Crowd Counting via Weighted VLAD on Dense Attribute Feature Maps

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Abstract—Crowd counting is an important task in computer vision, which has many applications in video surveillance. Although the regression-based framework has achieved great improvements for crowd counting, how to improve the discriminative power of image representation is still an open problem. Conventional holistic features used in crowd counting often fail to capture semantic attributes and spatial cues of the image. In this paper, we propose integrating semantic information into learning locality-aware feature sets for accurate crowd counting. First, with the help of convolutional neural network (CNN), the original pixel space is mapped onto a dense attribute feature map, where each dimension of the pixel-wise feature indicates the probabilistic strength of a certain semantic class. Then, locality-aware features (LAF) built on the idea of spatial pyramids on neighboring patches are proposed to explore more spatial context and local information. Finally, the traditional VLAD encoding method is extended to a more generalized form in which diverse coefficient weights are taken into consideration. Experimental results validate the effectiveness of our presented method.

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I. INTRODUCTION

Crowd counting, which is defined as the number of people in a crowd, has recently drawn great attention due to its wide application in the field of video surveillance, particularly in public security [1], [2]. Among existing approaches [3], [5], [6], [7], [8], [9], the regression-based framework that learns a regression function between image representations and count numbers has gained considerable interest [9]. The majority of these works usually construct crowd models from patterns of holistic hand-crafted features [1], [9], [10] such as foreground segment features, internal edge features and texture features.

Despite the success of hand-crafted features for crowd counting, there still exists two weaknesses. Firstly, they simply characterize the visual contents without capturing the underlying semantic information, which may lead to unsatisfactory performance. In the literature, there is limited work on exploring attribute features for crowd counting. Therefore, it is worth exploring the problem how to improve the discriminative power of feature representations by sufficiently mining the rich semantic information. Secondly, the holistic features directly obtained from entire images are typically unable to capture locally spatial information and describe the diversity in the crowd distribution, density and behaviors. Thus, it is important to encode spatial cues into the feature learning process for crowd counting.

In this work, we attempt to design a novel image representation which takes into consideration semantic attributes as well as spatial cues. In order to characterize the distribution of people number, we define semantic attributes at the pixel level and learn the semantic feature map via deep convolutional neural network (CNN). Then, a high-level concept named locality-aware feature (LAF) in the abstract semantic attribute feature map is presented to describe the spatial information in crowd scenes. Fig. 1 shows pixel-level attribute feature maps corresponding to two frames of the UCSD dataset. Every point in the feature map can be expressed as a vector of attributes, each element of which is a certain semantic class probability. After obtaining local descriptors LAF from adjacent sampled cells over the semantic feature map, our pipeline adopts an improved method Weighted VLAD (W-VLAD) to encode features into image representations.

Compared with the traditional method that directly obtains the image representation by aggregating holistic features [1], [9], [10], our pipeline that combines LAF with W-VLAD is more discriminative for creating instance representations. It can not only adapt to complex diversity in crowd [1], but also retain more useful information. The comparison between our proposed method and the traditional ones is shown in Fig. 2.

In summary, the main contributions of this paper are as follows.

- For the first time, a pixel-level semantic feature map learned by a deep learning model is constructed for local features extraction.
- A novel descriptor named LAF is proposed to combine both advantages of explicit semantic incorporation and spatial context encoding.
- An improved VLAD scheme termed W-VLAD is applied for encoding descriptors into the final representation.
- Extensive experiments on benchmarks demonstrate the effectiveness of our method, even when people in the frames are hard to identify.

The rest of this paper is organized as follows. After reviewing the related work in Section II, we introduce semantic locality-aware features in Section III. Then, the thorough experimental evaluations are carried out in Section IV. Finally, the paper is concluded in Section V.

