BOOSTING-BASED TRANSFER LEARNING FOR MULTI-VIEW HEAD-POSE CLASSIFICATION FROM SURVEILLANCE VIDEOS

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ABSTRACT

This work proposes a boosting-based transfer learning approach for head-pose classification from multiple, low-resolution views. Head-pose classification performance is adversely affected when the *source* (training) and *target* (test) data arise from different distributions (due to change in face appearance, lighting, *etc*). Under such conditions, we employ ***Xferboost***, a Logitboost-based transfer learning framework that integrates knowledge from a few labeled *target* samples with the *source* model to effectively minimize misclassifications on the *target* data. Experiments confirm that the ***Xferboost*** framework can improve classification performance by up to 6%, when knowledge is transferred between the CLEAR and FBK four-view headpose datasets.

Index Terms— Multi-view headpose classification, low-resolution, *Xferboost*, boosting-based transfer learning

1. INTRODUCTION

Despite much progress in head-pose estimation and tracking (see [1] for a detailed survey), most methods and benchmarking datasets [2, 3, 4] focus on determining pose from high-resolution imagery. However, recent works have actively attempted head-pose recovery from surveillance videos [5, 6, 7, 8] where faces are blurred and are at low resolution. These approaches classify head-pose to one of many discrete classes denoting a range of orientations.

This paper deals with head-pose classification as a person is imaged with multiple, large field-of-view cameras in a closed setting. Also, we seek to adapt existing models derived from available data to new situations through *transfer learning*. Figure 1 shows multiple instances of persons captured in two distinct settings. Images on the left are from the **CLEAR07** [9] head-pose dataset, which contains around 27000 4-view images with pose ground-truth. Likewise, 4-view images from the **FBK** dataset captured under different camera, illumination and environmental settings are shown on the right. Head-pose comprises *pan* and *tilt*[1], which denote out-of-plane horizontal and vertical head rotation, and examples with *downward*, *frontal* and *upward* head-tilt are respectively shown in the top, middle and bottom rows of Figure 1.

The rest of this paper discusses how models learnt from extensive *source* (CLEAR) data can be adapted to effectively work on novel *target* (FBK) data. As a preliminary step, we divided the CLEAR, FBK data into three parts corresponding to *downward* ($[-90^o, -20^o]$), *frontal* ($[-20^o, 20^o]$) and *upward* ($[20^o, 90^o]$) tilt, and then attempted eight-class head-pan classification (Figure 2) fixing the head-tilt. Apart from simplifying the pose-labeling problem to pan classification, fixing the head-tilt range allowed us to explore the adaptation problem under realistic settings. *E.g.*, how labeled head-pose examples acquired from boardroom meeting scenes (where head-tilt is typically *frontal*) can be utilized to determine what attracts peoples' attention in a supermarket/museum setting (where *downward*/*upward* head-tilt is generally expected).

Secondly, we trained a state-of-the-art ARCO descriptor [7] model for each of the *source* subsets, and tested these models on the different *source* and *target* subsets. Training and test data sizes for the considered *source*/*target* subsets are specified in Table 1. Table 2 lists classification accuracies obtained with the ARCO models for these combinations. It is evident from the tabulated results that while high accuracies are observed when training and test set distributions are the same (*i.e.,* same dataset, similar head-tilt), a significant drop in performance is observed even as the training and test set distributions vary. This is the case when (i) the face appearance changes due to head-tilt differences (even for the same dataset) and (ii) training and test data attributes vary (as for CLEAR and FBK).

To counter this problem, we propose ***Xferboost***, a boosting-

[1]We ignore *roll* (in-plane head rotation) here

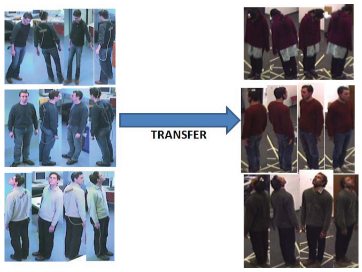


Fig. 1. Examples from the CLEAR (*source*) and FBK (*target*) head-pose datasets. We employ ***transfer learning*** to adapt *source*-based models for *target* data classification.

