

DR.VIC: Decomposition and Reasoning for Video Individual Counting

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Abstract

Pedestrian counting is a fundamental tool for understanding pedestrian patterns and crowd flow analysis. Existing works (e.g., image-level pedestrian counting, cross-line crowd counting et al) either only focus on the image-level counting or are constrained to the manual annotation of lines. In this work, we propose to conduct the pedestrian counting from a new perspective - Video Individual Counting (VIC), which counts the total number of individual pedestrians in the given video (each person is only counted once). Instead of relying on the Multiple Object Tracking (MOT) techniques, we propose to solve the problem by decomposing all pedestrians into the initial pedestrians who existed in the first frame and the new pedestrians with separate identities in each following frame. Then, an end-to-end Decomposition and Reasoning Network (DRNet) is designed to predict the initial pedestrian count with the density estimation method and reason the new pedestrian's count of each frame with the differentiable optimal transport. Extensive experiments are conducted on two datasets of congested pedestrians and diverse scenes, demonstrating the effectiveness of our method over baselines with great superiority in counting the individual pedestrians. Code: <https://github.com/taohan10200/DRNet>.

1. Introduction

The world population has witnessed rapid growth, along with the accelerated urbanization. It is expected that around 70% of the world's population will live in cities [10, 51], which brings significant challenges in the city management, such as transport management, public space design, evacuation planning, and public safety. To tackle these challenges, accurately obtaining the number of pedestrians of any region in a period of time, e.g., the number of people passed

Figure 1. Illustration of different crowd counting paradigms. Video Individual Counting count all pedestrians appearing in the video and each person is only counted once, e.g., count to get counting result 4. Single Image Crowd Counting targets on the image-level. Directly applying it to video individual counting will cause over-count, e.g., count pedestrians at frame t and $t+1$ getting result 6. Cross-line Crowd Counting targets on the video level but only focuses on the pedestrians passed the red virtual line, e.g., count to get result 1.

the intersection in the past 10 minutes, is a basic problem. Automatically estimating the pedestrian number from images/videos is a practical solution and attracts attentions of researchers from different perspectives. Specifically, Single Image Crowd Counting (SICC) [9, 18, 27, 39, 54] estimates the crowd number in the image level, which can reflect the degree of crowdedness at a certain time point. Video Crowd Counting (VCC) [15, 58, 59] further enhances SICC by exploring the information from the historical frames to achieve a more accurate and robust counting in the target frame. Different from SICC and VCC, the cross-line crowd counting techniques [11, 38, 63, 64] focuses on estimating the pedestrians in a period of time from videos. By manually setting a proper virtual line (e.g., the red line as illustrated in Fig. 1), cross-line crowd counting discovers the pedestrians passed this line, which could reflect the crowdedness and total crowd number in the video.

Different from the settings of the works discussed above, this work targets a similar but different task - Video Individual Counting (VIC), which counts the total number of pedestrians in the given video with separate identities. As illustrated in Fig. 1, people come from all directions into the

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camera view should be counted through time and each per-camera view region after an interval of 75 frames, while the person should only be counted once. The output of VIC is the total pedestrians number in the videos is 5230. Based on this idea, an efficient and end-to-end video individual counting framework named Decomposition and Reasoning Network (DRNet) is proposed. DRNet first samples frames from the video with a time window. Then each pair of frames formed by the adjacent frames are separately fed into neural networks for generating two CNN feature maps, based on which two density maps reflecting the head locations at each frame can be predicted separately. In the next step, two sets of features containing the descriptors of each located head are sampled from the CNN feature maps and then used by a pedestrian in-flow reasoning module implemented with differentiable Optimal Transport, from which the in-flow (pedestrians joining the latter frame) and out-flow (pedestrians leaving the former frame) of the input frame pair can be predicted. Finally, the total pedestrian count in the whole video can be obtained by integrating the crowd count of the first frame and all pedestrian in-flows in the following sampled frame pairs.

