FISHER VECTOR ENCODED DEEP CONVOLUTIONAL FEATURES FOR UNCONSTRAINED FACE VERIFICATION

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ABSTRACT

We present a method to combine the Fisher vector representation and the Deep Convolutional Neural Network (DCNN) features to generate a representation, called the Fisher vector encoded DCNN (FV-DCNN) features, for unconstrained face verification. One of the key features of our method is that spatial and appearance information are simultaneously processed when learning the Gaussian mixture model to encode the DCNN features. Evaluations on two challenging verification datasets show that the proposed FV-DCNN method is able to capture the salient local features and also performs well when compared to many state-of-the-art face verification methods.

1. INTRODUCTION

Learning invariant and discriminative features from images and videos is one of the central goals of research in many computer vision tasks such as object recognition and face recognition. Many approaches have been proposed in the literature that extract over-complete and high-dimensional features from images to handle large data variations and noise. For instance, the high-dimensional multi-scale Local Binary Pattern (LBP) [1] representation extracted from local patches around facial landmarks is reasonably effective for face recognition. Face representation based on Fisher vector (FV) has also shown to be effective for face recognition problems [2], [3], [4].

However, in recent years, deep convolutional neural networks (DCNN) have demonstrated impressive performances on several computer vision problems such as object recognition [5][6], object detection [7], and face verification [8]. It has been shown that a DCNN model can not only characterize large data variations but also learn a compact and discriminative feature representation when the size of the training data is sufficiently large.

Motivated by the success of FV and DCNN models for various computer vision problems, we propose to combine them for face verification. We adopt a network architecture similar to the one proposed in [9] which has demonstrated impressive performance for face recognition. The DCNN model is trained using the CASIA-WebFace dataset which consists of 10,575 subjects. This model builds a very deep architecture for convolutional neural network by stacking small filters (i.e. $3 \times 3$) together as VGGNet [10] and is trained with 10,575 subjects as the DeepID Net [11]. Finally, average pooling is applied right after the last convolutional layer to generate a global descriptor and reduce the number of parameters for the fully connected layers. When average pooling is used, the spatial information is often lost. Hence, to exploit the local appearance information, we propose to apply FV to encode the local convolutional features from each image into a high-dimensional vector instead of applying the average pooling operation.

Our work is somewhat similar to the previous work proposed by Cimpoi et al. [12] for texture recognition. They also propose to combine the FV and DCNN features. However, their approach does not take into account any spatial information. Compared to textures, human faces have well-defined structure (e.g. faces are approximately symmetric). Thus, the main distinction between the two works is that each local DCNN feature is augmented with spatial information in the image when we apply FV to encode DCNN features from an image. An example is illustrated in Section 4 to show how the learned GMM looks like with and without incorporating the spatial information. Furthermore, as was shown in [12], since lower layers contain less discriminative information, we focus on the conv52 features to incorporate the spatial information with FV.

2. RELATED WORK

In this section, we briefly review several recent works on face verification.

Robust feature learning is a key component in a face verification system. It can be roughly classified into two categories: handcrafted features and features learned directly from data. In the first category, Ahonen et al. [13] showed that the Local Binary Pattern (LBP) is effective for face recognition. Gabor wavelets [14] have also been widely used to encode multi-scale and multi-orientation information for face images. Chen et al. [1] demonstrated good results for face verification using the high-dimensional multi-scale LBP features extracted from patches around facial landmarks. In the

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second category, Simonyan et al. [2] and Parkhi et al. [3] used the FV encoding to generate over-complete and high-dimensional feature representation for still and video-based face recognition. Some of the other feature encoding methods include Bag-of-Visual-Words (BoVW) model [15], VLAD [16] and Super Vector Coding [17].

