



# A CODEBOOK OF BRIGHTNESS TRANSFER FUNCTIONS FOR IMPROVED TARGET RE- IDENTIFICATION ACROSS NON-OVERLAPPING CAMERA VIEWS

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# Outline

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- Introduction
- Related work
- Proposed method
- Experimental results

- Challenges in target re-identification
  - Variations in camera view
  - Illuminations
  - Appearance changes
- Major approaches re-id
  - Feature design/selection
  - Distance learning
  - Mid-level feature learning

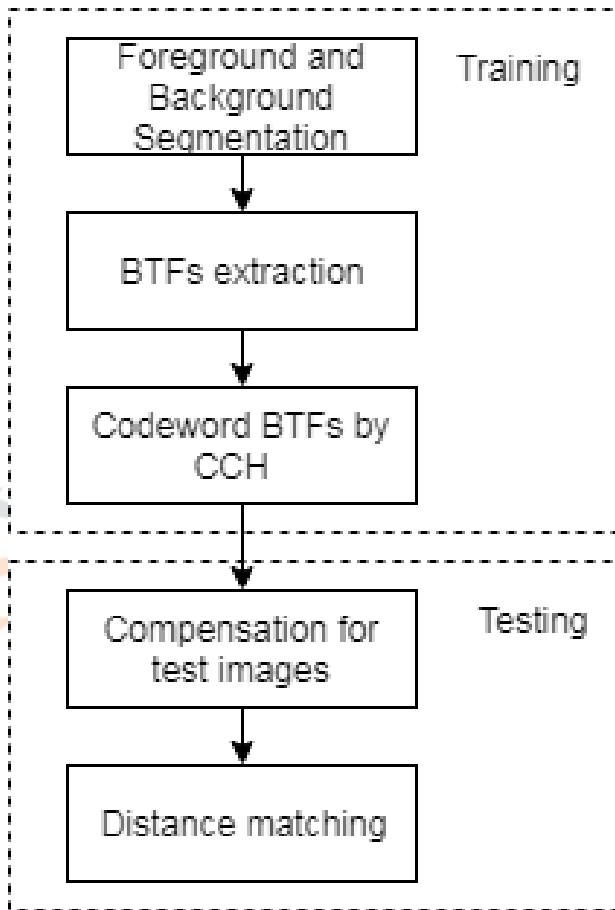


- Classic approaches

- Gaussian Mixture Model(GMM) for human target representation by Chae and JO.
- Cumulative color/incremental major color spectrum histograms representation by Cheng and Piccardi.
- Trajectories matching by Madden and Piccardi.

- BTF-based approaches

- Original BTF is used for inter camera color calibration by Porikli.
- Mean-BTF(MBTF) by Javed et al. average the appearances similarity that projected to low subspace.
- Cumulative-BTF(CBTF) by Prosser et al. compensate illumination change over time.
- Weighted-BTF by Datta et al. finds K training images that close to the target in background and then weighs BTFs.



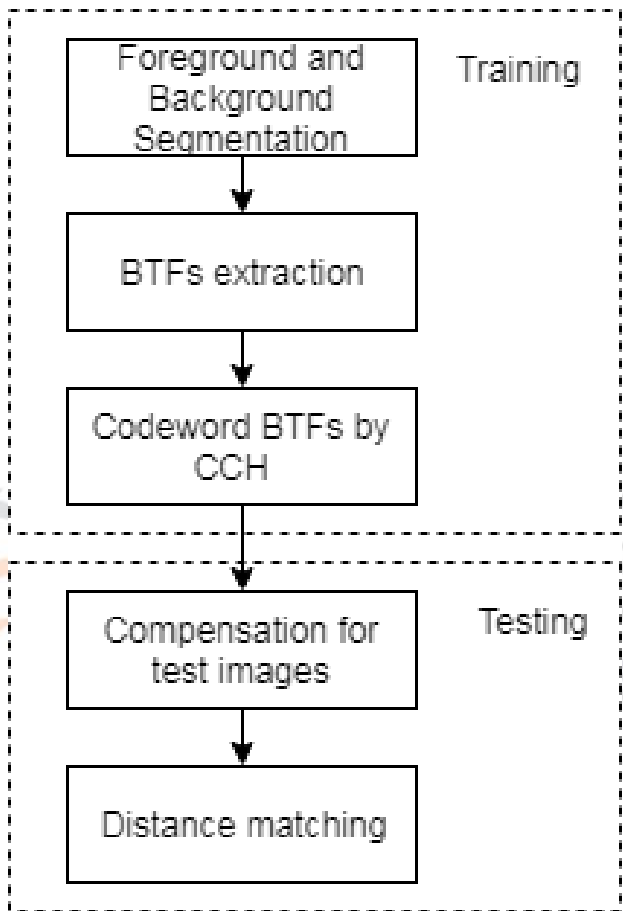
- Normalized cuts over-segment regions.
- Region growing to get the foreground and background model