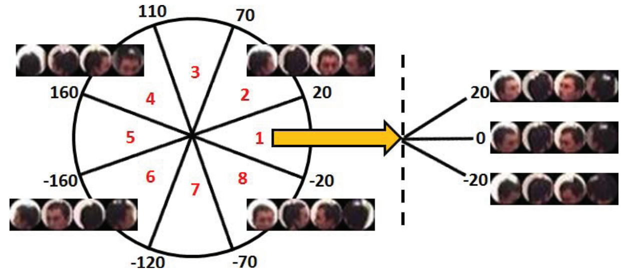


Fig. 2. Discretization of head-pan (8 classes) and tilt (*up*, *frontal* and *down*). In our experiments, we attempted 8-class pan classification with ARCO [7] on the tilt-based subgroups.

based transfer learning approach. Transfer learning [10, 11] allows for adaptation of models learnt from available *source* data to novel *target* data, using additional knowledge from a few labeled *target* samples. *Xferboost* integrates `Tradaboost` [11], which 'tunes' the *source* model to the *target* data by assigning greater importance to *target* samples, with the Logitboost learner employed by ARCO. Experimental results reveal that this tuning is more effective than simply learning a model with many *source* and few *target* samples, and can improve classification performance by more than 6%.

In summary, this paper represents one of the first works to explore a transfer-learning approach for multi-view head-pose classification. The next section evaluates related work to motivate the proposed approach, while Section 3 discusses *Xferboost* in detail. Experimental results are presented in Section 4 and we end with concluding remarks in Section 5.

2. RELATED WORK

We now review related work in (i) head-pose classification from low-resolution images and (ii) transfer learning.

2.1. Pose classification from low-resolution views

Recent and popular head-pose classification algorithms that work on low-resolution images are [8, 7]. In [8], a Kullback-Leibler (KL) distance-based facial appearance descriptor is found to be effective for pose classification on the i-LIDS dataset comprising footage of an underground scene. In [7], array-of-covariance (ARCO) descriptors, robust to scale/lighting variations and occlusions, produce 11% better classification on i-LIDS as compared to [8]. Combining a dynamic Bayesian network with Gaussian mixture-cum-Hidden Markov models, a visual focus-of-attention (VFOA) estimation algorithm for multiple subjects moving in front of a surveillance camera is proposed in [5]. However, all these works address head-pose estimation from a single view.

Among multi-view pose-estimation works, a robust approach to positional variations is proposed in [6], where face texture is mapped onto a spherical head model, and head-pose is determined from the face location on the unfolded texture map. Nevertheless, many cameras are required to generate an accurate texture map, while we explore a purely image-based approach for multi-view head-pose classification.

2.2. Transfer learning approaches

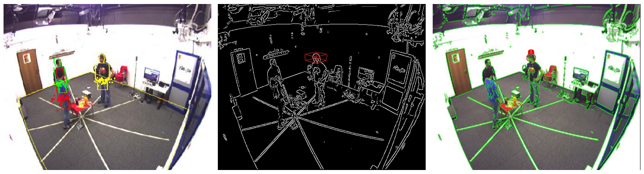
There are several approaches to transfer learning. *Instance-transfer* [11] involves reuse of *source* data in a related *target* domain assuming that certain parts of the *source* data are still useful in the *target* scenario. *Feature-representation-transfer* [12] involves finding a 'good' feature representation that reduces differences between the *source* and *target* data. *Parameter-transfer* [13] involves discovery of shared parameters or priors between the *source* and *target* models which can benefit from transfer learning. Transfer learning approaches have become very popular in computer vision- a transferable distance function is learned with sparse training data for action detection in [14]. We propose a transfer learning for pose classification in this work.

3. LOGITBOOST-BASED TRANSFER LEARNING

This section describes in detail, (i) the pre-processing steps involved (ii) the array of covariance descriptors (ARCO) algorithm and (iii) *Xferboost*, the proposed Logitboost-based transfer learning algorithm for head-pose classification.

3.1. Pre-processing

As large field-of-view cameras are used to acquire both *source* (CLEAR) and *target* (FBK) datasets, the first step involves facial appearance extraction in each of the camera views. To this end, we employ a multi-view color-based particle filter [15] which can handle multiple, moving subjects without manual initialization. Upon estimating the 3D body-centroid and height of the moving subject(s) with the tracker, particles are sampled around the 3D head-position within a search window. Assuming a spherical model of the head, a contour likelihood is computed for each particle by projecting a 3D



(a) (b) (c)

Fig. 3. (a-c) illustrate facial appearance extraction- (a) Estimated particles and target positions, (b) Edge image and search region for the yellow track in (a). (c) Determined face location with highest likelihood estimate.

sphere onto each view employing camera calibration information. Finally, the sample with the highest likelihood sum is determined as the head location. Upon face localization, the face crop is resized to 20×20 resolution prior to ARCO feature computation. Facial appearance extraction process is outlined in Figure 3.

