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Group Re-identification: Leveraging and Integrating Multi-Grain Information

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Targets:

Why it is needed?

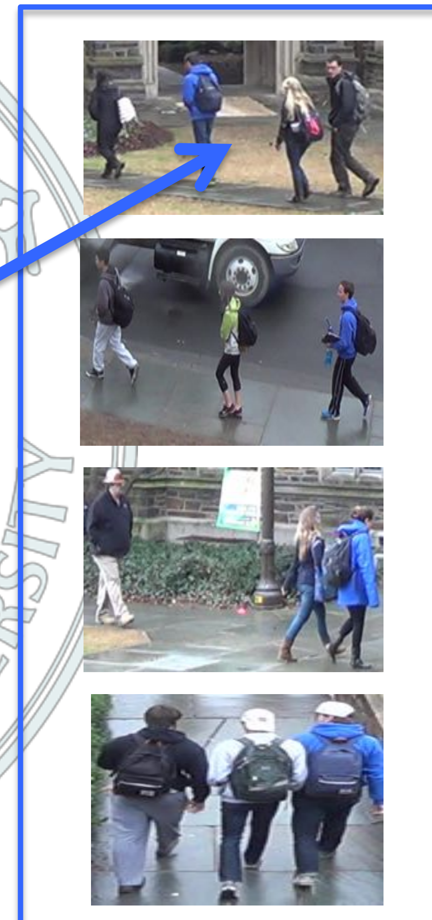
Multi-grain representation

Multi-order matching

Better handle interferences from group dynamics

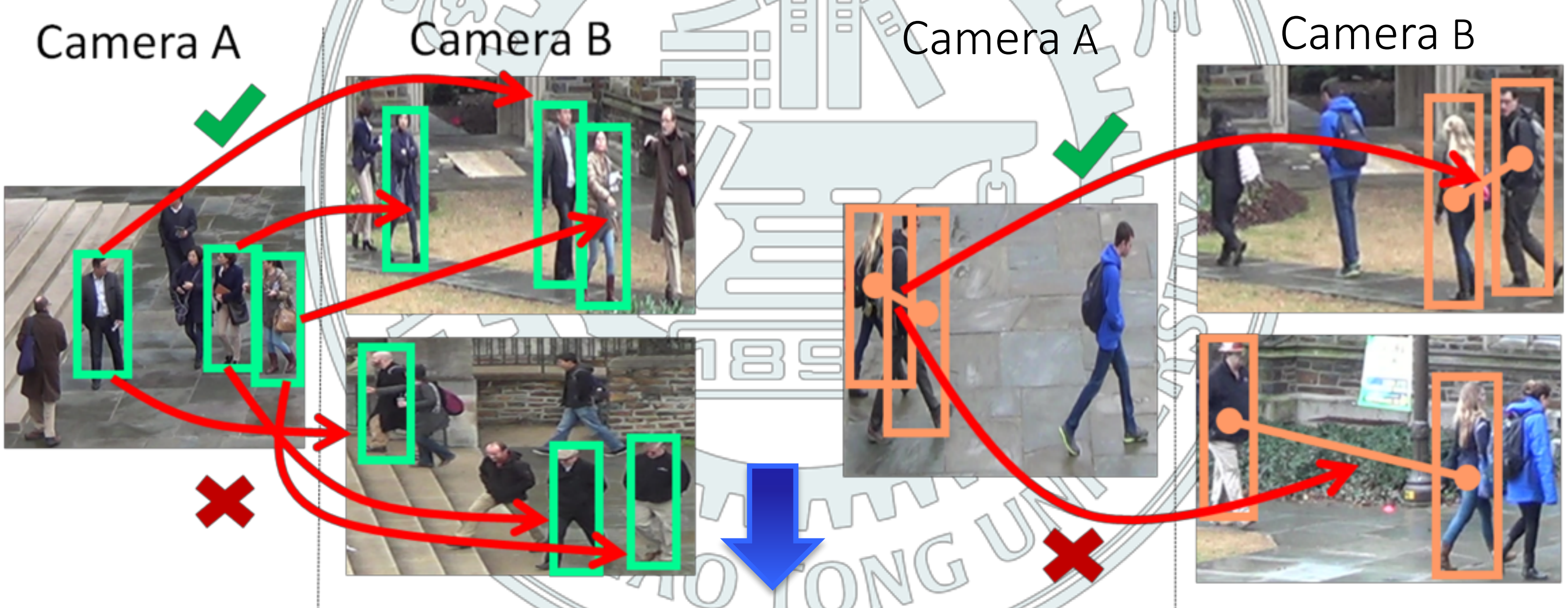
Probe image

Gallery image set



Group dynamics:

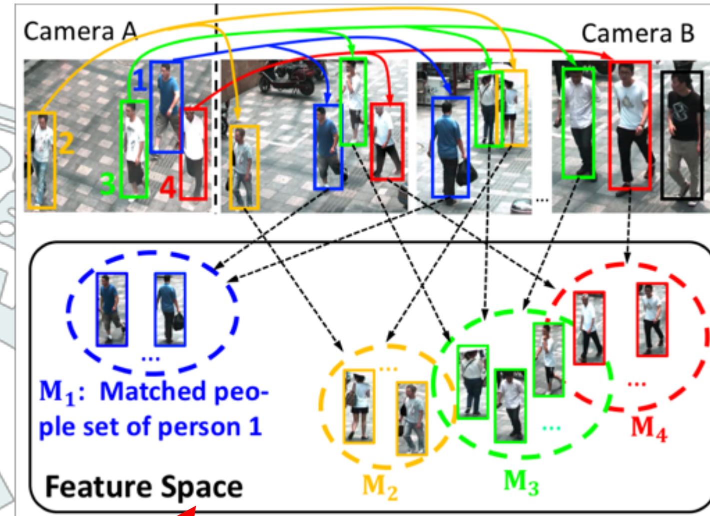
Group dynamics exist due to camera-view changes and dynamic movements of people



So we propose the multi-grain representation

Framework:

1. 4 different group granularities
2. Better characterize a group image
3. Handle layout and membership changes



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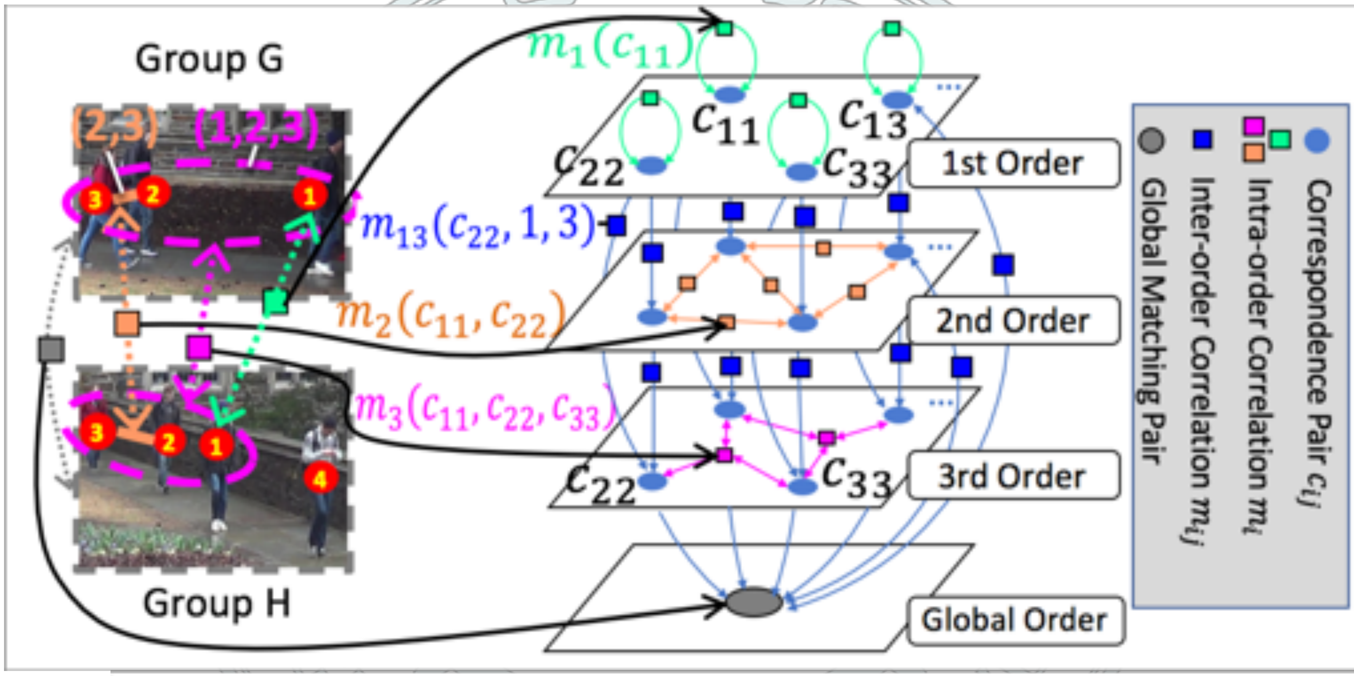
1896 1920 1987 2006

