FMCNet: Feature-Level Modality Compensation for Visible-Infrared Person Re-Identification

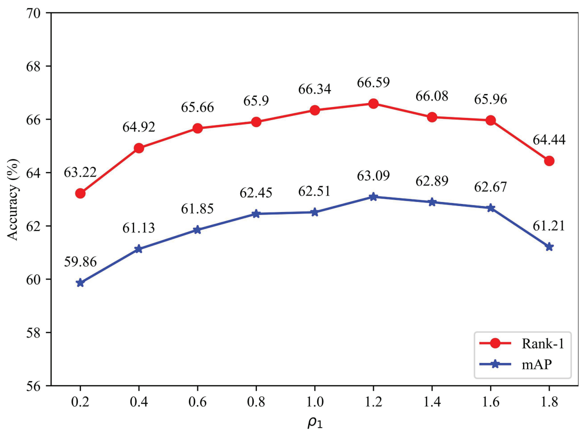

Figure 1. Evaluation results of parameter ρ_1 with different values.

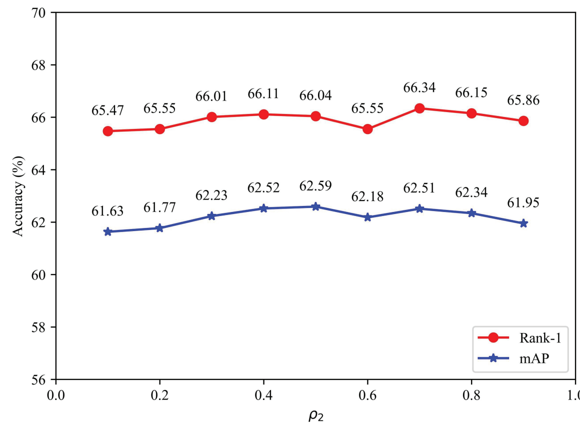

Figure 2. Evaluation results of parameter ρ_2 with different values.

1. Impacts of the Hyper-parameters

In this section, we will analyze the impacts of all the hyper-parameters in different loss functions on SYSU-MM01 dataset, including ρ_1 in Eq. (4), ρ_2 in Eq. (5), ρ_3 in Eq. (6), $\lambda 1$ and $\lambda 2$ in Eq. (7), and ρ_4 and β in Eq. (17).

1.1. Evaluation of different values of parameter ρ_1 in Eq. (4)

We first set $\rho_2 = \rho_3 = \rho_4 = 0.7$, $\beta = 2$ and $\lambda 1 = \lambda 2 = 0.5$, and then change ρ_1 from 0.2 to 1.8 with the interval of 0.2. As shown in Fig. 1, the accuracies are improved with the increase of ρ_1 at the first, and achieve the best when ρ_1 = 1.2. Therefore, we set $\rho_1 = 1.2$.

1.2. Evaluation of different values of parameter ρ_2 in Eq. (5)

We first set $\rho_1 = 1$, $\rho_3 = \rho_4 = 0.7$, $\beta = 2$ and $\lambda 1 = \lambda 2 = 0.5$, and then change ρ_2 from 0.1 to 0.9 with an interval of 0.1. As shown in Fig. 2, when $\rho_2 = 0.7$, our proposed model obtains the best performance. Therefore, we set $\rho_2 = 0.7$ in this paper.

1.3. Evaluation of different values of parameter ρ_3 in Eq. (6)

We first set $\rho_1 = 1$, $\rho_2 = \rho_4 = 0.7$, $\beta = 2$ and $\lambda 1 = \lambda 2 = 0.5$, and then change ρ_3 from 0.1 to 0.9 with an interval of 0.1. Fig. 3 reveals that our proposed model obtains the best performance. Therefore, we set $\rho_3 = 0.7$ in this paper.

1.4. Evaluation of different values of parameters $\lambda 1$ and $\lambda 2$ in Eq. (7)

We fitst set $\rho_1 = 1$, $\rho_2 = \rho_3 = \rho_4 = 0.7$, $\beta = 2$ and $\lambda 2 = 0.5$ ($\lambda 1 = 0.5$), and then change $\lambda 1$ ($\lambda 2$) from 0.1 to 0.9 with an interval of 0.1. As shown in Fig. 4, the performance of our proposed model reaches a peak when $\lambda 1 = 0.5$. Similary, Fig. 5 reveals that our model obtains the best performance when $\lambda 2 = 0.5$. Therefore, we set $\lambda 1 = \lambda 2 = 0.5$ in this paper.

1.5. Evaluating different values of parameters ρ_4 and β in Eq. (17)

When evaluating ρ_4, we first set $\rho_1 = 1$, $\rho_2 = \rho_3 = 0.7$, $\beta = 2$ and $\lambda 1 = \lambda 2 = 0.5$, and then change ρ_4 from 0.1 to 0.9 with an interval of 0.1. Fig. 6 shows that our model performs the best when $\rho_4 = 0.7$. Therefore, we set $\rho_4 =$

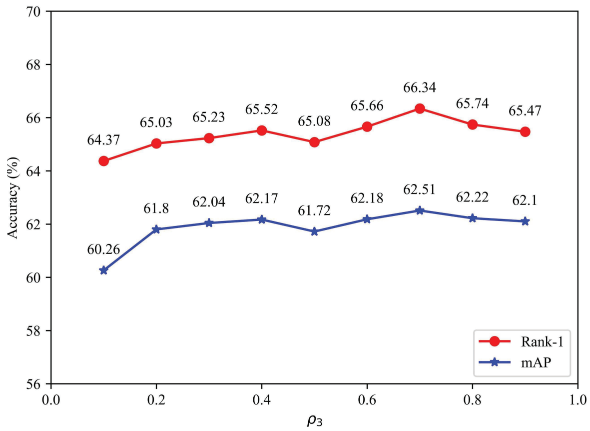

Figure 3. Evaluation results of parameter ρ_3 with different values.