II. RELATED WORK

Counting methods. Most previous work on crowd counting can be divided into three categories: counting pedestrians by detection [17], [18], [19], clustering [3], [5] and regression [1], [6], [9]. The performance of detection approaches highly depend on the whole pedestrian result which is suppressed in densely crowded scenes with significant occlusion. Clustering-based methods that coherent motion patterns are clustered to estimate the crowd number only work well for video frames at a high rate. Considering severe occlusions between people in the crowd scene and the requirements of high efficiency for real applications, many researchers utilize regressors trained on low-level features to predict the global counts [1], [6], [7], [8], [9]. Most of these methods are based on low-level features proposed in [9]. With the ever-growing data volume and computational capability, deep learning has begun a useful tool in several surveillance applications such as crowd behavior analysis [21] and crowd segmentation [23]. Zhang et al. [2] firstly try to develop a deep model for predicting crowd number and the superior performance validates that deep feature is more discriminative than shallow hand-craft one.

Attribute learning. Attributes are mid-level semantic properties of objects which bridge the gap between low-
level features and high-level representations [29]. In recent
years, attribute-based representations that describe a target by
multiple attribute classes have been widely used to represent
objects [24], faces [25] and actions [26]. The common
characteristics shared by different scenes can express more
information [22]. Shao et al. [21] utilize three attributes
"who", "where" and "why" to describe a crowd scene and
successfully apply them to analyze crowd behavior. Wang et
al. [35] propose that attributes and interdependencies among
them can help to improve object recognition performance.
Liu et al. [36] present an action recognition framework
built upon a latent SVM formulation where latent variables
capture the degree of each attribute to its action class.
Similarly, a binary cumulative attribute is converted from the
count number [14], which has realized the crowd counting
task effectively. However, cumulative attribute, only a coarse
description of the crowd distribution, is not sufficient for the
natural scene.

Spatial cues encoding. Recent works demonstrate that
it is vital to describe local features with spatial aware-
ness for minimizing the information loss and improving
the discriminative power of representations. Usually holis-
tic representations are sensitive to changes in the external
environment [9], [20]. Ryan et al. [1] propose a localized
approach that estimates the crowd number within different
groups and then obtains the total number by summing up
all the group results. Chen et al. [10] concatenate features
in all sub-regions of an image and propose a multi-output
regression model to learn the local count. He et al. [37]
advocate a spatial pyramid pooling (SPP) layer on the entire
convolutional feature map and then generates a fixed-length
representation for the following fully-connected layers. With
spatial information considered, these methods either require
manually local counting or lead to representations of huge
length.

VLAD encoder. As a simplified version of FV [27],
VLAD [28] only aggregates the first order information which
are displacements between features and the corresponding
dictionary element. Because of the low computation cost
and superior performance, VLAD has recently been applied
in many applications. Ng et al. [41] extract convolutional
features from different layers of CNN and apply VLAD
to encode features into a single vector for image retrieval.
Multi-VLAD [40] aims at constructing and matching VLAD
vectors of multi-level images. Peng et al. [39] improves
VLAD by optimizing the dictionary and considering high-
order statistics.

III. Locality-aware features in the dense
attribute feature map

The key difference between our approach and previous
works is that the input to a regression model is a novel and
discriminative representation instead of explicit or implicit
usage of the low-level feature [1], [6], [9], [10]. As shown
in the top part of Fig. 2, our proposed approach consists
of feature map construction, local feature extraction and
encoding. In this section, we introduce the three aspects in
detail.

A. Pixel-level attribute feature map

We attempt to learn image attributes at the pixel level so
that semantic information and the diversity of crowd number
are sufficiently described. To the best of our knowledge, this
is the first work that extracts frame features based on pixel-
level attributes of a crowd scene.

Inspired by the tremendous success of deep convolutional
neural network (CNN) in pixel labeling [11], [12], [13], we
learn the pixel-wise semantic feature map by an off-the-shelf deeply learned CNN model. In this paper, the state-of-the-art deep semantic segmentation method [13] is applied to train a model on the cityscape dataset [38], in which each pixel is annotated with labels such as person, road, tree and so on. Developed as a deep hierarchical structure, the learned CNN model processes the raw image pixels with several consecutive convolutional layers and contextual deep CRF, the output of which is up-sampled as high-level semantic feature map to model the distribution of people in crowd counting.