3.2. Array of covariance descriptors (ARCO)

The state-of-the-art ARCO algorithm [7] employs covariance features, robust to occlusions as well as scale and lighting variations, for head-pose classification from low-resolution images. Upon dividing the image into a number of overlapping patches, ARCO computes covariance-based patch descriptors. Subsequently, a multi-class Logitboost classifier is learnt for each patch, and the test sample is assigned a label based on majority vote of the patch-based classifiers.

The ARCO algorithm has many advantages. Firstly, covariance matrices are flexible, low-dimensional features. A requisite number of image features can be combined to generate covariance descriptors, which can effectively describe visual objects at prohibitively low resolutions. Also, each patch descriptor is only a $d \times d$ matrix, where d denotes the number of image features used. This can be further reduced to a $d(d+1)/2$ dimensional vector upon projecting covariance

	CLEAR *frontal*	CLEAR *up*	CLEAR *down*	FBK *frontal*	FBK *up*	FBK *down*
Train	7490	3013	2451	50	50	50
Test	7481	3010	2444	12406	7077	5941

Table 1. *Source* (CLEAR) and *Target* (FBK) training and test data sizes for the different tilt classes.

	CLEAR *frontal*	CLEAR *up*	CLEAR *down*	FBK *frontal*	FBK *up*	FBK *down*
CLEAR *frontal*	91.9	85.5	54.1	57.2	62.7	34.2
CLEAR *up*	72.5	93.1	22.5	58	72.3	28.8
CLEAR *down*	58.2	34.8	93.2	25.3	36.1	38.4

Table 2. Classification accuracies with ARCO for various train (along rows)/test (along columns) combinations.

features, originally spanning a Riemannian manifold, onto the Euclidian tangent space.

For all the results presented in this paper, we used the 12-dimensional feature set $\phi = [x, y, R, G, B, I_x, I_y, OG, Gabor_{\{0,\pi/6,\pi/3,4\pi/3\}}, KL]$. Here, x, y and R, G, B denote spatial positions and color values, while Ix, Iy and OG respectively denote intensity gradients and gradient orientation of the pixels. $Gabor$ is the set of coefficients obtained from Gabor filtering at aforementioned orientations (frequency = 16 Hz), while KL denotes maximal divergence between corresponding patches in the target face image and different pose-class templates computed as described in [8]. Also, 8×8 overlapping patches were used in all experiments.

3.3. *Xferboost*

The main contribution of this work is that we seek to adapt an existing model derived from many *source* training samples to novel *target* data, using additional knowledge from a few *target* training samples and minimizing the effort required to label *target* samples in the process. ARCO employs a multi-class Logitboost learner (strong classifier) $\{F_l\}$ for each image patch, comprising $l = 1..L$ weak classifiers. Given a training set $\{x_i\}$ with N samples corresponding to class labels $1..J$, the Logitboost algorithm iteratively re-weights training samples most difficult to classify, through a set of weights w_i and posterior probabilities, $P_j(x_i)$. Each weak learner solves a weighted-regression problem, whose goodness of fit is measured by the response value vector for the i^{th} training sample, $z_i = \{z_{ij}\}_{j=1}^{J}$.

The Logitboost learner learns until most training samples are classified correctly. Therefore, when presented with a training set containing many *source* and few *target* samples, the model could still be *source*-oriented, given varying attributes of the *source* and *target*. Instead, we adopt the methodology employed in `Tradaboost` [11], which prioritizes misclassified *target* samples in the boosting framework, so that the resulting model is 'tuned' to the *target*.

Given $N + M$ training data, with N *source* (*Src*) and M *target* (*Tgt*) samples, where $N >> M$, the *Xferboost* algorithm proceeds as follows. At every step, upon normalizing w_i's, the error on *target*, ϵ_t ($\epsilon_t < 0.5$) is computed for the misclassified *target* samples. Also, α_s and α_t, which are respectively the attenuating and boosting factors for misclassified *source* and *target* samples, are determined. Finally, weights of misclassified *target* data are boosted by a factor of e^{α_t}, so that more *target*-specific information can be learned, while misclassified *source* weights are attenuated by a factor of $e^{-\alpha_s}$ to discourage learning of these samples. The proposed *Xferboost* algorithm is summarized in Algorithm 1.

4. EXPERIMENTAL RESULTS

To evaluate *Xferboost* performance, we compiled the **FBK** multi-view headpose dataset. Head *pan*, *tilt* and *roll* measurements for various poses were recorded for 16 subjects using an accelerometer, gyro, magnetometer platform. The FBK data differs from CLEAR with respect to distance of cameras from the person, relative camera positions and illumination conditions. The FBK dataset contains over 25000 examples (Table 1), out of which 50 random samples were used for training while the remainder were used for testing.