The high-dimensionality of feature vectors makes these methods difficult to train and scale to large datasets. However, recent advances in deep learning methods have shown that compact and discriminative representation can be learned using DCNN from very large datasets. Tai et al. [18] learned a DCNN model on the frontalized faces generated with a general 3D shape model from a large-scale face dataset. Sun et al. [19][11] achieved results surpassing human performance for face verification on the LFW dataset using an ensemble of 25 simple DCNNs with fewer layers trained on weakly aligned face images from a much smaller dataset than the former. Schroff et al. [8] adapted the state-of-the-art deep architecture in object recognition to face recognition and trained on a large-scale unaligned private face dataset. Parkhi et al. [20] trained a very deep convolutional network based on VGGNet for face verification and demonstrated impressive results. These works essentially demonstrate the effectiveness of the DCNN model for feature learning and detection/recognition/verification problems.

3. PROPOSED METHOD

An overview of our FV-DCNN method for face verification is shown in Figure 1. Each training image is first passed through a pre-trained DCNN model to extract the convolutional features. Then, we learn the Gaussian mixture model over them and perform FV encoding over these local convolutional features which have already encoded the rich feature information. Finally, we learn the metric. In the testing phase, we extract the DCNN features and use the learned GMM to perform FV feature encoding. We then apply the learned metric to compute the similarity scores. In what follows, we describe the details of each of these components.

Face Preprocessing: Each face image is detected and aligned using the open-source library libf [21][22]. Each face is aligned into the canonical coordinate using the similarity transform and seven landmark points (i.e. two left eye corners, two right eye corners, nose tip, and two mouth corners). After alignment, the face image resolution is 100 × 100 pixels.

Fisher Vector Encoding: The FV is one of bag-of-visual-word approaches which encodes a large set of local features into a high-dimensional vector according to the parametric generative model fitted for the features. The FV representation is computed by encoding the local features with the derivatives of the log-likelihood of the learned model with respect to the model parameters. Similar to [23], we use a GMM in our work. The first-and second-order statistics of the features with respect to each component for the FV representation are computed as follows:

$$\Phi_{ik}^{(1)} = \frac{1}{N \sqrt{w_k}} \sum_{p=1}^{N} \alpha_k(v_p) \left( \frac{v_{ip} - \mu_{ik}}{\sigma_{ik}} \right), \quad (1)$$

$$\Phi_{ik}^{(2)} = \frac{1}{N \sqrt{2\pi w_k}} \sum_{p=1}^{N} \alpha_k(v_p) \left( \frac{(v_{ip} - \mu_{ik})^2}{\sigma_{ik}^2} - 1 \right), \quad (2)$$

$$\alpha_k(v_p) = \frac{w_k \exp\left(-\frac{1}{2} (v_p - \mu_k)^T \Sigma_k^{-1} (v_p - \mu_k) \right)}{\sum_{p=1}^{N} w_p \exp\left(-\frac{1}{2} (v_p - \mu_k)^T \Sigma_k^{-1} (v_p - \mu_k) \right)} \quad (3)$$

where $$w_k$$, $$\mu_k$$, $$\Sigma_k = \text{diag}(\sigma_{1k}, \ldots, \sigma_{dk})$$ are the weights, means, and diagonal covariances of the kth mixture component of the GMM. Here, $$v_p \in \mathbb{R}^{d \times 1}$$ is the pth feature vector and N is the number of feature vectors. The parameters are learned from the training data using the EM algorithm. $$\alpha_k(v_p)$$ is the posterior of $$v_p$$ belonging to the kth mixture component. The FV representation, $$\Phi(I)$$, of an image I is obtained by concatenating all the $$\Phi_{ik}^{(1)}$$'s and $$\Phi_{ik}^{(2)}$$'s into a high-dimensional vector $$\Phi(I) = [\Phi_{ik}^{(1)}]^T, [\Phi_{ik}^{(2)}]^T, \ldots, [\Phi_{ik}^{(1)}]^T, [\Phi_{ik}^{(2)}]^T]^T$$, whose dimensionality is $$D = 2Kd$$ where K is the number of mixture components, and d is the dimensionality of the local feature vector where we use $$d = 322$$ in this work.