Specifically, the deeply learned model is utilized as a mapping model $F : \mathcal{X} \rightarrow \mathcal{D}$, where $X \in \mathbb{R}^{m \times n}$ is the original image in a pixel space, $D \in \mathbb{R}^{m \times n \times p}$ is the corresponding semantic feature map; notions $m$, $n$, $p$ respectively denote the image width, height and the number of defined attribute types. The pixel-wise $p$ dimensional vector is the probability of $p$ attribute classes.

Instead of low-level simple intensity or texture information, the deeply learned semantic feature map characterizes each pixel with abstract attributes. As shown in Fig. 3, the attribute information indicates the co-occurrence of visual patterns (e.g., a person is likely to co-occur with the road), which can provide abundant information for sufficiently describing the crowd scene.

### B. Locality-aware features

On one hand, it is computationally inefficient to take vectors of every pixel as features. On the other hand, computing a feature vector over the entire pixel-wise probability map may lead to large information loss. The most common method is region division as He et al. [37] do, by which the image is partitioned into multiple cells and the concatenation of all cell-based pooling results is taken as the feature. Theoretically the finer the region is partitioned, the more information is retained and the longer the final representation is.

In order to obtain a balance between accuracy and computational complexity, locality-aware features are proposed in this paper. The process of LAF extraction is shown in the right part of Fig. 4 and the procedure is mainly summarized as the following three steps:

1) Given a semantic segmentation feature map $D \in \mathbb{R}^{m \times n \times p}$, we first partition it into $N$ cells from which local features are extracted.

2) Each local feature vector of LAF is extracted from each cell, in which spatial pyramid is applied to capture spatial relationship.

The spatial pyramid result of each cell is obtained by concatenating and normalizing the $M$ mean pooling vectors where $M$ is the partition number of a cell. If $p$ is defined as the number of attribute classes, then the local feature in each cell is expressed as $x \in \mathbb{R}^d$, where $d = Mp$. The feature vector $x$ is able to capture the co-occurrence of different semantic attributes.

3) Finally feature vectors of all cells are aggregated as LAF, which can be denoted as:

$$X = [x_1, x_2, \cdots, x_i, \cdots, x_N] \in \mathbb{R}^{d \times N}, 1 \leq i \leq N$$  \hspace{1cm} (1)

where $N$ is the number of LAF (namely the number of partitioned cells) in the image and $x_i$ is the feature vector of the $i$-th cell.

In contrast to the SPP feature extraction [37] which only incorporates the coarse spatial cues at the image level, the set of all $N$ cell-based features are simultaneously and equally used for subsequent feature encoding; spatial pyramid used in LAF is able to maximize the use of local spatial information and characterize context clues. In a word, LAF have advantages of capturing finer location information by localized spatial pyramid and controlling the vector length by aggregating local features.

### C. Feature encoder: W-VLAD

The encoder is utilized to encode a set of low-dimensional local descriptors (LAF here) to a single compact vector. Given a video frame, we first extract LAF $X = [x_1, x_2, \cdots, x_N] \in \mathbb{R}^{d \times N}$ described above. Let $\phi = [\tilde{x}_1, \tilde{x}_2, \cdots, \tilde{x}_N]$ be projected features related to $X$ by PCA+Whitening for better performance [34] and $\tilde{B} = [\tilde{b}_1, \tilde{b}_2, \cdots, \tilde{b}_K] \in \mathbb{R}^{N \times K}$ is the corresponding dictionary learned offline by k-means. The original version of VLAD is expressed as follows:

$$v_k = \sum_{i : NN(x_i) = b_k} (\tilde{x}_i - \tilde{b}_k)$$  \hspace{1cm} (2)

The final representation is gained by concatenating the all $v_k (k = 1, \cdots, K)$ vectors with normalization followed. It can be easily seen from the formula (2) that the weights for all residuals are assigned binary values 0 or 1. We try to modify the original VLAD into W-VLAD.

