Multi-view Spectral Polarization Propagation for Video Glass Segmentation (Supplementary Material)

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This supplementary document provides more details of the proposed PGV-117 dataset (§ 1), the formal definitions of the four quantitative metrics (§ 2), and the detailed calculation of key affinity (§ 3).

1. PGV-117 Dataset

The ground truth masks of the proposed PGV-117 dataset are annotated by annotation professionals, resulting in $144,686$ glass masks. Each ground truth mask is manually checked to ensure the quality of the annotations.

The proposed dataset consists of 117 sequences and $21,485$ frames. The training set offers 85 sequences, $15,838$ frames, and the testing set provides 32 sequences, $5,647$ frames. Figure 1 and Figure 2 show the number of frames for each sequence in the training and testing set, respectively.

2. Formal Definition of Evaluation Metrics

We adopt the four metrics used by Mei *et al.* [5] for evaluating all competing approaches, which are intersection over union (IoU), weighted F-measure (F_β) [4], mean absolute error (MAE), and balance error rate (BER) [6]. Here, we provide the formal definitions of these four metrics.

Intersection over union (IoU)

$$IoU = \frac{\sum_{i=1}^{H}\sum_{j=1}^{W}(G(i,j) * P_b(i,j))}{\sum_{i=1}^{H}\sum_{j=1}^{W}(G(i,j) + P_b(i,j) - G(i,j) * P_b(i,j))}, \tag{1}$$

where G is the ground truth mask in which the values of the glass region are 1 while those of the non-glass region are 0; P_b is the predicted mask binarized with a threshold of 0.5; and H and W are the height and width of the ground truth mask, respectively.

Weighted F-measure (F_β) takes a prediction map's precision and recall into account, which is a common metric used in salient object detection tasks. Based on recent studies [2, 3], the weighted F-measure [4] is more reliable than the traditional F_β [5], and it is used in our evaluation.

Mean Absolute Error (MAE) calculates the element-wise distance between a prediction map P and the corresponding ground truth mask G:

$$MAE = \frac{1}{H \times W}\sum_{i=1}^{H}\sum_{j=1}^{W}|P(i,j) - G(i,j)| \tag{2}$$

where $P(i,j)$ indicates the predicted probability score at location (i,j).

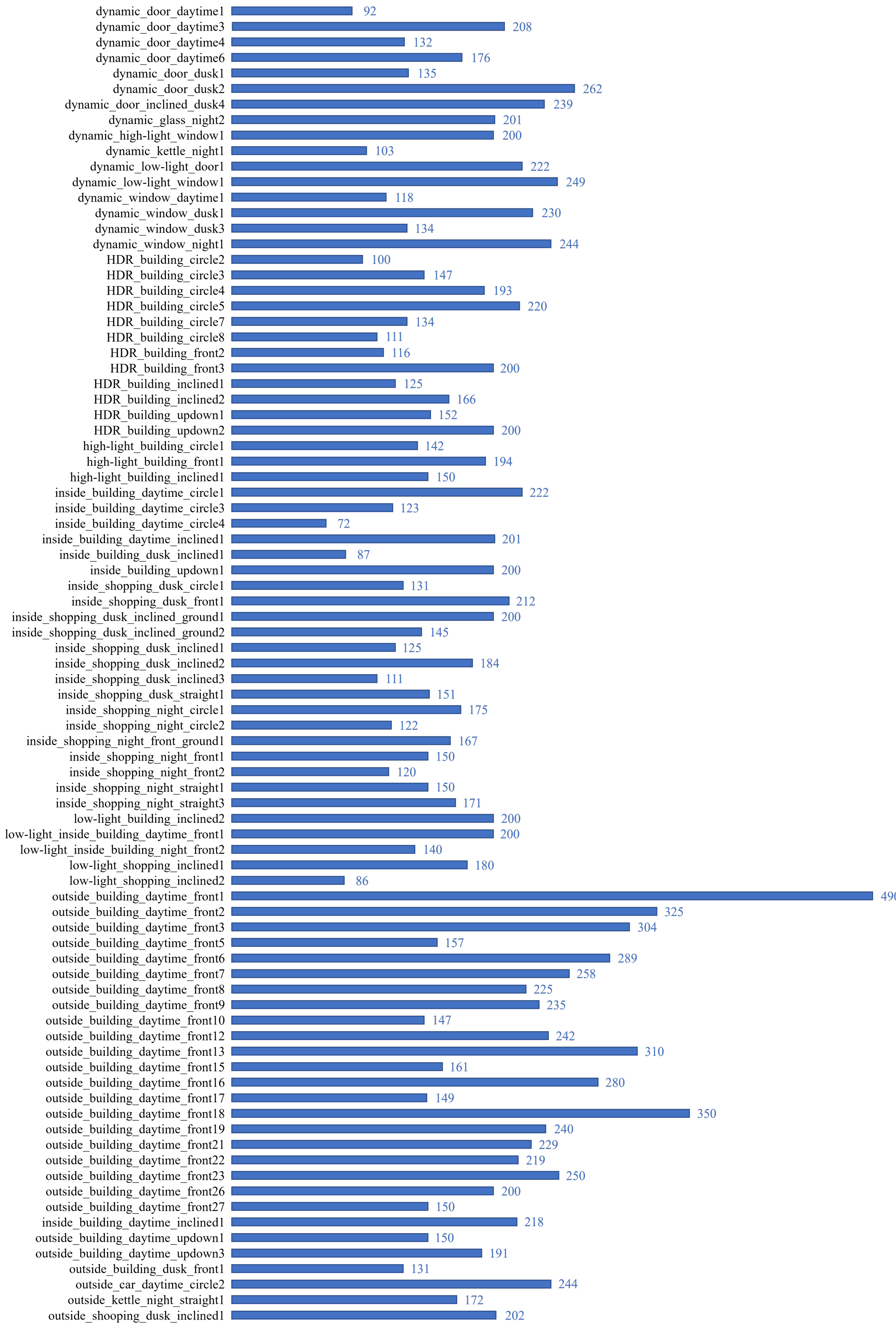

Figure 1. Summary for training set distribution of PGV-117, which includes 85 video sequences in total.