While sharing similarities, Video Individual Counting is challenging and cannot be directly solved by existing image-level pedestrian counting and cross-line counting methods. Image level pedestrian counting methods will inevitably count the same person multiple times in adjacent frames and hugely over-estimates the pedestrian number if directly summing the number of crowd at each frame. Cross-line counting methods only count the pedestrians passing the line and thus will miss the crowd staying in the video or disjointing with the line. Besides, it requires manual annotation of the line for different camera settings, which is not in accordance with the aim of computer vision researchers in making crowd counting automated, and is also time consuming when considering a single city like London might have 500,000+ CCTV cameras.

The potential existing solution for VIC is the Multi-Object Tracking (MOT) methods [50,61], which is a general technique to identify and track all objects in the video and has been explored for specific area (e.g., counting for bus entrance [49]). The number and states of tracks in MOT can be employed to not only reveal the total number of crowd in the video, but also the in-flows and out-flows (the number of people getting into and out of the scene, respectively) of a period. However, since MOT is designed for tracking instead of pedestrian counting, the accuracy and efficiency of using MOT for this task would be inferior for two reasons. For accuracy, the object association in MOT depends on the detection results of multiple frames and extremely suffers from the ID switch, which heavily influences the counting performance by over-counting. For efficiency, most MOT operates on each frame, which is time-consuming and not necessary for the crowd counting task.

We propose a new paradigm for Video Individual Counting without relying on the MOT. Instead of associating all pedestrians in the whole video as MOT, we only associate each pair of frames to identify the in-flow (i.e., new pedestrians) of each time slot. Specifically, we decompose all pedestrians into the initial pedestrians existed in the first frame and the new pedestrians with separate identities in the following frames. The rationale behind this idea is the observation that the crowd normally stay in or pass through a region (e.g., camera view region). Only in few cases, people may pop in and out of the camera view, which is neglectable compared with the counting error. Take CroHD [50] dataset as an example, only 17 pedestrians leave and re-enter there

Our core contributions are summarized as follows:

- We propose to decompose video individual pedestrians into the initial pedestrians and the new pedestrians at following frames, which avoids the complicated and error-prone video-level association in MOT and opens a new direction for pedestrian counting.
- We propose an efficient and end-to-end framework to achieve video individual counting, directly obtaining the new pedestrians of a frame by reasoning it with the preceding frame using differentiable optimal transport.
- Extensive experiments are conducted on two datasets covering congested crowds and diverse scenes. The experimental results demonstrate the effectiveness of the proposed methods over strong baselines.

2. Related Work

2.1. Image-level crowd counting

Image-level crowd counting refers to counting the number of people in a given static crowd image. In recent years, most state-of-the-art SICC methods concentrate on density map estimation, which integrates the density map as a count value. The CNN-based methods [5, 27, 33, 34, 57, 60, 62] show the powerful ability in feature extracting and representing than the models based on hand-crafted features [14, 36, 39, 55] directly exploit point-level labels to supervise counting models. Because density maps can only give a coarse count, the location distribution of people is still not available. Therefore, latest researches target to localization for counting. Image-Level counting from multiple frames. There are also some video-based crowd counting methods [15, 29,

[35, 58, 59], which exploit the temporal information to enhance the counting in the target frame.

Different to these works, our work focuses on individual pedestrian counting in the video level, which predicts the total number of the dynamic people over video frames. As discussed before, the targeted task of video individual counting cannot be solved by directly using image-level counting methods. However, since image-level counting methods can be used as a basic component in our design, the progress in image-level crowd counting can benefit our model for the sub-tasks of initial counting in the first frame and the head localization.