The formula (2) is extended to an alternative form, which is shown in (3):

$$v_k = \sum_{i=1}^{N} \alpha^k_i (x_i - b_k)$$  \hspace{1cm} (3)

For the standard VLAD, the assignment coefficients $\alpha^k_i$ can be defined as follows:

$$\alpha^k_i = \begin{cases} 1 & \text{if } NN(x_i) = b_k \\ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (4)

On one hand, the assignment method in (4) is similar to Hard-assignment coding [31], which may result in relatively high reconstruction error while coding. On the other hand, the coefficient $\alpha^k_i$ here can be interpreted as the degree of local feature $x_i$ to cluster center $b_k$. In fact, different features may have different relevance to the clusters and it is unreasonable to apply the same weight coefficients even though they are assigned to the same cluster word with the same residual value.

In this paper, we utilize local soft assignment coding (LSAC) [31] to compute weights for effectiveness and simplicity:
\[
\alpha_i^k = \frac{\exp(-\beta d(\hat{x}_i, \hat{b}_j))}{\sum_{j=1}^{K} \exp(-\beta d(\hat{x}_i, \hat{b}_j))}
\]

(5)

\[
d(\hat{x}_i, \hat{b}_j) = \left\{ \begin{array}{ll}
\|\hat{x}_i - \hat{b}_j\|^2 & \text{if } \hat{b}_j \in \mathbb{N}_\kappa(\hat{x}_i) \\
\infty & \text{otherwise}
\end{array} \right.
\]

(6)

where \(\mathbb{N}_\kappa\) denotes the \(\kappa\) nearest neighbors of \(\hat{x}_i\) in the dictionary and \(\beta\) is the smoothing factor controlling the softness of the assignment.

IV. EXPERIMENTS

Datasets. In order to explore whether our method is effective for the dataset in which persons are not easy to identify, we introduce a new dataset Caltech 10X (Caltech) [4] (originally utilized for pedestrian detection) besides the shopping mall dataset (Mall) [10], [14] and the established UCSD pedestrian (UCSD) [32]. As shown in Fig. 5, different from Mall and UCSD dataset, persons in some frames from Caltech are not clearly visible. We evaluate the proposed approach on the three datasets in this study for comparative evaluation.

![Example frames from three datasets](image)

Fig. 5. Example frames from three datasets: Row 1, Row 2 and Row 3 are sampled respectively from the Mall dataset, the UCSD dataset and the Caltech dataset.

Table I describes the details of all mentioned datasets. \(N_f\) means the frame number, \(D\) shows the range of crowd number in a frame ROI, and \(T_P\) indicates the total number of labeled pedestrians.

| Dataset | \(N_f\) | \(D\)  | \(T_P\) |
|---------|--------|-------|--------|
| Mall    | 2000   | 13-53 | 62325  |
| UCSD   | 2000   | 11-46 | 49885  |
| Caltech| 2000   | 6-14  | 15043  |

TABLE I

The details of three datasets.

Evaluation metric. We use two metrics to evaluate our method, namely mean absolute error (MAE) and mean squared error (MSE). For both metrics, the lower the values are, the better the experimental performance is.

\[
MAE = \sum_{i=1}^{N_f} |y_i - \hat{y}_i|
\]

(7)

\[
MSE = \sum_{i=1}^{N_f} (y_i - \hat{y}_i)^2
\]

where \(N_f\) is the total number of frames, \(y_i\) is the estimated crowd number in the \(i^{th}\) frame and \(\hat{y}_i\) is the corresponding ground truth.