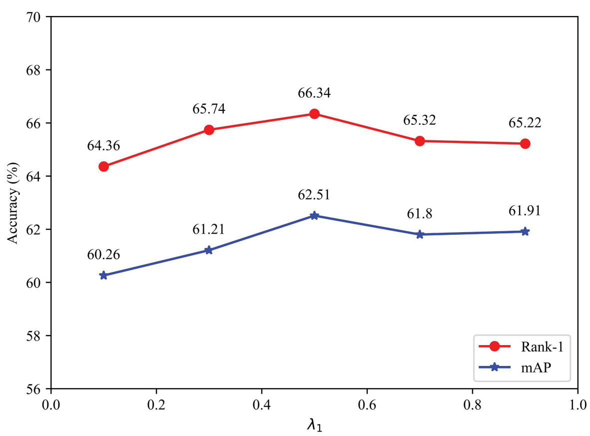

Figure 4. Evaluation results of parameter $\lambda1$ with different values.

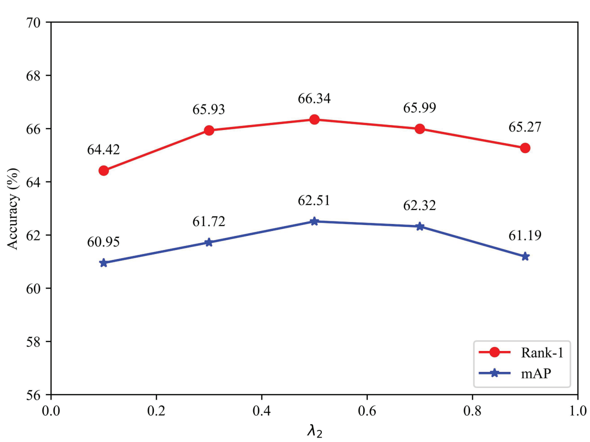

Figure 5. Evaluation results of parameter $\lambda2$ with different values.

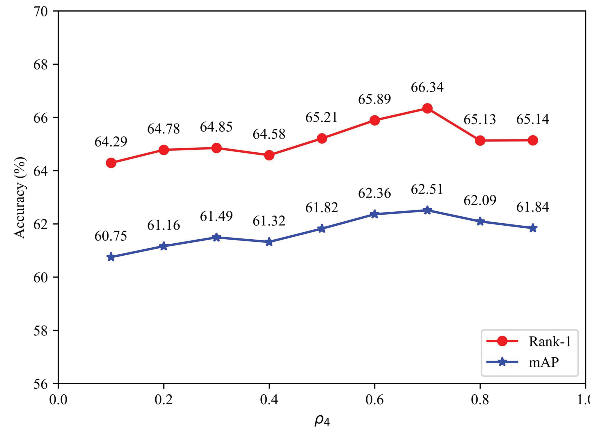

Figure 6. Evaluation results of parameter ρ_4 with different values.

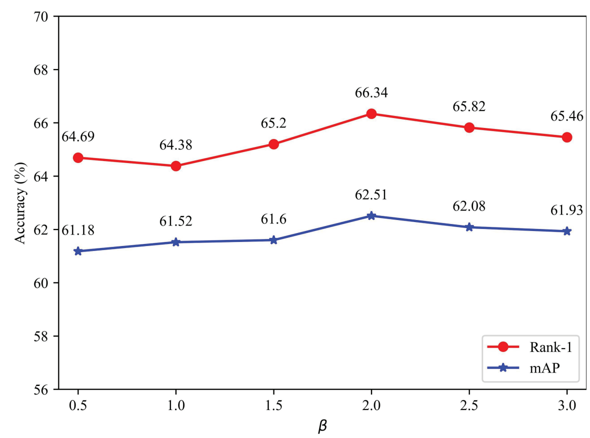

Figure 7. Evaluation results of parameter β with different values.

Setting	Rank-1	mAP
Base	57.09	53.11
Base+L_{shs}	61.93	56.84
Base+SFD+FMC	65.50	62.32

Table 1. Effectiveness of the L_{shs}.

0.7 in this paper.

When evaluating β, we first set $\rho_1 = 1$, $\rho_2 = \rho_3 = \rho_4 = 0.7$ and $\lambda1 = \lambda2 = 0.5$, and then change β from 0.5 to 3 with the interval of 0.5. As shown in Fig. 7, our model achieves the best performance when $\beta = 2$. Therefore, we set $\beta = 2$ in this paper.

2. Effectiveness of the modality-shared feature separation loss and cross-modal feature compensation

As shown in Table 1, the modality-shared feature separation loss L_{shs} can effectively reduce the modality discrepancy between the modality-shared visible and infrared features, which significantly improve the performance. Moreover, after compensating cross-modal feature by FMC module, our model further boosts the performance of VI-ReID by jointly using specific-shared features.