We compared *Xferboost* accuracies against the Logitboost learner fed with both *source* and *target* training data (baseline/no *Xferboost* condition). We analyzed the effect of varying the number of weak learners L and *target* training set size (with 5-30 *target* samples/class) on classification performance (Figure 4). Each point on the graph denotes *mean accuracy* obtained from five independent trials (employing randomly generated *target* training sets) for the given condition. Also, since we used multiple views for pose classification, we compared performance considering (i) *one-view accuracy* or the mean accuracy obtained using only one of the 4 views and (ii) *four-view accuracy*, the accuracy obtained upon feeding features from all views to the classifier.

Notice from Figure 4 that much higher accuracies are obtained employing features from all views instead of only one view, implying that multi-view information is more robust compared to single-view for head-pose classification on low-resolution images. Higher improvements in classification performance are obtained with *Xferboost* when a) fewer patch learners (implying less computation resources) and b) fewer *target* training samples are employed. Also, higher improvements are obtained with *Xferboost* when the *source* and *target* distributions vary significantly (*e.g.*, CLEAR *up*- FBK *down* combination), as compared to cases where they are similar (*e.g.*, CLEAR *up*- FBK *up*). *Target*-specific information is most beneficial when the *source* and *target* have minimal similarity, and transfer learning works best in such cases.

Table 3 presents the *best* improvements obtained with *Xferboost* when only 5 labeled *target* samples/class (¡0.5% of the *target* size) are employed for transfer learning. In the fourth and sixth columns, the *Xferboost* accuracies are presented along with the baseline accuracies (within parentheses). Here again, the maximum improvements with *Xferboost* are obtained for those cases where the *source* and *target* distributions vary significantly. Also, single-view improvements are higher as compared to employing all 4 views, suggesting that transfer learning perhaps works better when less information is available. Overall, a maximum performance gain of 6.2% is obtained with the *Xferboost* approach for the CLEAR *down*- FBK *up* combination.

Algorithm 1 *Xferboost*- Transfer learning with Logitboost

Input: Combined *Src* $(x_i, y_i \in \mathcal{T}_s)$, *Tgt* $(\mathrm{x}_i, \mathrm{y}_i \in \mathcal{T}_t)$ train set $\mathcal{T} = \{(x_1, y_1), \dots (x_N, y_N), (\mathrm{x}_{N+1}, \mathrm{y}_{N+1}), \dots, (\mathrm{x}_{N+M}, \mathrm{y}_{N+M})\}$, where $\{y_i\}, \{\mathrm{y}_i\} = 1..J$, number of learners L.
For $i = 1..N+M$, initialize weights $w_i = \frac{1}{N+M}$ and posterior probabilities $P_j(x_i) = \frac{1}{J}$, set of learners $\{F_l\} = \phi$,
Set $\alpha_s = \frac{1}{2} ln(1 + \sqrt{2 ln \frac{N}{L}})$
for $l = 1 \dots L$
Compute response values z_i and weights w_i from $P_j(x_i)$
if $L > 1$
Normalize the weight vector $w_1, \dots, w_{N+M}$
Compute the error on *Tgt*, $\epsilon_t = \sum_{j=1}^{J} \frac{w_j [y_j \neq h(\mathrm{x}_j)]}{\sum_{i=1}^{N+M} w_i}$,
where $\mathrm{x}_j = \{\mathrm{x}_i \in j\}$ with weights w_j
Set $\alpha_t = \frac{1}{2} ln(\frac{1-\epsilon_t}{\epsilon_t}), \epsilon_t < \frac{1}{2}$
Update weights
$w_i \leftarrow w_i e^{-\alpha_s (y_j \neq h(x_j))}$ (modify misclassified *Src* weights)
$w_i \leftarrow w_i e^{\alpha_t (y_j \neq h(\mathrm{x}_j))}$ (modify misclassified *Tgt* weights)
end if
Compute learner F_l using least-square regression with z_{ij}'s and modified w_i's.
Compute new $P_j(x_i)$'s and classifier labels $h(x_i)$.
end for
Output: Set of learners $\{F_l\}$ (for each image patch)

5. CONCLUSIONS

The paper proposes *Xferboost*, a boosting-based transfer learning approach for pose classification from multiple, low-resolution views. Experimental results confirm that the effectiveness of *Xferboost*, which improves classification performance significantly when the *source* and *target* distributions are very different. Future work involves integrating information from multiple sources for transfer learning, and exploiting temporal constraints for efficient head-pose tracking.