Implementation details. In Table II, parameters of the second & third column respectively show a partition number over the entire frame & the partitioned cell (\(\beta\) part of Sec III). The fourth and the last column of Table II empirically defines the dictionary size and the number of nearest neighbors for the W-VLAD encoding process (\(C\) part of Sec III).

| Dataset | \(N\) | \(M\) | \(K\) | \(\kappa\) |
|---------|------|------|------|------|
| Mall    | 20\times20 | 2\times2 | 100  | 10   |
| UCSD   | 20\times20 | 2\times2 | 100  | 10   |
| Caltech| 20\times20 | 2\times2 | 80   | 10   |

TABLE II

The parameters settings for three datasets.

Comparative study. Under the regression-based framework, we try to explore the performance of different image representations. In order to investigate the effectiveness of all parts in our proposed method, we conduct a series of baselines:

- Holistic Feature (HF). The image representation is obtained by direct mean pooling over the entire dense attribute feature map.
- SPP Feature (SPPF). The image representation is similar to HF except applying spatial pyramid on the entire feature map.
- LAF + VLAD (LFV). The image representation is gained by using the original VLAD method to encode our proposed locality-aware features LAF.

A. Mall dataset

Captured at different time of a day, the Mall dataset is challenging for its diverse crowd densities (from spare to dense) and various activity patterns (from static to moving) [10]. We follow the training and test partition as [10], [14], in which the first 800 frames are conducted as training samples with the remaining as a testing set. The crowd prediction result by our proposed approach is shown in Fig. 6, from which it can be easily observed that our method can perfectly predict the crowd number despite huge fluctuations of crowd density.

We utilize parameters shown in the first line of Table II and plot the curve of MAE/MSE vs. the size of nearest neighbors \(\kappa\) in Fig. 7. Experimental results are affected by the parameter \(\kappa\) selection and in the Mall dataset we set \(\kappa = 10\) for better performance.

Table III shows comparison results by our approach and some existing methods. It can be easily seen from Table
III that the proposed method outperforms all published works and achieves the state-of-the-art. It validates that the learned crowd representation is highly representative and discriminative for the Mall dataset.

### TABLE III
**Comparison with previous work on the Mall dataset.**

| Method       | MAE  | MSE   |
|--------------|------|-------|
| MLR [15]     | 3.90 | 23.9  |
| GPR [9]      | 3.72 | 20.1  |
| MORR [10]    | 3.15 | 15.7  |
| NCA-RR [14]  | 3.43 | 17.7  |
| CA-RR [14]   | 3.43 | 17.7  |
| **Our method** | **2.86** | **13.05** |

Table IV lists the performance of our method and baselines. The simplest representation HF has been comparable to or even exceeded some methods listed in Table III, which indicates the effectiveness of our pixel-level attribute feature map. Incorporating the spatial information, SPPF significantly outperforms HF using two measures. The phenomenon that SPPF is still inferior to our proposed method shows the weakness of low-level holistic features.

Further, we combine LAF and VLAD to gain a high-level representation LFV. One evaluation index MAE falls in between HF and SPPF while MSE is superior to the above methods. The fact shows that localized methods make the distribution of errors between groundtruth and prediction be more uniform than that of holistic approaches. Next, the proposed W-VLAD is applied instead of original VLAD, the result of which is shown in the last row of Table IV (namely our method) and reports the best performance under our framework.

### TABLE IV
**Experimental results of baselines on the Mall dataset.**

| Method       | MAE  | MSE   |
|--------------|------|-------|
| HF           | 3.93 | 24.28 |
| SPPF         | 3.17 | 20.84 |
| LFV          | 3.46 | 18.44 |
| **our method** | **2.86** | **13.05** |

In order to show the discrimination of representations, we randomly choose three frames with different crowd numbers (frame a: 19, frame b: 30, frame c: 30) and lists corresponding similarities in Table V, in which the linear function is utilized here to evaluate the similarity between two vectors. The data show that the inter-class distance is larger than the inner-class distance. By our proposed method, the difference between inter-class and inner-class distance is the largest among all baselines, which validates the discriminative power of the final representation by our proposed approach.

