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Research on Intelligent Vehicle Pedestrian Detection Technology

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ABSTRACT: *With the progress of science and technology, intelligent vehicle research has been developed rapidly, and pedestrian detection is an important part of smart cars. Therefore, pedestrian detection research has become very popular. Pedestrian detection has become very complicated in the real-time driving environment due to pedestrian walking posture, pedestrian dress, pedestrian complicated background, and external conditions such as light. Therefore, pedestrian detection can not have a "universal" system can detect pedestrians in any scene can only be a specific problem-specific analysis.*
In this paper, the HOG+SVM pedestrian detection method proposed by previous researchers is improved. HOG+SVM detects the pedestrian's speed is relatively slow, and the detection accuracy is not very good. This paper proposes a PCA (principal component analysis) dimension reduction for HOG and also interpolates it. Reduces the dimensionality of individual HOG features and increases their accuracy, and fuses them with LBP features. The features of the fusion of HOG features and LBP features can not only express pedestrian profile information but also obtain pedestrian texture information, which can improve the speed of pedestrian detection and improve the accuracy of detection.

KEY WORDS: *HOG feature, LBP feature, PCA dimension reduction, sliding window*

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I. Overall Implementation Plan Of Intelligent Car Pedestrian Detection System

As a future trend of smart driving, its complex structure and what can be explored is very much. The article mainly focuses on the pedestrian detection part. The whole smart car pedestrian detection can be divided into the following several parts: information acquisition part, comprehensive feature extraction, classification training, implementation detection as shown in Figure 1-1 below:

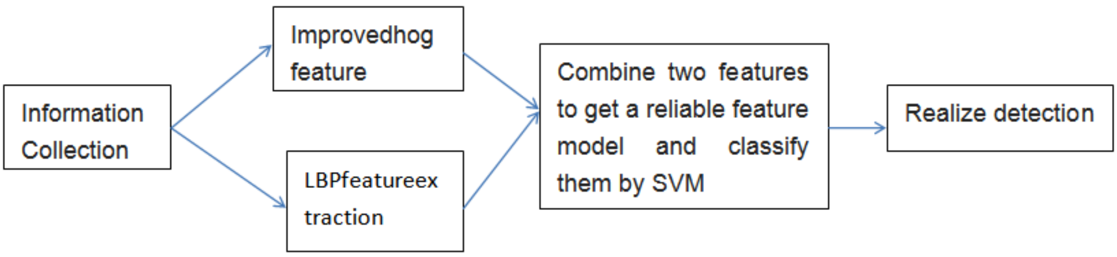

Figure 1-1 Pedestrian inspection system

II. Establishment Of Ihog-PCA Model

This section will integrate the simplified three-line interpolation and PCA dimensionality reduction method to improve the HOG based on the original HOG features.

(1) Improved three-line interpolation for two-dimensional cubic convolution interpolation during Hog algorithmIn the above section, we know the flow of the HOG algorithm. The process of HOG feature extraction given by Dalal in the 2005 paper is shown in Figure 2-1..

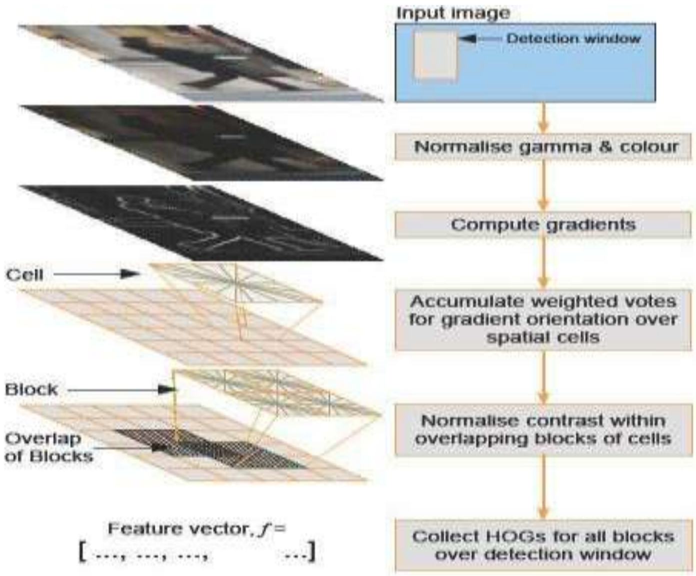

Figure 2-1 Schematic diagram of hog feature extraction

In the third step of the HOG, a gradient histogram is generated for each cell. Here, the generated gradient histogram is generated for each block independently, and overlapping blocks are generated when the cell in the fourth step merges the regions. Its schematic diagram is shown in Figure 2-2.