6. ACKNOWLEDGEMENTS

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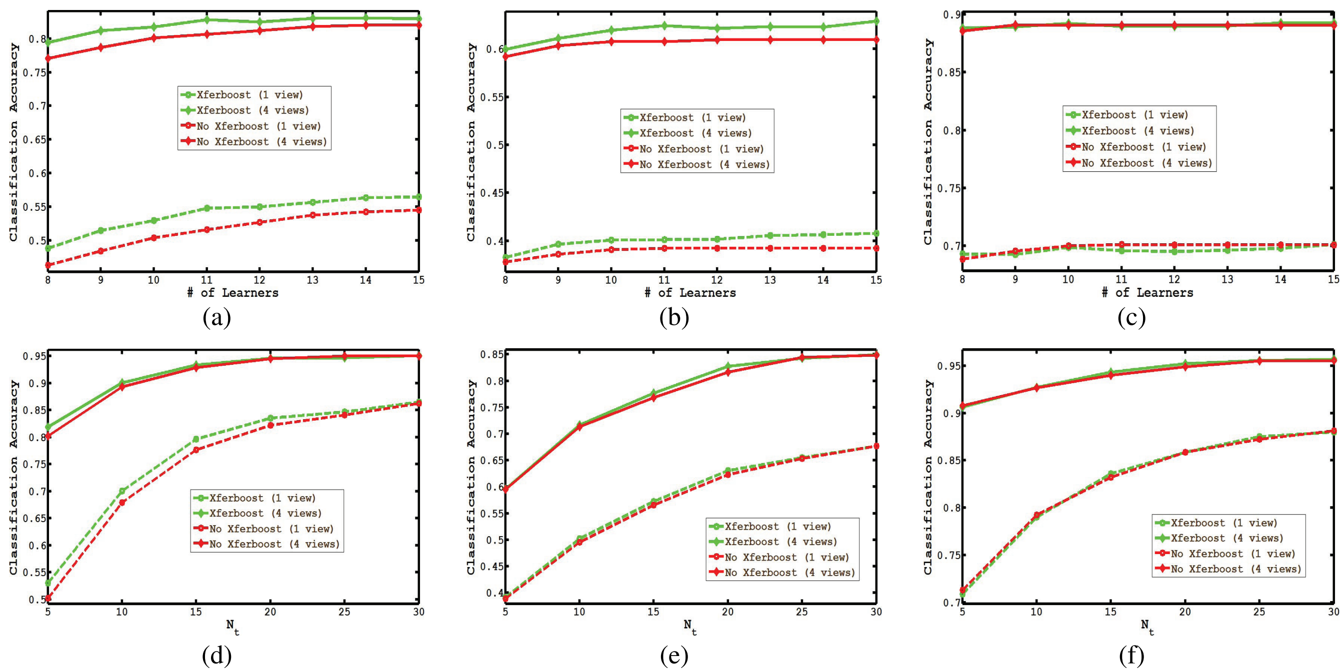

Fig. 4. Variation in classification accuracy with the number of learners (top) and *target* samples (bottom). Results presented for *Src*-*Tgt* combinations CLEAR *down*-FBK *up* (a,d), CLEAR *frontal*-FBK *down* (b,e) and CLEAR *up*-FBK *up* (c,f).

Train	Test	L	Accuracy (1-view)	% gain	Accuracy (4-view)	% gain
CLEAR *down*	FBK *down*	8	42.7 (41.3)	**3.4**	66.5 (64.5)	**3.1**
	FBK *frontal*	9	40.8 (38.6)	**5.8**	65.5 (62.7)	**4.4**
	FBK *up*	9	51.5 (48.5)	**6.2**	81.2 (78.7)	**3.2**
CLEAR *frontal*	FBK *down*	10	40.1 (39.1)	**2.5**	61.9 (60.8)	**1.9**
	FBK *frontal*	8	54.1 (52.3)	**3.5**	78.8 (77.1)	**2.2**
	FBK *up*	8	63.7 (62)	**2.7**	87 (86)	**1.1**
CLEAR *up*	FBK *down*	10	40 (38.3)	**4.5**	59.7 (57.7)	**3.6**
	FBK *frontal*	8	58.1 (57.3)	**1.4**	80.6 (80.1)	**0.6**
	FBK *up*	9	69.3 (68.9)	**0.7**	88.8 (88.6)	**0.3**

Table 3. Best improvements obtained with *Xferboost* for different combinations. L denotes number of weak learners.

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