25th INTERNATIONAL CONFERENCE
ON PATTERN RECOGNITION

Pose Variation Adaptation for Person Re-identification

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Outline

- Background and Motivation
- Problem Statement
- Our Solutions
- Experiments
- Conclusion

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Background

- **Person Re-identification**
  - Definition

    A retrieval task that aims to recognize and identify a pedestrian across multiple camera views at different times.
  - Application

    Human retrieval, human tracking and activity analysis.

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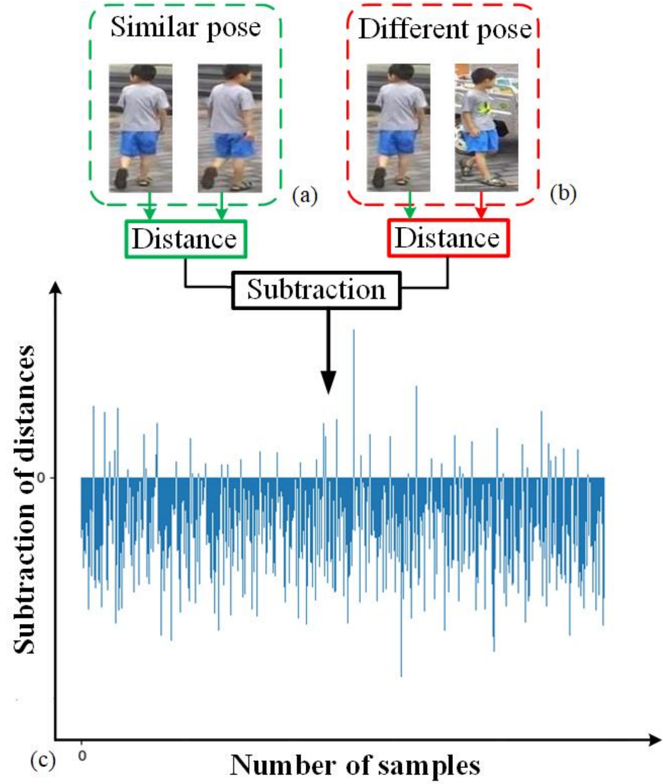
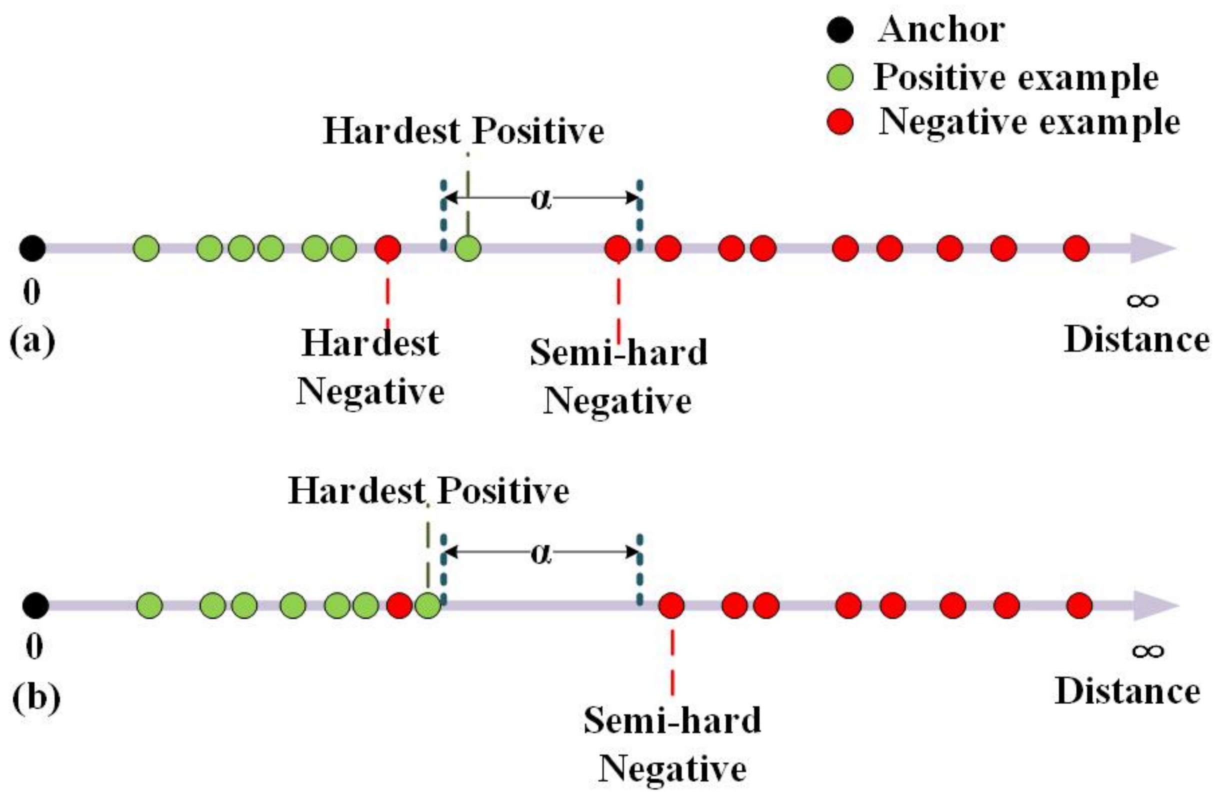
Problem Statement

- Generate samples for data augmentation
  - Two images from the same person with similar poses appear more similar than the same person in quite different poses.