Multi-order matching:



Fused Matching Score:

$$S(I_p, I_g) = \sum_k \sum_{(i_1..i_k)\in\mathcal{R}_p} \frac{w_k(\mathbf{f}_{i_1..i_k}, \alpha_{i_1..i_k}, \mathbf{f}_{M(i_1..i_k)}, \alpha_{M(i_1..i_k)})}{|\mathcal{R}_p|}$$

$$- \lambda_s \cdot \sum_k \left(\sum_{(i_1..i_k)\in\overline{\mathcal{R}}_p} \frac{a_{i_1..i_k}}{|\overline{\mathcal{R}}_p|} + \sum_{(j_1..j_k)\in\overline{\mathcal{R}}_g} \frac{a_{j_1..j_k}}{|\overline{\mathcal{R}}_g|} \right)$$

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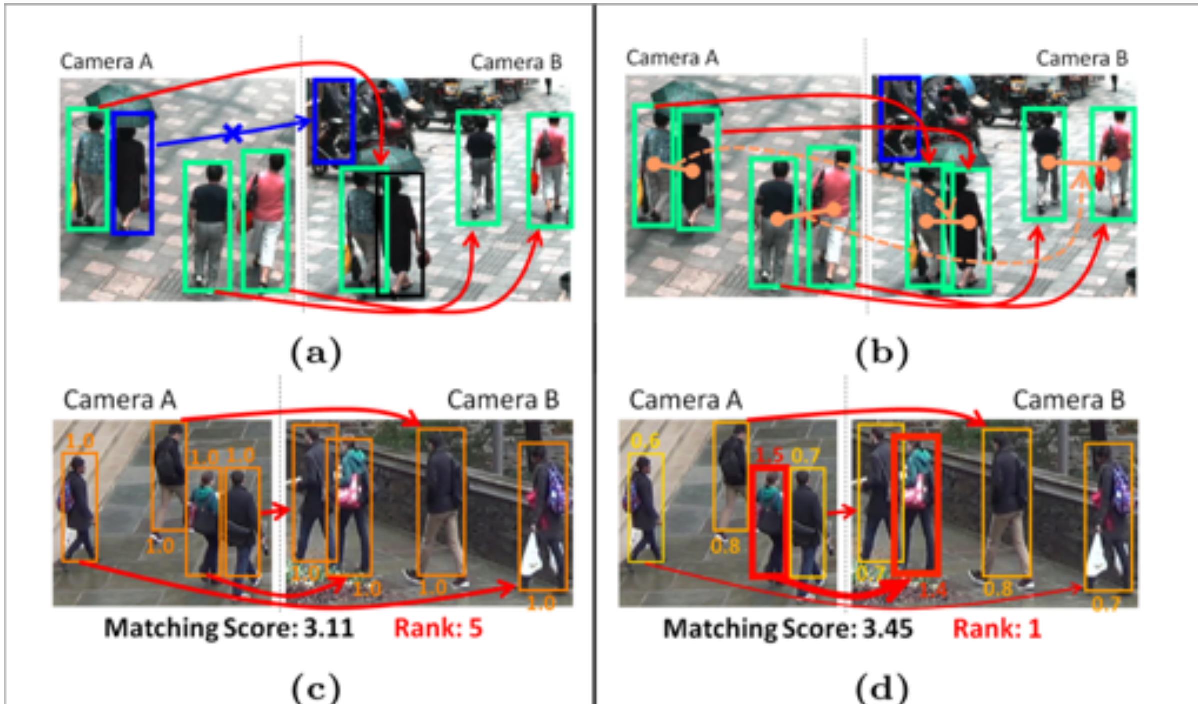
Results:



Matching results by:
(a) only using information of individuals;
(b) using multi-grain information;
(c) setting equal importance weights for all individuals/subgroups;
(d) using our importance evaluation process to obtain importance weights.