Fig. 1: Example results from foreground (target) - background segmentation (a) Original image, (b) the segmented image obtained with the proposed approach, (c) the segmented image obtained with the approach in [19].







- Chain Code Histograms(CCH) is employed to check the similarity between two BTF functions.

$$D = 1 - \frac{\sum_{i=0}^{N-1} (r_i - \bar{r})(s_i - \bar{s})}{\sqrt{\left[ \sum_{i=0}^{N-1} (r_i - \bar{r})^2 \sum_{i=0}^{N-1} (s_i - \bar{s})^2 \right]}}$$

$$\bar{r} = \frac{1}{N} \sum_{i=0}^{N-1} (r_i), \quad \bar{s} = \frac{1}{N} \sum_{i=0}^{N-1} (s_i),$$

where  $r$  and  $s$  are N-dimensional feature vectors. In our case, the vector for CCHs is of size eight, since eight directions are used while constructing the chain codes.

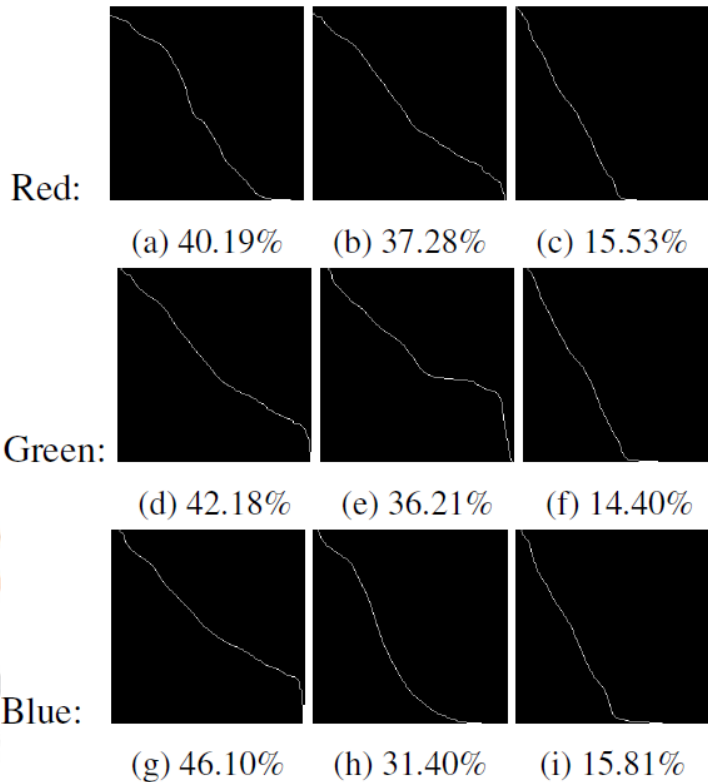


Fig. 2: Top three most frequently occurring BTFs for red, green and blue channels when  $\rho = 0.05$ .

- If two histograms are identical, then the dissimilarity distance between them becomes zero.
- As the histograms start to deviate from each other, the dissimilarity distance increases.
- If this distance is greater than the threshold  $\rho$ , a new codeword is generated. We used the same value for  $\rho$  in all the evaluations.



- **Image representation**

- An image is divided into 15 horizontal stripes
- 20 dimensional histogram of RGB, HSV and YCbCr color features
- 405 dimensional HOG feature histogram
- 12 channel feature vector with 20925 dimensions, where each channel is obtained by concatenating features across all stripes.
- The distance between two images is computed by taking the average of 12 Bhattacharyya distance.

- **Datasets**

- VIPeR, 632 objects, 2 camera views
- CUHK01, 971 objects, 2 camera views
- CAVIAR4REID, 50 objects , 2 camera views

- Color correlation comparison

Avg. color corr. score	5-fold			3-fold		
	Proposed	CBTF	improvement	Proposed	CBTF	improvement
VIPER	0.3494	0.2909	20.1%	0.3963	0.3832	20.3%
CUHK01	0.4062	0.3475	16.9%	0.4554	0.3954	15.2%
CHUK02	0.4405	0.3727	18.2%	0.4749	0.4069	16.7%

Tab. 1 Color correlation score improvement obtained by the proposed method compared to CBTF on VIPeR, CUHK01 and CUHK02 datasets.