2.2. Video-level crowd counting

2.2.1 Tracking in crowd

Tracking in crowd [28, 37] means to extract the temporal information of the crowd in a continuous sequence of images in a video. Considering the group motion behavior is consist of individual behaviour, Kratz and Nishino [23] propose a Bayesian framework that uses a space-time model for tracking individuals in a crowd. Bernt et al. [7] propose a real-time algorithm, AdaPT, to calculate individual trajectory in a crowd scene. SSIC can be integrated to crowd tracking as well, Rer et al. [43] propose a tracking-by-counting method, which jointly model detection, counting, and tracking for capturing complementary information. Since tracking explicitly distinguish the identity of each person in the video, it can also be used for real-time people counting. Sun et al. [49] propose a RGB-D dataset that collected from the bus entrance door in surveillance view and utilize tracking to identify and count the entering and exiting people. Recently, Sundararaman [56] et al. propose a congested Heads Dataset (CroHD), a head detector with a Particle Filter, and a color histogram based re-identification module to track multiple people in crowded scene.

While our method also calculates cross-frame association, it does not rely on detection or video-level association. We only utilize cross-frame association to get the in flows of each time interval and integrate them together with the counting in the first frame to get the total individual number in the whole video. In this way, our design is more robust to detection and tracking errors.

2.2.2 Cross-line crowd counting

Cross-line crowd counting is a constrained direction of video pedestrian counting, which aims to count the number of pedestrian across a detection line or inside a specified region. Early works [3, 6, 8] utilize multiple lines to count the entering or existing people. These methods, however, need to perform counting independently for each line belonging to the counting zone, which is inefficient. Besides, it does not count the people who stay in the scene but do not

cross the line. More importantly, it does not allow to sample the frame for reducing temporal redundancy with long interval. Cong et al. [11] regard pedestrians across the line as uid ow and devise a algorithm to estimate the ow velocity. The nal count is obtained by integrating the pixels in Line of Interest (LOI) at each frame. To tackle some drawbacks in blob-centric method [11], Mao et al. [38] propose an integer programming approach to estimate the instantaneous counts on the LOI, which cuts the frames in a video to a set of temporal slices and then counts the people in these slice images with SICC methods. To further eliminate the limitation of the temporal slice, Zhao et al. [63] propose to directly estimate the crowd counts with pair of images, which resolves the LOI crowd counting by estimating the pixel-level crowd density map and crowd velocity map. The following work [64] further improves the [63] to obtain a fine-grained estimation of local crowd densities.

In general, cross-line crowd counting is limited in real application as it highly depends on the virtual line, which is hard to set for numerous videos and capture pedestrians entering and existing with random directions (e.g., squares). In contrast, our method can handle multi-direction pedestrians, and thus is applicable to more general scenes.

3. Problem Formulation

Given a video clip $\mathcal{V} = \{I_0; I_1; \dots; I_{T-1}\}$ of length T for a scene (e.g., intersection, square, exhibition), where the t th frame I_t contains $N(t)$ subjects, each subject normally appears in many consecutive frames because of the relatively high sensing frequency of cameras (e.g., 25 frames per second). Our target is to count the total number of people $N(0 : T-1)$ shown in this video with distinct identities.

Instead of relying on the MOT techniques to directly obtain the crowd count with the track number, we propose a new solution for video individual counting. Specifically, we formulate the video individual counting problem as two sub-problems: 1) inferring crowd count $N(0)$ at the start time point, and 2) identifying the number of new identities entering the scene (in flow) at each following frame $N_{in}(t)$, which requires associating the subjects in frame $t-1$ and t . By solving these two sub-problems, the overall video pedestrian count can be easily obtained via:

$$N(0 : T-1) = \sum_{t=1}^{T-1} N_{in}(t) + N(0); \quad (1)$$

Considering that video frames are highly redundant, the in flow of most frames would be 0. Thus, we further simplify Eq. 1 by inferring the in flow every frames:

$$N(0 : T-1) = \sum_{k=1}^{K} N_{in}(k) + N(0); \quad (2)$$

where $N_{in}(t)$ is the in flow of frame t compared with I_{t-1} .

