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Pedestrian Detection Based on Sparse and Low-Rank Matrix Decomposition

Cheng Ke-yang*[1,2], Mao Qi-rong[2], Zhan Yong-zhao[2]
[1]College of Computer Science and Technology, Nanjing University of aeronautics & astronautics, Nanjing, Jiangsu, China, 210016, Ph./Fax: +8625-84892830
[2]College of Computer Science and Telecommunication Engineering, Jiangsu University, Zhenjiang, Jiangsu, China, 212013, Ph./Fax: +86511-88780371
*Corresponding author, e-mail: kycheng@ujs.edu.cn

Abstract

This article puts forward a novel system for pedestrian detection tasks, which proposing a model with sparse and low-rank matrix decomposition, jointly alternating direction method to solve the convex relaxation problem. We present an efficient pedestrian detection system using mixing features with sparse and low-rank matrix decomposition to combine into a Kernel classifier. Results presented on our data set show competitive accuracy and robust performance of our system outperforms current state-of-the-art work.

Keywords: *pedestrian detection, matrix decomposition, sparse, low-rank, alternating direction method*

1. Introduction

Pedestrian counting in public places plays a key role in many applications, such as evacuating from a dense region to a sparse one when an emergency happens, or optimizing the design of traffic infrastructures to provide better transportation services. Furthermore, social security and surveillance strongly depend on the effectiveness of pedestrian counting. A wide variety of pedestrian detection methods have been proposed [1-6].

Matrix representations of complex systems and models arising in various areas often have the character that such a matrix is composed of a sparse component and a low-rank component. Such applications include the model selection in statistics, system identification in engineering, partially coherent decomposition in optical systems, and matrix rigidity in computer science, see e.g. [7-13]. Practically, it is of significant interest to take advantage of the decomposable character of such a complex system. One necessary way towards this goal is to recover the sparseand low-rank components of a given matrix without prior knowledge about the sparsity pattern or the rank information. In paper, we put forward a novel framework for pedestrian detection tasks based on sparse and low-rank matrix decomposition (SLRMD).

2. Research Method

2.1. Feature Extractions

Obviously, the choice of features is the most critical decision when designing a detector, and finding good features is still largely an empirical process with few theoretical guidelines. We evaluate different combinations of features, and introduce a new feature based on the similarity of colors in different regions of the detector window, which significantly raises detection performance. The pedestrian region in our detection window is of size 48*96 pixels.

Histograms of oriented gradients (HOG) are a popular feature for object detection, first proposed in [14]. They collect gradient information in local cells into histograms using trilinear interpolation, and normalize overlapping blocks composed of neighboring cells. Interpolation, local normalization and histogram binning make the representation robust to changes in lighting conditions and small variations in pose. HOG was recently enriched by Local Binary Patterns (LBP), showing a visible improvement over standard HOG on the INRIA Person data set [15]. In

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our experiments we compute histograms with 9 bins on cells of 8*8 pixels. Block size is 2*2 cells overlapping by one cell size.

HOF Histograms of flow were initially also proposed by Dalal et al. [16]. We have shown that using them (e.g. in [16]'s IMHwd scheme) complementary to HOG can give substantial improvements on realistic datasets with significant ego motion. Here, we introduce a lower-dimensional variant of HOF, IMHd2, which encodes motion differences within 2*2 blocks with 4 histograms per block, while matching the performance of IMHwd (3*3 blocks with 9 histograms). Figure 2(d) schematically illustrates the new coding scheme: the 4 squares display the encoding for one histogram each. For the first histogram, the optical flow corresponding to the pixel at the ith row and jth column of the upper left cell is subtracted from the one at the corresponding position of the lower left cell, and the resulting vector votes into a histogram as in the original HOF scheme. IMHd2 provides a dimensionality reduction of 44% (2520 instead of 4536 values per window), without changing performance significantly. We used the publicly available flow implementation of [17]. In this work we show that HOF continues to provide a substantial improvement even for flow fields computed on JPEG images with strong block artifacts (and hence degraded flow fields).

Several authors have reported improvements by combining multiple types of low-level features [18-20]. Still, it is largely unclear which cues should best be used in addition to the now established combination of gradients and optic flow. Intuitively, additional features should be complementary to the ones already used, capturing a different part of the image statistics. Color information is such a feature enjoying popularity in image classification [15] but is nevertheless rarely used in detection. Furthermore, second order image statistics, especially co-occurrence histograms, are gaining popularity, pushing feature spaces to extremely high dimensions [19, 21].