Taking LFV and our proposed method for example, we intuitively plot the corresponding representations shown in Fig. 8. By W-VLAD encoder, representations between frames with the same crowd number (frame b & frame c) are more similar and those with different crowd numbers (frame a & frame b) have larger differences.

### TABLE V
**The similarities between different representations.**

|       | HF    | SPPF  | LFV   | our method |
|-------|-------|-------|-------|------------|
| S(a,b) | 0.9547| 0.7598| 0.0857| 0.6261     |
| S(b,c) | 0.9953| 0.8985| 0.1807| 0.8074     |
| S(a,b)-S(b,c) | 0.0406| 0.1387| 0.0950| 0.1813     |

B. UCSD dataset

The UCSD dataset is recorded at a campus scene by a hand-held camera. It contains 2000 frames, 610-1400 of which are employed as a training set and the rest for testing. Table VI lists results by previous methods and our approach. It can be seen that MAE/MSE achieves 2.41/9.12, which is a comparable result.

### TABLE VI
**Experimental results of baselines on the UCSD dataset.**

| Method       | MAE  | MSE   |
|--------------|------|-------|
| MLR [15]     | 2.60 | 10.1  |
| GPR [9]      | 2.24 | 7.97  |
| MORR [10]    | 2.29 | 8.08  |
| NCA-RR [14]  | 2.35 | 11.9  |
| RFR [14]     | 2.42 | 8.47  |
| **Our method** | **2.41** | **9.12** |

Baselines are also utilized to verify effectiveness of our proposed parts. As shown in in Table VII, SPPF achieves a more superior result than HF since spatial cue is taken into consideration. Compared with SPPF, LFV can obtain improved MAE and comparable MSE because constructing final representation by encoding local descriptors can retain more locality information than holistic representation. For the UCSD dataset, results of our method and LFV show that computing weights by soft-assignment coding in W-VLAD is more effective than binary assignments in the original VLAD.

C. Caltech 10X dataset

Although the crowd density is more sparse than Mall and UCSD, it is more difficult to pick out pedestrians because of severe occlusion, the changing scenes and so on. As shown in the bottom row of Fig. 5, sometimes we cannot even identify persons from images by our naked eyes. We choose the first 2000 frames that contain more than six persons in the
Caltech training dataset as the entire crowd counting dataset, in which the first 800 images are used for training with others for testing. The annotations provided in Caltech are directly utilized as crowd groundtruth.

The discriminative power and effectiveness of our proposed method are validated on three benchmarks.

