1. Introduction

Person Re-Identification (re-id):

Task: Matching person identity in person images across non-overlapping camera views.

Limitations of existing methods: Assuming accurately labelled person bounding boxes by manually cropping (MC). However, in practice person bounding boxes must be automatically detected (AD) for scalability.

Motivation:
- Automatically detection person suffering from the misalignment (Fig. 1 a,d,e) and occlusion problems (Fig. 1 c).
- Re-id performance drop on AD, compared to MC (8% rank-1 drop CUHK03).

Contributions:
- A novel Identity Discriminative Attention reinforcement Learning (IDEAL) model for re-id attention selection.
- IDEAL model is trained by pairwise re-id constraints without the need for accurate object bounding box annotations, more scalable to large size data.

2. Methodology

Reinforcement learning re-id attention sequence: Specific Markov Decision Process for re-id attention selection in auto-detected bounding boxes.

Environment: Input person bounding box image.

Actions: Each action defined by changes in location and size of input image.

State: Defined by the current attention window feature and an action history vector.

Reward: Directly relating to the re-id matching criterion.

3. Model Framework and Reward Design

4. Experiments

5. Conclusion

IDEAL model has two subnetworks:
- A multi-class discrimination network trained by a set of auto-detected person bounding boxes (Fig. (a)).
- A re-identification attention network by reinforcement learning recursively selecting a salient subregion (Fig. (b)).

Notations:
- \( l_i \): Current attention window
- \( l_{id} \): Same identity, different camera
- \( l_{id} \): Different identity, same camera
- \( l_{att} \): Attention window after action a \( x_{id}^1 \) , \( x_{id}^2 \) and \( x_{id}^3 \); the feature for \( l_i \), \( l_{id} \), \( l_{id} \), \( l_{att} \).