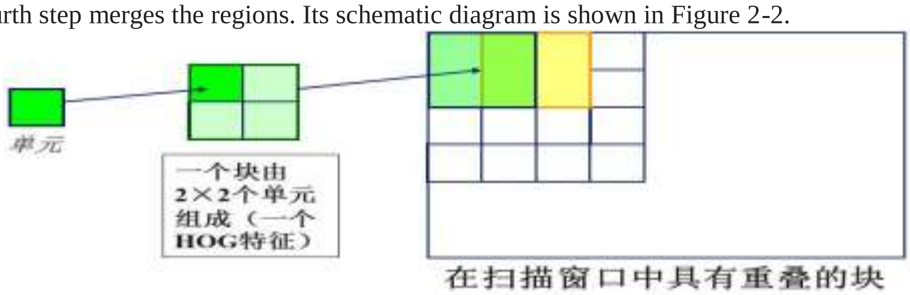

Figure 2-2 Schematic diagram of the extraction of hog blocks

Each unit extracted here is independent of each other, taking into account the mutual influence between the blocks and the blocks, in order to obtain better features, to better express the image information. According to the idea of the three-line interpolation mentioned in the previous section, three-line interpolation is widely used in hog, which solves the aliasing effect in the hog algorithm. However, the interpolation of three-line interpolation in the three-dimensional space is used in the sliding window, which will increase the calculation cost and waste resources. According to the study of three-line interpolation is not applicable to the integral image, this article uses the integral image to solve the sliding window problem. Therefore, without affecting the effect of interpolation, the simplified three-line interpolation is proposed as a two-dimensional cubic convolution interpolation. By this simplification, the integral histogram can be integrated, which greatly contributes to the improvement of the detection efficiency of the sliding window. Its simplification process is as follows:

In the HOG, the direction of the gradient of each pixel is discretely divided into nine directions. Therefore, at each pixel, the gradient is a two-dimensional vector with real-valued magnitude and discretization direction (even possible directions are evenly distributed between $[0, \pi]$). During the construction of the HOG integral image, If the characteristic value of each pixel is treated as a 2D vector, three-line interpolation between pixels cannot be performed. To solve this problem, the eigenvalue of each pixel is treated as a 9D vector in which the value in each dimension is an interpolated magnitude in the corresponding direction. The interpolation can be done by convolution before building the integral image. The simplified process is shown in Figure 2-3.

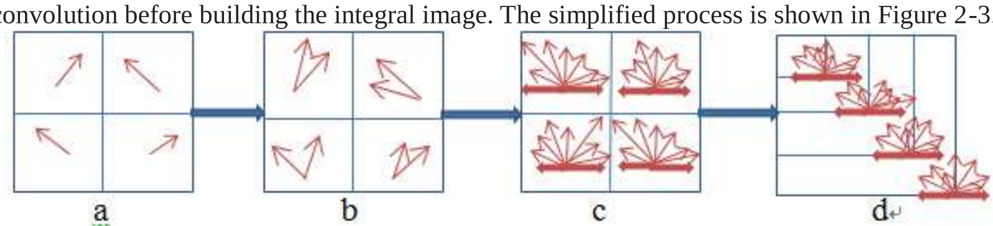

Figure 2-3 Two-dimensional cubic convolution interpolation

In this paper, a 7×7 convolutional kernel is designed to implement fast interpolation. The weights are assigned to adjacent areas according to the linear distance. First, you need to vote the real-valued gradient between 0 and π into 9 discrete bins based on their orientation and size. Using two-dimensional linear interpolation, the size of the gradient is assigned to two adjacent bins (as shown in the b grid of Figure 2-3). Then, the kernel in equation (2-1) is used to perform a convolutional bin image to achieve fast interpolation. The intermediate result is a fast-interpolation gradient image (shown in the c-square diagram in Figure 2-3). The fast interpolation section is completed. Interpolation of the image is completed as long as the entire image is interpolated in the same way. It is to be noted here that the method of this paper does not increase the spatial complexity of the image integration method. The results of the intermediate fast interpolation can be stored using the space allocated to the integral image. The size of the fast-interpolation gradient histogram image is the same as the integral image, so no extra calculation time is added. The equation (2-3) in the text is as follows:

$$\mathrm{conv(k)} = \frac{1}{256}\begin{vmatrix} 1 & 2 & 3 & 4 & 3 & 2 & 1 \\ 2 & 4 & 6 & 8 & 6 & 4 & 2 \\ 3 & 6 & 9 & 12 & 9 & 6 & 3 \\ 4 & 8 & 12 & 16 & 12 & 8 & 4 \\ 3 & 6 & 9 & 12 & 9 & 6 & 3 \\ 2 & 4 & 6 & 8 & 6 & 4 & 2 \\ 1 & 2 & 3 & 4 & 3 & 2 & 1 \end{vmatrix} \qquad (2\text{-}1)$$

Here, the three-dimensional three-dimensional interpolation is simplified to a two-dimensional convolution process. The two-dimensional interpolated cubic spline interpolation, that is, the integrated image histogram, will make the data more delicate. Figure 2-4 below shows the effect of two-dimensional interpolation in three-dimensional space.