Figure 2. An overview of the DRNet architecture. DRNet is an end-to-end Video Individual Counting (VIC) framework, which takes the frames at t and $t + 1$ as input and reasons the in-flow compared with t . Based on the image representations obtained by a shared backbone network, two density maps can be obtained to guide the extraction of head descriptors. The pedestrian in-flow in pair-wise images are given by reasoning their head descriptors to

4. Method

According to the formulation defined in Sec. 3, our method should have the ability to count all pedestrians in the frame level and identify new pedestrians in a frame compared with its previous frame. We achieve this goal by designing an end-to-end network, called DRNet, to decompose video pedestrian counting as image-level pedestrian counting and cross-frame reasoning, which is composed of an image representation module, a head descriptor extraction module, and an in-flow reasoning module.

Image representation. The image representation module maps two input images to feature maps in the high-level embedding space separately with a shared neural network.

As elucidated in Fig. 2, we sample a pair of images and I_{t+1} with a time interval from $f_0; I_1; \dots; I_T$. The crowd images are transformed to corresponding multi-scale feature representations F_t and $F_{t+1} \in \mathbb{R}^{C \times H=4 \times W=4}$ with a backbone network, e.g., VGG-16 backbone [46] and Feature Pyramid Network (FPN) [30] in this work.

Head Descriptor Extraction. Following existing density based crowd counting works [2, 17, 20, 32, 48, 53], we use the feature maps from the image representation module to locate the head positions, which can be used to generate the descriptors (e.g., features) for each head center proposals. The details are elaborated in Sec. 4.1. The density map can also be used to generate the image level crowd count for the first frame directly in the testing phase.

Pedestrian In-flow Reasoning. Given the head descriptors of two frames from the head descriptor extraction module, the pedestrian in-flow reasoning module targets on differentiation which subject is new in I_{t+1} compared with I_t by optimal transport. The details are elaborated in Sec. 4.2.

4.1. Head Descriptor Extraction

As shown in the middle part of Fig. 2, the head description extraction module has two branches, one is head localization branch and the other is descriptors generation

Figure 3. The sketch of the crowd transportation. With a proper solution of the transportation matrix \bar{R} , the last row in \bar{P} corresponds to the in-flow for frame $t + 1$ that we want, i.e., the last column in \bar{P} describes the out-flow regarding frame t , i.e. pedestrian \neg , and matched pairs \neg .

branch. The localization branch packs several convolution and two deconvolution layers to map each image representation to a head density map, where the ground-truth head points are blurred with a Gaussian kernel G_{σ} (window size = 15). Thus, the coordinates of the local maximums in the density map are the head center proposals.

Denote the sets of head center proposals for frame t and I_{t+1} by $p_i^t := f(h_i^t; w_i^t)g_{i=1}^M$ and $p_i^{t+1} := f(h_i^{t+1}; w_i^{t+1})g_{i=1}^N$ respectively. We first add some noises to augment these head proposals for improving the robustness,

$$p_i^t \rightarrow p_i^t + z_1; \quad p_i^{t+1} \rightarrow p_i^{t+1} + z_2 \quad (3)$$

where $z_1, z_2 \sim \mathcal{N}(0; 1)$. α controls the noise level and is empirically set as 2. Then, the augmented proposals are expanded to 8 regions for pooling. Finally, two sets of head descriptors are extracted with the Precise RoI Pooling [21] on the final feature maps F_t^0 and F_{t+1}^0 (output by several convolution layers with F_t and F_{t+1}), denoted as

$X := \{x_1; \dots; x_m\} \in \mathbb{R}^{D \times 1}$ for M subjects in I_t and $Y := \{y_1; \dots; y_n\} \in \mathbb{R}^{D \times 1}$ for N subjects in I_{t+1} . D is the descriptor dimension and the default setting is 256.