Metric Learning: For the face verification task, the standard protocol defines the same and different pairs for comparison which can be also used to train discriminative similarity function to improve the verification performance. In this work, our focus is on robust feature representation, and thus we choose to use joint Bayesian approaches which are widely used for face verification [24]. The joint Bayesian approach models both intra-class, $$P(x_i, x_j|H_i) \sim N(0, \Sigma_i)$$, and inter-class, $$P(x_i, x_j|H_E) \sim N(0, \Sigma_E)$$, joint feature distribution of ith and jth images as Gaussians. In addition, each face feature vector is modeled as $$x = \mu + \epsilon$$, where $$\mu$$ stands for the identity and $$\epsilon$$ for pose, illumination, and other variations. Both $$\mu$$ and $$\epsilon$$ are also assumed to be independent zero-mean Gaussian distributions, $$N(0, \Sigma_i)$$ and $$N(0, \Sigma_E)$$, respectively.

The closed-form log likelihood ratio of intra- and inter-classes, $$r(x_i, x_j)$$, can be written as

$$r(x_i, x_j) = \log \frac{P(x_i, x_j|H_i)}{P(x_i, x_j|H_E)} = x_i^T M x_i + x_j^T M x_j - 2x_i^T R x_j,$$

(4)

where $$M$$ and $$R$$ are both negative semi-definite matrices [24]. If we let $$B = R - M$$, then (4) can be rewritten as $$(x_i - x_j)^T M (x_i - x_j) - 2x_i^T B x_j.$$ With this, one can directly optimize the distance in a large-margin framework as follows:

$$\text{argmin}_{M, B, \epsilon} \sum_{i,j \in \mathcal{I}} \max [1 - y_{ij} (b - (x_i - x_j)^T M (x_i - x_j) + 2x_i^T B x_j), 0], \quad (5)$$

where b is the bias, $$M = W^T W$$, and $$B = V^T V$$ (i.e., $$W, V \in \mathbb{R}^{d \times D}$$ and $$d \ll D$$. We use $$d = 100$$ in this paper). The model parameters can be updated using the stochastic gradient descent algorithm. More details can be found in [4].

Deep Face Feature Representation: The DCNN model used in this paper is similar to the one proposed in [9] which includes 10 convolutional layers, 5 pooling layers and 1 fully connected layer. The model is trained using the CASIA-WebFace dataset which contains 10,575 subjects. The differences between the proposed method and the one proposed in [9] are that we train the model only with softmax identification loss and without modeling the pair-wise verification cost. Each activation function, the rectified linear unit (ReLU), is replaced with the parametric ReLU (PReLU) [25] which allows negative responses and usually improves the network performance. The dimensionality of the input layer is 100 × 100 × 1 for gray-scale images. Most recent works in face verification like [26] and [27] use similar architecture as [9] and take the pool5 features followed by L2-normalization to perform recognition. The training details of DCNN model can be found at [28].

Since pool5 takes the average pooling to aggregate the DCNN features of the last convolutional layer, conv52, its features contain the global information of the appearance. However, average pooling also causes the loss of spatial and local appearance information. In the next Section, we combine both the FV and DCNN features to utilize spatial information for face verification. Furthermore, we only
focus on the conv52 features to incorporate the spatial information with FV as the lower layer contains less discriminative information [12].

**FV Encoded DCNN Features (FV-DCNN):** For human faces, the appearances around facial local regions are different. Thus, instead of using the global pool5 features for the verification task as used in [9] [27] (i.e. the pool5 feature \( \in \mathbb{R}^{20 \times 1} \) is the average of 7 \( \times \) 7 features of the conv52 layer \( \in \mathbb{R}^{7 \times 7 \times 320} \)), the spatial information should be taken into consideration as well. In order to incorporate the spatial information into the model, we augment two additional dimensions (normalized x and y coordinates with respect to image width and height, \( \frac{y - \frac{1}{2}}{\frac{y}{2}} \), s) spatial features) to the original conv52 features and apply FV encoding on these augmented features. Then the learnt GMM will not only cluster the features with similar appearance, but also consider their spatial relationships. Hence, the FV will mostly be encoded by the features in the neighborhoods of the corresponding Gaussians.