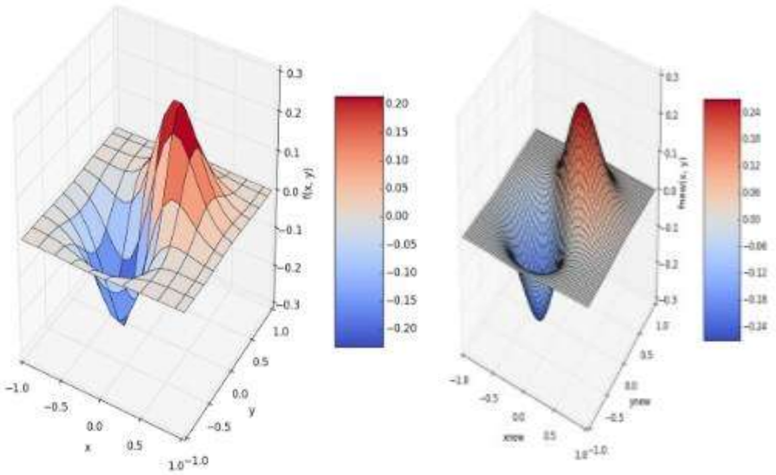

Figure 2-4 Two-dimensional interpolation of the effect of three-dimensional space

III. Pedestrian Detection With Fusion IHOGP-LBP Feature Multiple Training

The previous section mainly studied the improved method of HOG algorithm.Through the simplified three-line interpolation and PCA dimension reduction of HOG, thecalculation speed of HOG is improved and the accuracy of its detection is also improved. Its effectcan be reflected in the following experiments. HOG can describe the edges and gradients of objects very well during feature extraction but lacks description of texture informationfor some pedestrians. Here we will fuse LBP descriptors, combine pedestriantextureinformation, and better express pedestrian information through the integration of multi-feature integration graphs, making the detection effect more perfect.Firstly prepare the positive and negative samples, then extract the IHOG features of the positive and negative samples and then reduce the dimension. After training, the IHOGP detector is obtained. Then the negative samples are detected by the detector and then the features of the hardexample are extracted, and the IHOGP characteristics before the fusion are obtained. Continue training and eventually get the appropriate detector. The right frame shows the process of extracting LBP. Its process is the same as the model training process on the left. The final result is the LBP detection operator. Pedestrian detection of the main line of thought is the middle of the framework of the order, the left and right sides of the middle of the process.

In the specific algorithm, the detection scheme for the fusion IHOGP-LBP feature multiple training is shown in Figure 3-1:

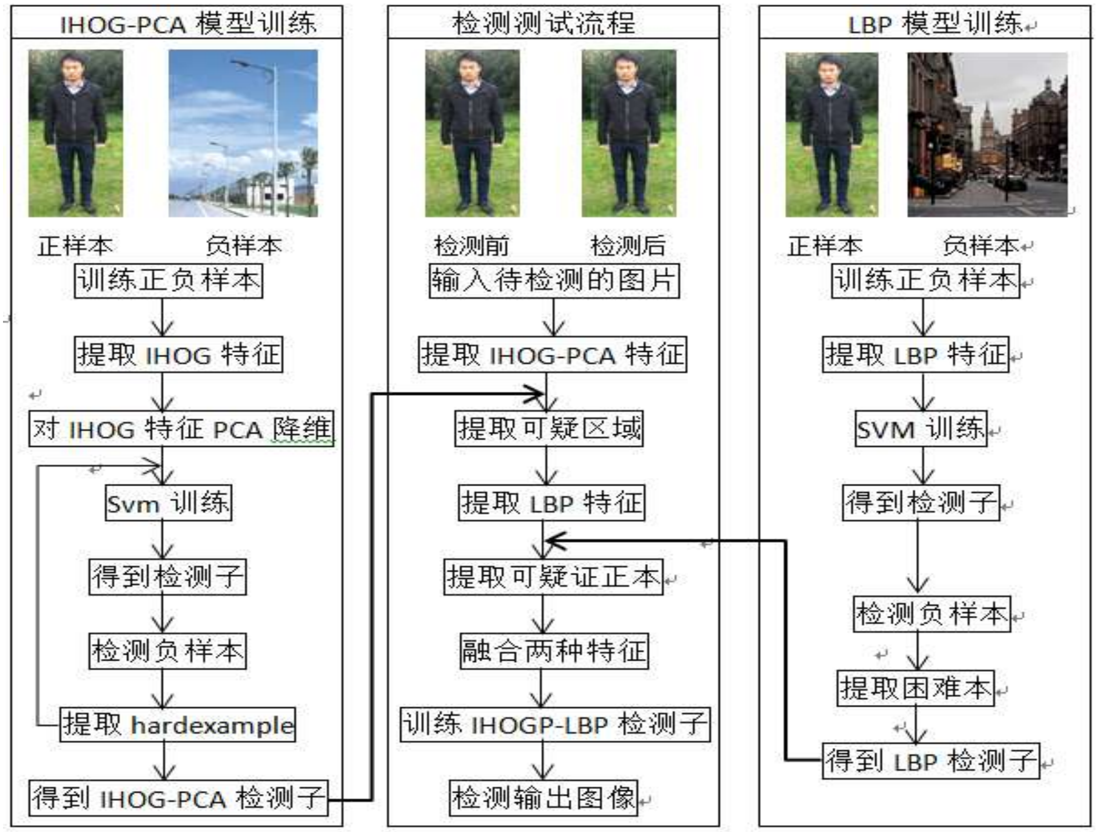

Figure 3-1Improved algorithm for pedestrian detection

Pedestrian detection of the main line of thought is the middle of the framework of the order, the left and right sides of the middle of the process. It can be seen from the above figure that after the picture is input, the IHOGP feature is extracted first, and then input into the SVM classifier to train to obtain a suspicious pedestrian area, but it is not sure whether it is a pedestrian. The LBP descriptors are then extracted and classified to obtain suspicious positive samples. Finally, the two characteristics are combined to train, and a more reliable pedestrian detector is obtained. Through the last pedestrian detector, the pedestrian in the image is detected. Can accurately detect the location of a person. Figure 3-2 is a schematic diagram of IHOGP-LBP feature fusion.

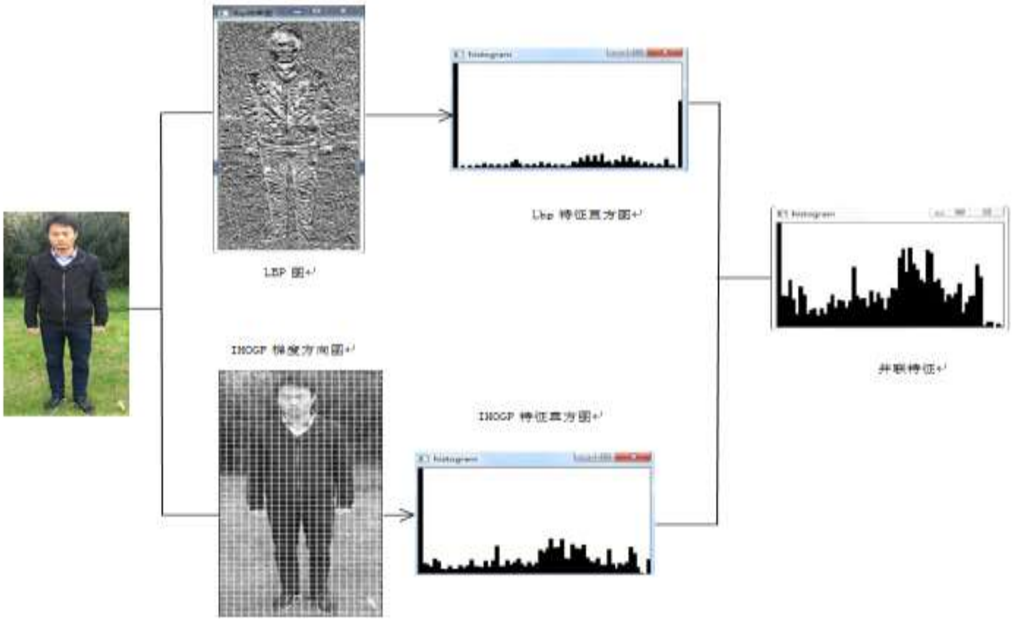

Figure 3-2Fusion of IHOGP-lBP features

The above figure is the process of feature fusion and can be expressed by Equation (3-1).
F_(IHOGP-LBP) (I)=F_IHOGP (I)+F_LBP (I) (3-1)

Where I is represented as a sample, F_IHOGP (I) is represented as the IHOGP feature of the sample, and F_LBP (I) is the lbp feature of the sample. The samples are first extracted from the IHOGP features, then the LBP features are extracted, and finally they are combined in parallel to form a fusion feature. From the above figure, we can see that the feature histogram of fusion has become more prominent, which shows that the features of the pedestrian after fusion are more obvious, making the probability of detecting pedestrians even higher.

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