4.2. Pedestrian In ow Reasoning

Target. Given the descriptors of the head center proposals obtained from the head descriptor extraction module (Sec. 4.1), the pedestrian in ow reasoning module is used for getting the in ow by associating the head center proposals. As illustrated in Fig. 3, given subjects X and Y , pedestrian in ow reasoning divides them into three categories, 1) matched instance pairs $(X \rightarrow Y)$ containing the people appearing in both t and $t + 1$ frame, 2) unmatched in ow instances $I(Y)$ containing the people only appearing in $t + 1$ frame, and 3) unmatched out ow instances $O(X)$ containing the people only appearing in t frame. Thus, during the time duration, the size of set I is the number of in ow that we want to get, i.e. the $N_{in}(t + 1)$ in Eq. 2. The out ow set O is a supernumerary output.

Theoretic basis. The problem above is a typical assignment problem, for which the Hungarian algorithm [40] is a feasible solution. However, Hungarian algorithm requires a predefined distance threshold as classification basis, which would cost huge efforts to find the optimal threshold. More importantly, Hungarian algorithm is a non-differential process and only gives a hard matching (either zero or one). Hence it does not allow to optimize the image representation with the matching result. To avoid these issues, we chose the Optimal Transport (OT) theory [42] to reason this assignment problem, which is widely used to plan the transportation between two target groups under some constraints. OT also provides a differentiable association process, which makes DRNet an end-to-end trainable network.

The reasoning for in ow. Inspired by the solutions used in the graph matching and the key-point matching tasks [13, 45], the pedestrian in ow in our paper can be obtained by solving a augmented Kantorovich's OT problem,

$$L_{\bar{C}}(\bar{a}; \bar{b}) = \min_{\bar{P} \in \mathcal{U}(\bar{a}; \bar{b})} \sum_{i=1}^M \sum_{j=1}^{N+1} \bar{C}_{ij} \bar{P}_{ij}; \quad (4)$$

where \bar{P} is a transportation matrix. As depicted in Fig. 3, its element \bar{P}_{ij} ($0 \leq i < M$; $0 \leq j < N$) represents the probability of the i -th pedestrian in preceding frame is associated with the j -th people in the current frame. Note that the augmented row $\bar{P}_{(M+1:j)}$ ($0 \leq j < N$) is defined to collect the pedestrian in ow (i.e. in ow container),

$$N_{in}(t + 1) = \sum_{j=1}^N \bar{P}_{(M+1:j)}; \quad (5)$$

Eq. 5 shows pedestrian in ow reasoning is a transportation reasoning problem, predicting the probabilities of staying in the scene and matching to the in ow/out ow. Similarly, the supernumerary out ow can be collected by the augmented column $\bar{P}_{(i:M+1)}$ ($0 \leq i < M$) (i.e. out ow container). \bar{C} is

the cost matrix and actually is a similarity matrix calculated with descriptor sets X , Y and two augmented bins in this paper,

$$\bar{C} = \begin{bmatrix} C_{M:N} & c_{M;1} \\ c_{1:N} & c_{1;1} \end{bmatrix} \in \mathbb{R}^{(M+1) \times (N+1)}; \quad (6)$$

where $c_{M;1}$, $c_{1:N}$ and $c_{1;1}$ are expanded by a learnable parameter c , and act as thresholds to discriminate whether or not a person existed in both two frames. $c_{M;1}$ and $c_{1:N}$ represent the possibilities for the person matched to the out ow container and in ow container, respectively.

The $(i; j)$ -th element C_{ij} in matrix $C_{M:N}$ uses the features of the i -th person at frame t and the j -th person at frame $t + 1$ to measure their similarity as follows:

$$C_{ij} = x_i^T y_j; \quad 0 \leq i < M, 0 \leq j < N \quad (7)$$

The $\bar{U}(\bar{a}; \bar{b})$ in Eq. 4 is a discrete measure with respect to probability vectors \bar{a} and \bar{b} ,

$$\bar{U}(\bar{a}; \bar{b}) \stackrel{\text{def.}}{=} \bar{P} : \bar{P} \mathbf{1}_N = \bar{a} \text{ and } \bar{P}^T \mathbf{1}_M = \bar{b}^0; \quad (8)$$