- Re-id performances

Methods	p=316 (# of test images)				p = 432				p = 532			
	r = 1	r = 5	r = 10	r = 20	r = 1	r = 5	r = 10	r = 20	r = 1	r = 5	r = 10	r = 20
<b>CB w/ prop. seg.</b>	<b>23.35</b>	<b>47.81</b>	<b>61.90</b>	<b>77.12</b>	<b>17.10</b>	<b>35.91</b>	<b>52.34</b>	<b>65.63</b>	<b>14.24</b>	<b>32.09</b>	<b>43.75</b>	<b>59.27</b>
<b>CB w/ seg. in [19]</b>	23.01	47.17	60.58	76.70	16.93	35.84	51.63	64.49	13.75	31.85	43.67	57.69
WBTF[19]	21.99	46.84	59.97	75.95	15.05	35.76	50.81	64.24	13.72	31.77	42.86	57.42
CBTF [18]	19.27	38.85	53.54	64.69	14.25	31.75	43.96	53.49	12.95	28.76	35.97	46.06
MBTF [17]	18.81	38.47	50.90	63.58	14.12	29.70	43.91	52.34	12.63	26.24	33.09	45.75
CPS[6]	21.84	46.00	57.21	71.50	-	-	-	-	-	-	-	-
SDALF[27]	20.00	38.00	48.50	65.00	-	-	-	-	-	-	-	-
PRDC[28]	15.66	38.42	53.86	70.09	12.64	31.97	44.28	59.95	9.12	24.19	34.40	48.55

Tab. 2 Correct match in the top r returned images. p is the number of images in the test set (out of 632 images in the VIPeR dataset).

Methods	p=485			
	r=1	r=5	r=10	r=20
<b>CB w/ prop. seg.</b>	<b>15.01</b>	<b>28.98</b>	<b>42.40</b>	<b>65.85</b>
<b>CB w/ seg. in [19]</b>	13.42	26.37	41.29	65.17
WBTF [19]	10.93	22.19	35.51	57.83
CBTF [18]	9.62	20.34	33.86	56.39
MBTF [17]	8.73	19.75	33.72	55.52

Tab. 3 The percentage of images, for which the correct match is in the top r returned images. p is the number of images in the test set (out of 971 images for CUHK01 dataset).

Fig. 3 (a) and (b) images from 1st and 2nd camera, respectively, (c) transferred version of column (a) image by proposed method, (d) transferred version of column (a) image by CBTF, (e) codewords used by the proposed method for R,G,B channels (top to bottom).

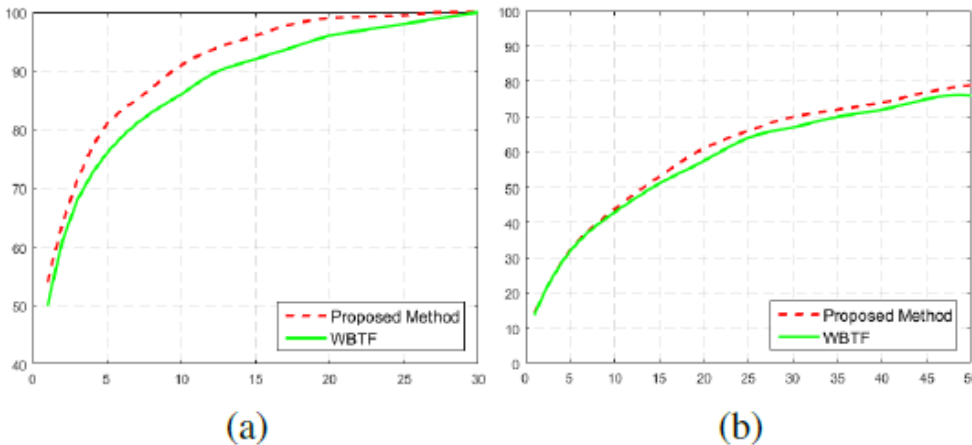


Fig. 4 CMC curves obtained with the proposed method and WBTF [19] for (a) CAVIAR4REID, (b) VIPeR ( $p = 532$ ) datasets.



Thank you!  
Questions?