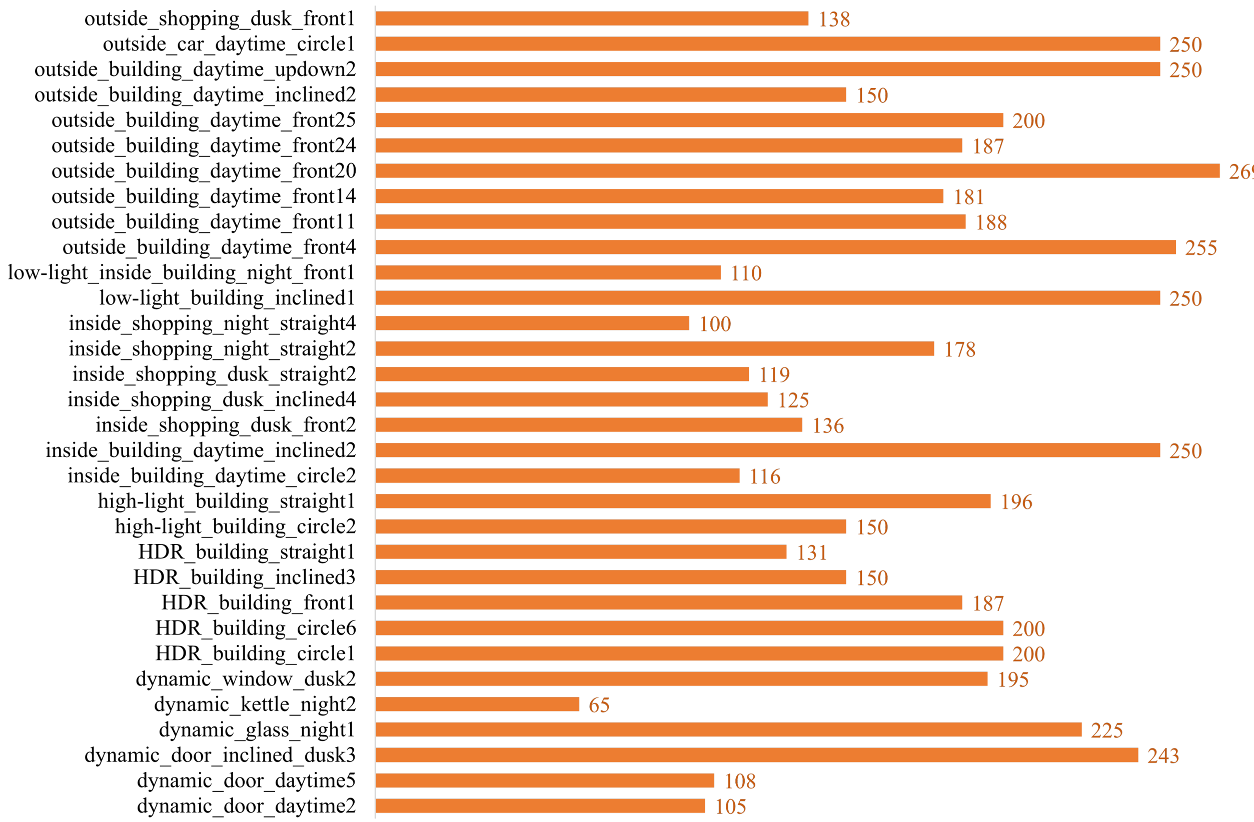

Figure 2. Summary for testing set distribution of PGV-117, which includes 32 video sequences in total. In order not to lose generality, all lighting conditions, camera motion patterns, and dynamics are also included in the testing set.

Balance error rate (BER) is a common metric used in shadow detection tasks. Formally, it is defined as:

$$BER = (1 - \frac{1}{2}(\frac{TP}{N_p} + \frac{TN}{N_n})) \times 100 \tag{3}$$

where TP, TN, N_p, and N_n represent the numbers of true positive pixels, true negative pixels, glass pixels, and non-glass pixels, respectively.

3. Computing Affinity

For the query frame t, we relate multi-view RGB-P information by exploring the relationship between the PGI key of t with the keys in the memory (0 to $t-1$). After generating the query key k^Q and memory keys k^M, we refer to [7, 1] to calculate the affinity between k^Q and k^M:

$$\begin{aligned} a &= \xi[(k^M)^2], \\ b &= 2 * [(k^M)^T \circledast k^Q, \\ A &= (-a+b)/\sqrt{CK}, \\ A &= \frac{exp(A_{ij})}{\sum_n (exp(A_{nj}))}. \end{aligned} \tag{4}$$

where $\xi[\cdot]$ represents the summation and unsqueeze operation, $\circledast$ means matrix multiplication. CK is the number of channels for the key features, and i denotes the affinity value at the i-th position. The affinity considers both RGB similarity and multi-view spectral consistency between the query and memory frames. The value encoder output v^M corresponding to k^M contains features from the tripartite memory values, and the multiplication of affinity and v^M correlates the query frame and historical information to obtain v^Q to participate in the readout of the memory bank.

References

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