where $\mathbf{1}$ is the column vector of ones. To solve Eq. 4, we need to give a reasonable prior probability vector \bar{a} (for X) and \bar{b} (for Y) in advance. Actually, instances X or Y can be regarded with the same probability to be matched as they are of equal importance in pedestrian counting. Hence their masses are all set as 1. As for in ow row and out ow column, their masses are respectively defined as N and M so as to create equal constraints. Finally, two histogram vectors $\bar{a} = [\mathbf{1}_M^T \ N]^T$ and $\bar{b} = [\mathbf{1}_N^T \ M]^T$ are used to solve Eq. 4.

The overall objective of OT problem is to find matrix \bar{P} reasoning the pedestrians X towards Y so that $\bar{P}^T \bar{C}$ is the maximum. In fact, this is a linear programming problem (Eq. 4) with $N + M + 2$ constraints (Eq. 8).

Differentiable and approximate solution of OT (DOT). The final step of DRNet is to use a differentiable algorithm to solve the assignment weight matrix \bar{P} so that we can optimize the head descriptors with the assignment results. The standard solution of the original Kantorovich's OT problem has high time complexity and it is hard to solve. An approximated solution of the regularized Kantorovich's OT problem in [42] is given as,

$$\bar{P}_{ij} = u_i K_{ij} v_j; \quad (9)$$

where $K_{ij} = e^{-\bar{C}_{ij}}$, is the regularization coefficient and we set it as 1, and the vectors u and v are variables, which are solved by the Sinkhorn algorithm [12, 47]. According to the Eq. 8 and 9, we can update u and v by alternately iterating the following two equations,

$$u^{(\cdot+1)} \stackrel{\text{def.}}{=} \frac{\bar{a}}{K v^{(\cdot)}} \quad \text{and} \quad v^{(\cdot+1)} \stackrel{\text{def.}}{=} \frac{\bar{b}}{K^T u^{(\cdot+1)}}; \quad (10)$$

where $\bar{a} = \frac{a}{MN}$ and $\bar{b} = \frac{b}{MN}$ are, respectively, the normalized versions of a and b . $v^{(0)}$ is initialized by $\mathbf{1}_N$. I is the iterations and the default setting is 100. Sadral [45] provide a fast-speed computation of the Sinkhorn algorithm and the time consumption is extremely low with 100 iteration, which accounts for approximately 3% training time in DRNet. Eq. 10 reveals that inferring \bar{g} is a completely differential process.

4.3. Loss Functions

Two loss functions are used in this framework: 1) A standard MSE loss supervises the density prediction task as widely used in the image-level crowd counting [27, 44, 62]. 2) a matching loss $\mathcal{L}_{\text{match}} = \mathcal{L}_p + \mathcal{L}_h$ can maximize the likelihood probability for positive samples and minimize the likelihood probability for hard negative samples,

$$\mathcal{L}_p = \sum_{(i,j) \in \arg(\bar{P}_g == 1)} \log \bar{P}_{ij}; \quad (11)$$

$$\mathcal{L}_h = \sum_{(i,j) \in \arg(\bar{P}_h == 1)} \log(1 - \bar{P}_{ij}); \quad (12)$$

where the $\bar{P}_g \in \mathbb{R}^{f \times f}$, $\mathbf{1}_g^{(m+1) \times (n+1)}$ is ground truth assignment matrix, which is generated by the the annotated association labels. $\arg(\bar{P}_g == 1)$ returns the indexes of the elements in \bar{P}_g with the value as 1. Eq. 11 enforces the feature presentations of the same person to be similar in the different frames. Eq. 12 is designed to enlarge the distance between a person and his/her hard samples. Its ground truth matrix \bar{P}_h is adaptively generated by finding the hardest sample for each instance according to prediction

5. Experiments

5.1. Datasets

We find two benchmark datasets, i.e., CroHD [50] and SenseCrowd [25], are suitable for VIC. Both of them have annotations for head locations and associations of pedestrians. Tab. 1 describes the detailed statistics of them. These two datasets contain diverse spots, especially congested spots. For CroHD, we use four videos for training and validation, and five videos for testing as the official splitting. For SenseCrowd, all video clips are randomly divided into training (50%), validation (10%), and testing (40%). Besides, since SenseCrowd is large-scale and contains diverse scenes, we further manually label all videos with different scene labels for a more comprehensive analysis.