By combining these ideas, we use second order statistics of colors as additional feature. Color by itself is of limited use, because colors vary across the entire spectrum both for people (respectively their clothing) and for the background, and because of the essentially unsolved color constancy problem. However, people do exhibit some structure, in that colors are locally similar—for example (see Figure 1) the skin color of a specific person is similar on their two arms and face, and the same is true for most people's clothing. Therefore, we encode color self similarities within the descriptor window, i.e. similarities between colors in different sub-regions. To leverage the robustness of local histograms, we compute D local color histograms over 8*8 pixel blocks, using trilinear interpolation as in HOG to minimize aliasing. We experimented with different color spaces, including 3*3*3 histograms in RGB, HSV, HLS and CIE Luv space, and 4*4 histograms in normalized rg, HS and uv, discarding the intensity and only keeping the chrominance. Among these, HSV worked best, and is used in the following.

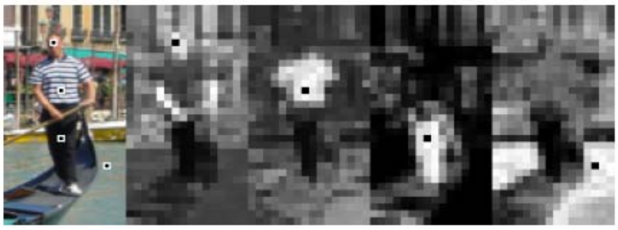

Figure 1. Self-similarity Encodes Relevant Parts

2.2. Supervised Discriminative Learning Based on Sparse and Low-Rank Matrix Decomposition

The heuristics of using the ℓ1-norm as the proxy of sparsity and the nuclear norm as the surrogate of low-rank are widely used in many areas such as statistics and image processing (see e.g. [22-25]). This inspires us to put forward a supervised discriminative learning model based on sparse and low-rank matrix decomposition:

$$\min_{A,B,\theta}\{c(yf(B,\theta))+\lambda_1\|x-\mathrm{A}-\mathrm{B}\|_2+\lambda_2\|A\|_{1_1}+\lambda_3\|B\|_*+\lambda_4\|\theta\|_2\} \quad (1)$$

Where $x \in R^{m\times n}$ is the given pedestrian image matrix to be decomposed; $A \in R^{m\times n}$ represent the sparse components of x, which contains the discriminative information of pedestrian image; $B \in R^{m\times n}$ represent the low-rank components of x, which contains the noise information; $||\cdot||_2$ is the ℓ2 norm; $||\cdot||_1$ is the ℓ1 norm defined by the component-wise sum of absolute values of all entries; $||\cdot||_*$, s the nuclear norm defined by the sum of all singular values; and λ>0 is a trade-off constant for these components.

In this paper, we use the ADM approach for solving (1) by taking full advantage of its separable structure. As we will analyze in detail, the ADM approach is attractive for (1) because the computational of each iteration is dominated by only one singular value decomposition (SVD).

Roughly speaking, ADM is a practical variant of the classical augmented Lagrangian method (ALM, see e.g., [26, 27]) for solving linearly constrained convex programming problem whose objective function is the sum of two individual functions without coupled variables. The ADM has found applications in many areas including convex programming, variational inequalities and image processing, see, e.g. [28-39]. In particular, novel applications of ADM for solving some interesting optimization problems have been discovered very recently, see e.g. [40-48]. The augmented Lagrangian function of (1) is:

$$L(A,B,Z,\beta) := c(yf(B,\theta)) + \lambda_1 ||A+B-x||_2 + \lambda_2 ||A||_{l_1} + \lambda_3 ||B||_* + \lambda_4 ||\theta||_2 - <Z, A+B-x>$$

Where $Z \in R^{m*n}$ is the multiplier of the linear constraint; <·, ·> denotes the standard trace inner product. Clearly, the classical ALM is applicable, and its iterative scheme starting from Z^k is given as follows:

$$\begin{cases} (A^{k+1}, B^{k+1}, \theta^{k+1}) \leftarrow \arg\min_{A,B,\theta} L(A,B,Z^k,\theta,\lambda) \\ Z^{k+1} = Z^k - \lambda_1(A^{k+1} + B^{k+1} - x) \end{cases} \quad (2)$$

The direct application of ALM, however, treats (1) as a generic minimization problem and performs the minimization with respect to A,B andθsimultaneously.