Table 1: Group Re-ID results on Road Group dataset

Rank	1	5	10	15	20	30
Global	15.8	31.6	43.0	48.6	54.8	61.7
Fine	62.0	82.2	89.6	95.1	96.5	97.3
Fine+Medium	66.7	87.2	93.3	96.0	96.8	97.3
Fine+Medium+Coarse	71.1	89.4	94.1	97.0	97.3	97.5
Equal-weight	55.8	78.0	88.1	92.1	93.6	97.8
Proposed-no spatial	69.6	88.6	94.0	96.2	96.5	97.4
Proposed-auto	72.3	90.6	94.1	97.1	97.5	98.0
Proposed-GT	**76.0**	**91.8**	**95.3**	**97.2**	**98.0**	**98.0**

Table 2: Matching and Re-ID results on Road Group dataset (*MA*: matching accuracy between individuals; *R*-1*(Gr)*: Rank-1 CMC for group Re-ID; *R*-1*(In)*: Rank-1 CMC for individual Re-ID)

Method	Single	No inter	No dis	Hyp-E	**Proposed-Auto**
MA(%)	83.1	87.0	88.2	86.4	**88.2**
R-1(Gr)	62.0	70.1	65.8	55.1	**72.3**
R-1(In)	60.1	68.9	63.4	53.3	**71.4**

Results:

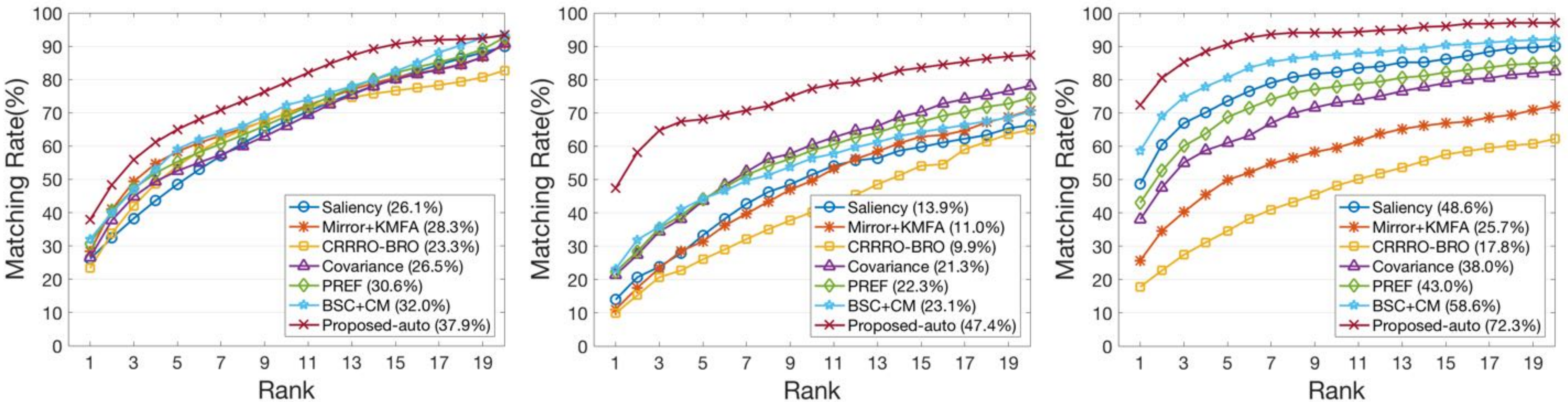


Table 3: CMC results of Group Re-ID on different datasets

Method \ Rank	i-LIDS MCTS					DukeMTMC Group					Road Group				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Saliency [39]	26.1	48.5	67.5	80.3	89.9	13.9	33.3	51.5	59.8	66.3	48.6	73.6	82.2	86.2	90.1
Mirror+KMFA [8]	28.3	58.4	69.8	80.5	90.6	11.0	31.5	49.7	62.9	70.8	25.7	49.9	59.5	66.9	72.1
CRRRO-BRO [42]	23.3	54.0	69.8	76.7	82.7	9.9	26.1	40.2	54.2	64.9	17.8	34.6	48.1	57.5	62.2
Covariance [5]	26.5	52.5	66.0	80.0	90.9	21.3	43.6	60.4	70.3	78.2	38.0	61.0	73.1	79.0	82.5
PREF [15]	30.6	55.3	67.0	82.0	92.6	22.3	44.3	58.5	67.4	74.4	43.0	68.7	77.9	82.2	85.2
BSC+CM [44]	32.0	59.1	72.3	82.4	93.1	23.1	44.3	56.4	64.3	70.4	58.6	80.6	87.4	90.4	92.1
Proposed-auto	**37.9**	**64.5**	**79.4**	**91.5**	**93.8**	**47.4**	**68.1**	**77.3**	**83.6**	**87.4**	**72.3**	**90.6**	**94.1**	**97.1**	**97.5**

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