5.2. Evaluation Metrics

Follow existing counting tasks (e.g. crowd counting [62], vehicle counting [26]), we use Mean Absolute Error

Dataset	Videos	Frames	Head labels	Pedestrians	Time (s)
CroHD	9	11,463	2,276,838	5,230	498
SenseCrowd	634	62,938	2,344,276	43,178	12,588

Table 1. Summary of the video datasets for pedestrian counting.

(MAE) and Mean Square Error (MSE) for evaluation. Different from image-level crowd counting, we calculate them based on the whole video pedestrian count with the same person only counted once. Besides, we also use a Weighted Relative Absolute Errors (WRAE) to balance the performance on videos with different lengths and pedestrian numbers,

$$\text{WRAE} = \sum_{i=1}^K \frac{T_i}{\sum_{j=1}^K T_j} \frac{|N_i - \hat{N}_i|}{N_i} \times 100\%; \quad (13)$$

where N_i and \hat{N}_i respectively represent the annotated and estimated pedestrian number for the i -th test video. K is the total number of videos. T_i is the total number of frames for the i -th video. Since our method involves association within two frames, we further use the Mean In/Out Absolute Error (MIAE/MOAE) to reflect the association quality. (More descriptions are given in the Supplementary.)

5.3. Implementation Details

Training details: For efficient training, the time interval for each image pair is randomly sampled from range 2s - 8s to guarantee the pair contain both matched and unmatched samples. For data augmentation, we use the random horizontal flipping, scaling (0.8 - 1.25), and cropping (768 - 1024) strategies. The learning rate is initialized to $5e-5$ except the $1e-2$ for c , and they are updated by a step decay strategy with 0.95 rate at each epoch. Adam [22] algorithm is adopted to optimize the framework. The VGG-16 backbone is initialized with the pre-trained weights on ImageNet [24]. The model is built upon the PyTorch framework [41] and implemented on an TITAN RTX GPU (24G memory) with batchsize 4.

Testing details: In the testing phase, the time interval is fixed as 3s except for the time interval analysis presented in Sec. 5.5.

5.4. Overall Comparison

Comparison methods: To evaluate the effectiveness of our method, we adapt some relevant works to the individual counting task for comparison. These works are classified into two categories. 1) Tracking-based: the tracking results of three advanced MOT methods, i.e., HeadHunter-T [50], FairMOT [61], and PHDTT [52] are employed to estimate the pedestrian flow by counting their tracks. For the CroHD dataset, we first try to directly use the tracking results provided in MOTChallenge [1], but the errors (MAE/MSE) is

Methods	val set			Counting results in ve testing scenes					Metrics on test set		
	CroHD01 85	MIAE#	MOAE#	CroHD11 133	CroHD12 737	CroHD13 734	CroHD14 1040	CroHD15 321	MAE#	MSE#	MRAE(%)#
PHDTT [52]*	183	9.1	18.1	380	4530	5528	1531	1648	2130.4	2808.3	401.6
FairMOT [61]	214	6.0	6.7	144	1164	1018	632	472	256.2	300.8	44.1
HeadHunter-T [50]	145	5.1	6.2	198	636	219	458	324	253.2	351.7	32.7
LOI [63]	65.5	-	-	72.4	493.1	275.3	409.2	189.8	305.0	371.1	46.0
DRNet	113.0	6.1	4.4	164.6	1075.5	752.8	784.5	382.3	141.1	192.3	27.4

Table 2. Video individual counting performance on CroHD dataset. *: the code is not available and results come from the submission of MOTChallenge [1]. The underlines represent ground truth. '-' means the metrics cannot be calculated with the corresponding algorithms. Overall, DRNet obtains more accurate counts than the tracking methods [50, 52, 61] and cross-line counting method [63].