Problem Statement

- Triplet Selection
  - Inferior examples for training



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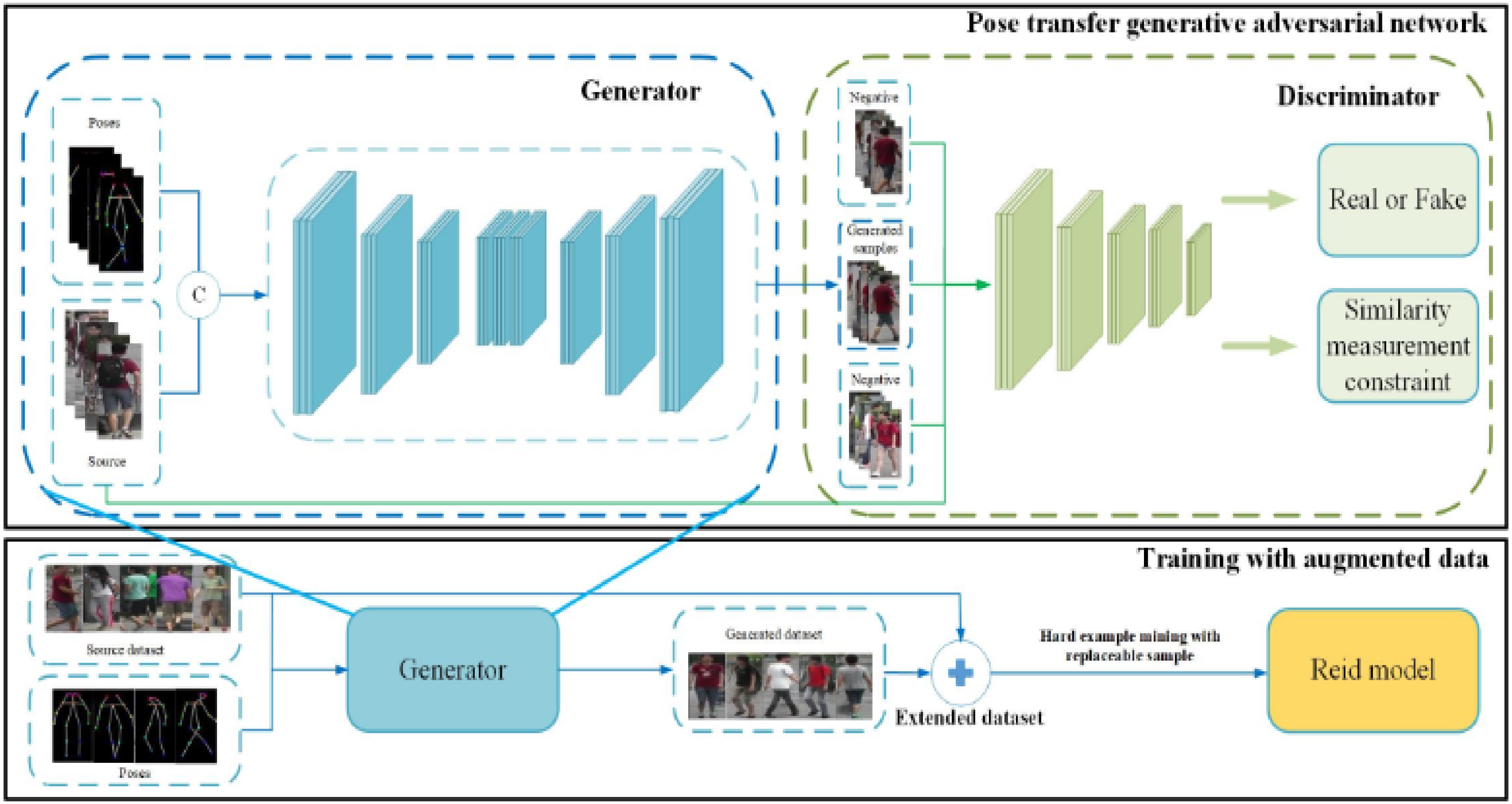
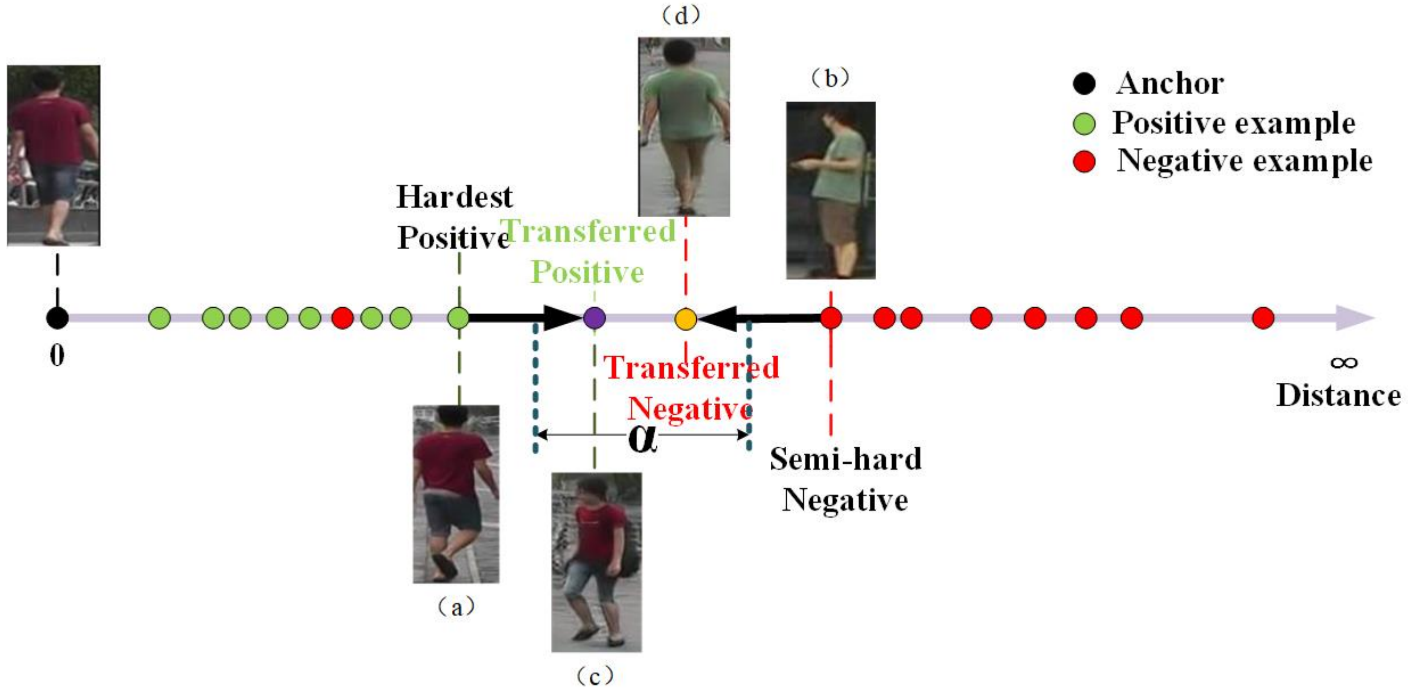
Our Solutions