In contrast, ADM splits the minimization task in (2) into two smaller and easier subproblems, where A and B are minimized separately. Specifically, the original ADM (see [34]) solves the following problems to generate the new iterate:

$$A^{k+1} = \arg\min_A L(A, B^k, \theta^k, Z^k, \lambda) \quad 3(a)$$

$$B^{k+1} = \arg\min_B L(A^{k+1}, B, \theta^{k+1}, Z^k, \lambda) \quad 3(b)$$

$$\theta^{k+1} = \arg\min_\theta L(A^{k+1}, B^{k+1}, \theta, Z^k, \lambda) \quad 3(c)$$

$$Z^{k+1} = Z^k - \lambda_1(A^{k+1} + B^{k+1} - x) \quad 3(d)$$

By doing so, the subproblems (3a), (3b) and (3c) both have closed-form solutions. Thus, iterative processes for solving the inner subproblems are avoided. This fact contributes significantly to the computational efficiency of ADM for solving (1). We now elaborate on strategies of solving the subproblems (3a), (3b) and (3c). First, problem (3a) turns out to be a shrinkage problem (see e.g [40]) and its closed-form solution is given by:

$$A^{k+1} = Z^k/\lambda_1 - B^k + x - P_{\Omega_\infty^{\lambda_2/\lambda_1}}(Z^k/\lambda_1 - B^k + x)$$

Where $P_{\Omega_\infty^{\lambda_2/\lambda_1}}(.)$ denotes the Euclidean projection onto the set:

$$\Omega_\infty^{\gamma\,\lambda_2/\lambda_1} := \{X \in R^{m\times n} \mid -\lambda_2/\lambda_1 \le X_{i,j} \le \lambda_2/\lambda_1\}$$

$$B^{k+1} = \arg\min_{B} \{c(yf(B,\theta^{k+1})) + \lambda_3 \|B\|_* + \lambda_4 \|\theta^{k+1}\|_2 + \lambda_1 \|B - (x - A^{k+1} + Z^k / \lambda_1)\|_2\} \quad (4)$$

$$B^{k+1} = U^{k+1} diag(\max\{\sigma_i^{k+1} - 1/\lambda_1, 0\})(V^{k+1})^T \quad (5)$$

$$U^{k+1} \in R^{m \times r}, V^{k+1} \in R^{n \times r}$$

$$x - A^{k+1} + Z^k / \lambda_1 = U^{k+1} \sum{}^{k+1} (V^{k+1})^T \text{ with } \sum{}^{k+1} = diag(\{\sigma_i^{k+1}\}_{i=1}^{r\,\lambda_2})$$

$$\theta^{k+1} = \arg\min_{\theta} \{c(yf(B^{k+1}, \theta) + \lambda_4 \|\theta\|_2\}$$

Based on above analysis, we now describe the procedure of applying the ADM to solve (1). For given (B^k,Z^k), the ADM takes the following steps to generate the new iterate (A^{k+1},B^{k+1},Z^{k+1}):

Step 1. Generate Ak+1:

$$A^{k+1} = Z^k / \lambda_1 - B^k + C - P_{\Omega_\infty^{\gamma/\beta}}(Z^k / \lambda_1 - B^k + C)$$

Step 2. Generate Bk+1:

$$B^{k+1} = U^{k+1} diag(\max\{\sigma_i^{k+1} - 1/\lambda_1, 0\}(V^{k+1})^T$$

where U^{k+1}, Vk+1 and {σ_i^{k+1}} are generated by the following SVD:

$$x - A^{k+1} + Z^k / \lambda_1 = U^{k+1} \sum{}^{k+1} (V^{k+1})^T \text{ , with}$$

$$\sum{}^{k+1} = diag(\{\sigma_i^{k+1}\}_{i=1}^{r})$$

Step 3. Generateθ^{k+1}:

$$\theta^{k+1} = \arg\min_{\theta} \{c(yf(B^{k+1}, \theta) + \lambda_4 \|\theta\|_2\}$$

Step 4. Update the multiplier:

$$Z^{k+1} = Z^k - \lambda_1 (A^{k+1} + B^{k+1} - x)$$

Figure 2. The ADM Algorithm for SLRMD Problem

3. Results and Analysis

To evaluate the performance of the proposed algorithm, we carry out a series of experiments on a dataset extracted 500 images of size 128*64 from MIT database. If the image contains a pedestrian, the label of it will be 1, otherwise -1. Figure 3(a) shows several images with label 1. Figure 3(b) shows several images with label -1. 100 images from the dataset are selected as the test examples. Different number images of the dataset are selected as the training examples to compare the accuracy rate.