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REFERENCES

[1] D. Ryan, S. Denman, C. Fookes, and S. Sridharan. Crowd Counting Using Multiple Local Features. In Proc. Int. Conf. Digital Image Computing: Techniques and Applications, 2009.
[2] C. Zhang, H. Li, X. Wang, X. Yang. Cross-scene Crowd Counting via Deep Convolutional Neural Networks. In Proc. IEEE Conf. Comp. Vision and Pattern Recognition, 2015.
[3] G.J. Brostow, R. Cipolla. Unsupervised Bayesian detection of independent motion in crowds. In Proc. IEEE Conf. Comp. Vision and Pattern Recognition, 2006.
[4] P. Dollar, C. Wojek, B. Schiele, P.Perona. Pedestrian detection: An evaluation of the state of the art. IEEE Trans. Pattern Analysis and Mach. Intelligence, vol. 34, no. 4, pp. 743-761, 2012.
[5] V. Rabaud, S. Belongie. Counting crowded moving objects. In Proc. IEEE Conf. Comp. Vision and Pattern Recognition, 2006.
[6] A.B. Chan, N. Vasconcelos. Counting people with low-level features and bayesian regression. IEEE Trans. Image Process., vol. 21, no. 4, pp. 2160-2177, 2012.
[7] C. Loy, K. Chen, S. Gong, T. Xiang. Crowd Counting and Profiling: Methodology and Evaluation. Modeling, Simulation and Visual Analysis of Crowds. vol. 11, pp. 347-382, 2013.
[8] A. Davies, J. Yin, S. Velastin. Crowd monitoring using image processing. Electronics&Communication Engineering Journal. vol. 7, no. 1, pp. 3747, 1995.
[9] A.B. Chan, Z.-S. J. Liang, and N. Vasconcelos. Privacy preserving crowd monitoring:counting people without people models or tracking. In Proc. IEEE Conf. Comp. Vision and Pattern Recognition, 2008.
[10] K. Chen, C. C. Loy, S. Gong, and T. Xiang. Feature mining for localised crowd counting. In Proc. British Mach. Vision Conf., 2012.
[11] J. Long, E. Shelhamer, T. DarrellFully Convolutional Networks for Semantic Segmentation. In Proc. IEEE Conf. Comp. Vision and Pattern Recognition, 2015.
[12] L. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A. Yuille. Semantic Image Segmentation with Deep Convolutional Nets and Fully Connected CRFs. In Int. Conf. Learn. Representations, 2015.
[13] G. Lin, C. Shen, I. Reid, A. Hengel. Efficient Piecewise Training of Deep Structured Models for Semantic Segmentation. In Proc. IEEE Conf. Comp. Vision and Pattern Recognition, 2016.
[14] K. Chen, S. Gong, T. Xiang, and C. C. Loy. Cumulative attribute space for age and crowd density estimation. In Proc. IEEE Conf. Comp. Vision and Pattern Recognition, 2013.
[15] X. Wu, G. Liang, K.K. Lee, and Y. Xu. Crowd density estimation using texture analysis and learning. In IEEE International Conference on Robotics and Biomimetics, 2006.
[16] H. Jegou, F. Perronnin, M. Douze, J. Sanchez, P. Perez, and C.Schmid. Aggregating local image descriptors into compact codes. IEEE Trans. Pattern Analysis and Mach. Intelligence, vol. 34, no. 9, pp. 4-6, 2012.
[17] M. Li, Z. Zhang, K. Huang, and T. Tan. Estimating the number of people in crowded scenes by mid based foreground segmentation and head-shoulder detection. In Proc. Int. Conf. Pattern Recognition, 2008.
[18] T. Zhao, R. Nevatia, and B. Wu. Segmentation and tracking of multiple humans in crowded environments. IEEE Trans. Pattern Analysis and Mach. Intelligence, vol. 30, no. 7, pp. 1198-1211, 2008.
[19] G. Guo, Y. Fu, C. Dyer, and T. Huang. Image-based human age estimation by manifold learning and locally adjusted robust regression. IEEE Trans. Image Process, vol. 17, no. 7, pp. 1178-1188, 2008.
[20] H. Rahmalan, M. Nixon, and J. Carter. On crowd density estimation for surveillance. In *the Institution of Engineering and Technology Conference on Crime and Security*, 2006.

[21] J. Shao, K. Kang, C. C. Loy, and X. Wang. Deeply Learned Attributes for Crowded Scene Understanding. In *Proc. IEEE Conf. Comp. Vision and Pattern Recognition*, 2015.

[22] C. Castellano, S. Fortunato, and V. Loreto. Statistical physics of social dynamics. *Reviews of modern physics*. vol. 81, no. 2, pp. 591, 2009.

[23] K. Kang, X. Wang. Fully convolutional neural network for crowd segmentation. In *Proc. IEEE Conf. Comp. Vision and Pattern Recognition*, 2015.

[24] T. L. Berg, A. C. Berg, and J. Shih. Automatic attribute discovery and characterization from noisy web data. In *Proc. Eur. Conf. Comp. Vision*, 2010.