Methods	Overall					Density (for MAE)				
	MAE#	MSE#	MRAE(%)#	MIAE#	MOAE#	D0	D1	D2	D3	D4
FairMOT [61]	35.4	62.3	48.9	4.9	4.4	13.5	22.4	67.9	84.4	145.8
HeadHunter-T [50]	30.0	50.6	38.6	4.0	4.1	11.8	25.7	56.0	92.6	131.4
LOI [63]	24.7	33.1	37.4	-	-	12.5	25.4	39.3	39.6	86.7
DRNet	12.3	24.7	12.7	1.98	2.01	4.1	8.0	23.3	50.0	77.0

Table 3. Video individual counting performance on SenseCrowd dataset. D0-D4 respectively indicate ve pedestrian density ranges: [0; 50); [50; 100); [100; 150); [150; 200); 200. More results about the performance with different locations, day&night, indoor&outdoor are reported in Appendix.

very large. By lowering the frame rate to 0.33 FPS for FairMOT and 1 FPS for HeadHunter-T, tracking-based methods produce their best results. For the SenseCrowd dataset, we use the official public code to get the tracking results (PHDTT is omitted for SenseCrowd as the code is not available). 2) Density-based: the representative cross-line crowd counting method LOI [63] is re-implemented and assessed with our evaluation system.

Results on CroHD: To the best of our knowledge, we are the first to conduct video pedestrians counting on such a congested dataset. Tab. 2 outlines the pedestrian numbers in each scene of the testing set as well as three metrics on all videos. DRNet outperforms all tracking-based methods and cross-line method with an obvious improvement. The overall MAE and MSE are lowered to 141.1 and 192.3, respectively. The errors of some tracking methods are more than tenfold those of our MAE and MSE if we don't change its FPS in testing. The reason is that wrong associations are normal in the extremely congested scenes, which would accumulate to following associations and make tracks lose targets. In the following frames, new tracks would be added for existing pedestrians frequently. However, the reasoning error will not influence the following matching in DRNet own to the decomposition. Besides, DRNet also requires less association steps, which are only conducted in sampled frames. This also can be used to explain why DRNet surpasses other methods substantially despite the MIAE and MOAE being only slightly better than other methods. Notably, the numbers estimated by LOI [63] are all fewer than the GTs, which meets the expectation and verifies it is not a stable method to count all pedestrians in complex scenarios.

Results on SenseCrowd: Tab. 3 shows the results on SenseCrowd. DRNet makes the best predictions on the overall dataset as well as the different density subsets (D0-D4), demonstrating its effectiveness. Especially, the errors are much smaller than those in CroHD since SenseCrowd is sparser. Our MRAE (2.7%) is relatively low, making it possible to be deployed in the future. The overall counting performance would be better if the assignment and head localization accuracies are further improved.

5.5. Ablation Study

Assignment Methods: Besides the Differential Optimal Transport (DOT) in this paper, we also consider two heuristic matching methods to achieve pedestrians association from a pair of frames: Data association in MOT [50, 61] and the Hungarian algorithm [40]. In the ablation study, we first train the network with the full DRNet and then replace the DOT module with other association methods for testing. Tab. 4 shows that the association method in MOT has the largest error, whereas the Hungarian algorithm [40] can make a better matching performance with an appropriate threshold. In fact, DOT is a differential version of the Hungarian algorithm, it makes the best counting results with end-to-end learning.

Head Proposals: During training, we can use either the combination of predicted head proposals and GT points or only the GT points. Here, we analyse the contribution of the predicted head proposals. The results in the last row and the third last row in Tab. 4 show that the predicted head centers at training stage substantially improves the counting performance, decreasing MAE and MRAE by 68.0% and 26.7%, respectively.

* The official source code is not available.

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