally, based on our experiments, the magnitudes of gradients are found to be insignificant for object detections. Thus the magnitude for every point can be simply set to unity when building the oriented gradients map. The angular direction $\phi$ is discretized to an integer bin number, ranging from 0 to $N_b - 1$, where $N_b$ is the number of angular bins, see the Fig[2].

For the simplest method, each pixel for each given image will be associated with a bin number. In the implementation of the OpenCV, each pixel’s HOG magnitude part will be distributed to two bins when building histogram features, but this does effect the application of the integral image. In the rest part of this paper, we only focus on the simplest case, i.e, each position of an image only associated with a
3. Application Integral Image

Integral Image is also known as summed area table, which is commonly used for quickly and efficiently generating the sum of values in a rectangular subset of a grid, it allows for very fast feature evaluation, e.g., an image input for object detection [7][8][1]. In this paper, we only concern 2D grid data since the oriented gradients map is arranged in 2D pattern.

3.1. Integral Image Representation

Assume the 2D grid data is of size $W \times H$, its value at location $(x, y)$ is $i(x, y)$. Its integral image value at $(x, y)$ is denoted as $ii(x, y)$, then $ii(x, y)$ can be calculated using the Eq.2. An example of doing the integral over a small area is shown in the Fig. 3.

$$ii(x, y) = \sum_{x' \leq x} \sum_{y' \leq y} i(x', y')$$  \hspace{1cm} (2)$$

To calculate the area sum ($V_R$) of an interested region $R$ (e.g., the shaded area in the Fig. 3), we do not have to add up the value of every single point inside that area. Instead, its integral image representation can be used to compute the sum easily as shown in Eq. 3.

$$V_R = ii(4) + ii(1) - ii(2) - ii(3)$$  \hspace{1cm} (3)$$

An oriented gradients map of an image comprises a 2D grid of bin numbers (for zero-based, these numbers are from $0 \sim N_b - 1$). This map can be used to build the HOG features for a region inside it. To determine if a region contains object of interested, the HOG features in that region should be constructed. Typically, the full feature representation of a region is formed by connecting the oriented gradient histograms from its overlapped sub areas, as showed in the Fig. 4.

3.2. Build Integral Image for HOG

To apply the integral image method to the calculation of the HOG features, first we recall how the histogram for each area inside a region is computed. Let the number of bins be $N_B$ (e.g., Fig. 4). Inside an area, the number of bins with same values are counted and grouped to form a histogram, the resulting histogram has the length equal to the number of bins. Some bins are empty (have zero value), such as the 6th, 2nd, 3rd and 8th bins for the first histogram in the Fig. 4.
By observation, in order to speed up counting the bin values, we can have $N_B$ integral images, with different bin value corresponds to one of them. For the $n_{th}$ integral image, its value at point $(x, y)$ is equal to one when the value of the image $i$ at that point has value equal to $n$, i.e.

$$i_n(x, y) = \begin{cases} 1, & \text{if } i(x, y) = n \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The Fig 5 shows how these integral images of an oriented gradients map are built. The image in the first row is decomposed into $N_B$ images (the second row) with value at different points given by Eq (4). Then the integral over each image is carried out (Eq 5) and we get $N_B$ integral images for every bin value (the third row).

$$i_{ii}(x, y) = \sum_{x' \leq x, y' \leq y} i_n(x', y') \quad (5)$$

### 3.3. Generate Histogram from Integral Images

To compute the full histogram for a region (e.g. Fig 4), integral images generated in last sub section can be used to get the histogram value for each bin $B$ in different area $R$, denoted as $V^B_R$:

$$V^B_R = \{ i_{ii}(4) + i_{ii}(1) - i_{ii}(2) - i_{ii}(3) \} \quad (6)$$

Other tips such as discard of the magnitude as mentioned in Sec. 2, which will speed up the oriented gradients calculation. The selection of salient features using AdaBoost [6] or other methods [9] can reduce the dimensionality of the resulted features, which can speed up the training procedure and the inner product calculation during objectness evaluation. For some embed systems, such as application...
of a digital signal processor, if the input image is small enough (e.g. 352 × 288 YUV videos from some cameras) that the usage 16-bit data types for integral images will not overflow, the speed can be doubled if codes are properly engineered.

In a common personal desktop computer with a Intel i5 CPU, the modified HOG descriptor (my implementation) takes about 30 ms to detect objects for an image of size 800 × 600. If the code is built to 64-bit version, it only takes about 15 ms if the source code is properly engineered. If the size of the input image is 352 × 288, it takes about 8 ms, or less than 5 ms for 64-bit version.

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For more information, please check the online video on the application of the modified HOG descriptor for vehicle detection https://www.youtube.com/watch?v=ge3HPE_qHCC

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