Our Solutions

- Hard example mining with replaceable sample
  - Optimize the manner of samples used



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Experiments

- Datasets:
  - DukeMTMC-reID
  - Market-1501

- Baseline:
  - A strong baseline:[CVPRW2019]
  - IDE:[CVPR2018]
  - PN-GAN:[ECCV2018]

Experiments

Input Pose Camstyle FD PN Ours GT Input Pose Camstyle FD PN Ours GT

Comparison of the generated images and real images on Market-1501 across the different methods including Camstyle, FD-net, PNGAN, and our approaches

Experiments

Methods	Market-1501		DukeMTMC-reID	
	Rank-1	mAP	Rank-1	mAP
BoW+kissme [2]	44.4	20.8	25.1	12.1
XQDA [3]	-	-	30.8	17.0
DNS [5]	55.4	29.9	-	-
Gated [16]	65.9	39.6	-	-
IDE [1]	72.5	46.0	65.2	45.0
SVDNet [17]	82.3	62.1	76.7	56.8
TriNet [31]	84.9	69.1	72.4	53.5
Part-aligned [32]	91.7	79.6	84.4	69.3
VPM [19]	93.0	80.8	83.6	72.6
Mance [33]	93.1	82.3	84.9	71.8
M^3 [34]	95.4	82.6	84.7	68.5
LSRO(w/o) [8]	84.0	66.1	67.7	47.1
PT(w/o) [12]	87.7	68.9	78.5	56.9
PN-GAN(w/o) [26]	89.4	72.6	73.6	53.2
Camstyle(w/o) [11]	89.5	71.6	78.3	57.6
FD-GAN(w/o) [35]	90.5	77.7	80.0	64.5
DG-net(w/o) [25]	94.8	86.0	86.6	74.8
Base1(w/o) [30]	94.1	85.7	86.2	75.9
Ours	**95.7**	**88.0**	**89.9**	**78.2**
DG-net(w/) [25]	95.4	92.5	90.3	88.3
Base1(w/) [30]	95.4	94.2	90.3	89.1
Auto-ReID(w/) [36]	95.4	94.2	91.4	89.2
Ours+re-ranking	**96.1**	**94.5**	**92.0**	**89.3**

Comparison with state-of-the-art on Market-1501 and DukeMTMC-reID

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Conclusion

- Introduce a pose transfer generative adversarial network to synthesize images for data augmentation

- Propose hard example mining with replaceable sample to optimize the manner of the pose-transferred sample usage

- Experimental results show that our approach outperforms or shows comparable results to the existing best perform methods on both datasets.

Q & A

Thank You