[25] N. Kumar, A. C. Berg, P. N. Belhumeur, and S. K. Nayar. Attribute and simile classifiers for face verification. In *Proc. Int. Conf. Comp. Vision*, 2009.

[26] Y. Fu, T. M. Hospedales, T. Xiang, and S. Gong. Attribute learning for understanding unstructured social activity. In *Proc. Eur. Conf. Comp. Vision*, 2012.

[27] J. Krapac, J. Verbeek, F. Jurie. Modeling spatial layout with fisher vectors for image. In *Proc. Int. Conf. Comp. Vision*, 2011.

[28] H. Jegou, F. Perronnin, M. Douze, J. Sanchez, P. Perez, and C. Schmid. Aggregating local image descriptors into compact codes. *IEEE Trans. Pattern Analysis and Mach. Intelligence*. vol. 34, no. 9, pp. 4-6, 2012.

[29] K. Liang, H. Chang, S. Shan, X. Chen. A Unified Multiplicative Framework for Attribute Learning. In *Proc. Int. Conf. Comp. Vision*, 2015.

[30] J. Delhumeau, P. Gosselin, H. Jgou, P. Prez. Revisiting the VLAD image representation. In *ACM Multimedia*, 2013.

[31] L. Liu, L. Wang, X. Liu. In defense of soft-assignment coding. In *Proc. Int. Conf. Comp. Vision*, 2011.

[32] A. Chan and N. Vasconcelos. Counting people with low-level features and Bayesian regression. *IEEE Trans. Image Process.*, vol. 4, no. 21, pp. 2160-2177, 2012.

[33] X. Wu, G. Liang, K.K. Lee, and Y. Xu. Crowd density estimation using texture analysis and learning. In *IEEE International Conference on Robotics and Biomimetics*, 2006.

[34] X. Peng, L. Wang, X. Wang, Y. Qiao. Bag of visual words and fusion methods for action recognition. Comprehensive study and good practice. CoRR abs/1405.4506 (2014).

[35] Y. Wang and G. Mori. A discriminative latent model of object classes and attributes. In *Proc. Eur. Conf. Comp. Vision*, 2010.

[36] J. Liu, B. Kuipers, S. Savarese. Recognizing Human Actions by Attributes. In *Proc. IEEE Conf. Comp. Vision and Pattern Recognition*, 2011.

[37] K. He, X. Zhang, S. Ren, J. Sun. Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition. In *Proc. Eur. Conf. Comp. Vision*, 2014.

[38] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele. The Cityscapes Dataset for Semantic Urban Scene Understanding. In *Proc. IEEE Conf. Comp. Vision and Pattern Recognition*, 2016.

[39] X. Peng, L. Wang, Y. Qiao, Q. Peng. Boosting VLAD with Supervised Dictionary Learning and High-Order Statistics. In *Proc. Eur. Conf. Comp. Vision*, 2014.

[40] R. Arandjelovic and A. Zisserman. All about VLAD. In *Proc. IEEE Conf. Comp. Vision and Pattern Recognition*, 2013.

[41] J.Y. Ng, F.Yang, L. S. Davis. Exploiting Local Features from Deep Networks for Image Retrieval. In *Proc. IEEE Conf. Comp. Vision and Pattern Recognition*, 2015.
Fig. 3. Illustration of pixel-level semantic information corresponding to different attribute classes.

Fig. 4. Comparison between LAF extraction and the traditional SPP features. The right part shows LAF extraction in which mean pooling is adopted and the concatenation is operated along the green arrow direction on the M-grid structure (here $M = 2 \times 2$); the left part illustrates the traditional SPP features [12] where spatial information is constructed at the coarse image level.
Fig. 6. The prediction result for Mall dataset.

Fig. 7. Two evaluation measures MAE & MSE with respect to nearest neighbor sizes on the Mall dataset.
Fig. 8. Representations obtained by VLAD and W-VLAD with the same descriptors LAF.