Figure 3(a). Images with Label 1

Figure 3(b). Images with Label -1

Figure 4 shows the compare results of recognition between with HOG, HOF and Color features respectively and the corresponding features with sparse and low-rank matrix decomposition. Figure 5 shows the result of using mixing features to compare the two methods. As shown in the graph, our method performs better than the method directly using HOG, HOF and Color features to recognition with the classifier SVM. In addition, with the increasing number of training samples, our method performs better.

Figure 6 shows the result of these two methods using shading images to test. Compared with the traditional method, our method has better recognition accuracy and shows good robustness.

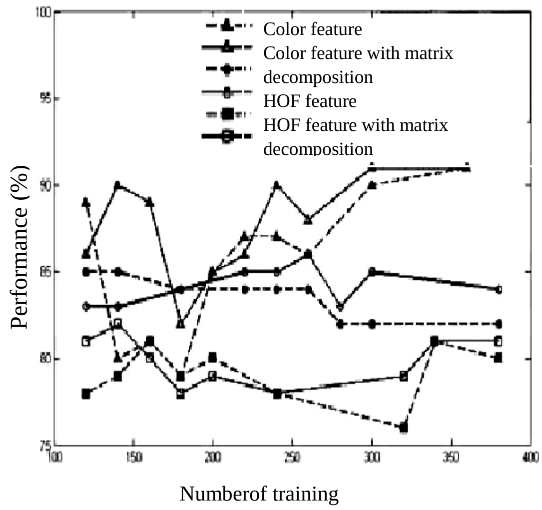

Figure 4. The Compare Results of Recognition between with HOG, HOF and Color Features Respectively and the Corresponding Features with Sparse and Low-rank Matrix Decomposition

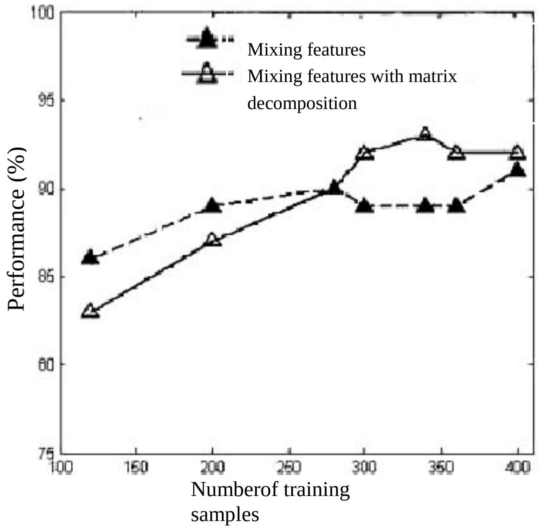

Figure 5. The Result of Using Mixing Features to Compare the Two Methods

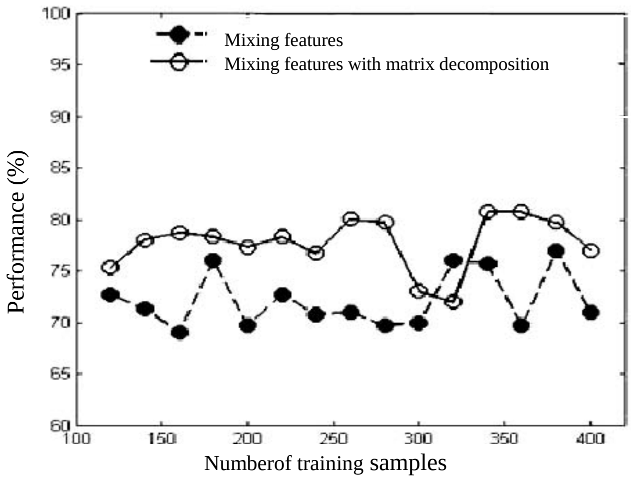

Figure 6. The Result of these Two Methods Using Shading Images to Test

4. Conclusion

We proposed a system for pedestrian detection with very good accuracy. To achieve good classification performance, we put forward a novel framework for pedestrian detection tasks, which proposing a model with sparse and low-rank matrix decomposition, jointly alternating direction method to solve the convex relaxation problem. We present an efficient pedestrian detection system using mixing features with sparse and low-rank matrix decomposition of HOG, FOG and CSS to combine into a Kernel classifier. Results presented on our data set show competitive accuracy and robust performance of our system outperforms current state-of-the-art work. Although we use the system for the detection of pedestrians, the general idea can be applied to the detection of other object classes as well.

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