To balance the strength of appearance and spatial features, we take the square root and perform \( L_2 \) normalization on appearance features before augmenting spatial features. Moreover, we introduce an encoding scheme called “spatial encoding”. Instead of using the original posterior (3), by spatial encoding, we enforce the feature to be encoded by its neighborhood, which is defined as

\[
\bar{a}_k(v_p) = \frac{w_i \exp \left[ \frac{1}{2} (\bar{v}_p - \bar{\mu}_k)^T \Sigma^{-1} (\bar{v}_p - \bar{\mu}_k) \right]}{\sum_i w_i \exp \left[ \frac{1}{2} (v_p - \mu_i)^T \Sigma^{-1} (v_p - \mu_i) \right]},
\]

where \( \bar{\mu}_k \) and \( \Sigma_k \) are the mean and covariance of the two-dimensional spatial features for the \( k \)th Gaussian. The new posterior only considers the spatial distance between Gaussians and dense features, instead of the distance calculated among all dimensions. Spatial encoding improves the performance with well-aligned images and reliable spatial information.

![Fig. 2](image_url)

**Fig. 2.** Errors made by different methods on the split 10 of the LFW dataset. (a) FV-DCNN errors . (b) pool5 errors. (c) FV-DCNN + pool5 errors. Errors are significantly reduced when FV-DCNN and pool5 features are fused for verification.

While conducting our experiments, what we observed is that the error patterns are different between pool5 and FV-DCNN features. Figure 2 shows the errors made in the split 10 of the LFW dataset by FV-DCNN shown in (a) and pool5 features shown in (b). It is interesting to see how much the error is reduced when the FV-DCNN and pool5 features scores are fused. This can be seen by comparing the errors shown in (c) with (a) and (b) where (c) is attained by summing the similarity scores of pool5 and FV-DCNN with a linear weight.

### 4. EXPERIMENTAL RESULTS

We evaluate the proposed FV-DCNN method on two challenging face verification datasets: Celebrities in Frontal-Profile (CFP) Dataset [29] and Labeled Face in the Wild (LFW) dataset [30]. The algorithms are evaluated using various measures, including the receiver operating characteristic curves (ROC), equal error rate (EER), area under curve (AUC), and accuracy based on the test protocols defined for each dataset.

For the LFW dataset, we learn sixty four Gaussians but use spatial encoding. A whitening PCA is applied as the initialization of joint Bayesian metric learning. For the CFP dataset, we learn 64 Gaussians and use traditional encoding. This is because the alignment for profile faces is not reliable. (i.e., since only half of facial landmarks are available for the profile faces of the dataset, we use two eye corners of either left or right eye, nose tip, one mouth corner of either left or right side with similarity transform to the canonical coordinate defined for the frontal face as mentioned in Section 3.) Similarly, the whitening PCA is applied for initializing the joint Bayesian metric learning. Given the scores from the FV metric learning and the cosine distance of pool5 features, score level fusion is done by summing the similarity scores of pool5 and FV-DCNN with a linear weight.

**Celebrities in Frontal-Profile Dataset (CFP)[29]:** First, to investigate how pose variations influence the performance of the proposed FV-DCNN method, we conduct experiments on the recently introduced CFP face verification dataset. This dataset focuses on the unconstrained frontal to profile face verification protocol where most profile faces are in extreme poses. Sample face pairs are shown in Figure 3. The dataset contains 500 subjects, and each subject contains 10 frontal and 4 profile images. Similar to the LFW dataset, the CFP dataset consists of 20 splits in total, 10 for frontal-to-frontal and the other 10 for frontal-to-profile face verification tasks. Each split has 350 same and 350 different pairs, respectively. For this dataset, the human performance for the frontal-to-profile verification is 94.57% accuracy and frontal-to-frontal is 96.24% accuracy. The dataset has been evaluated in [29] using previous state-of-the-art algorithms, including Fisher vector based on SIFT features, Sub-SML [32], and a deep learning approach which uses a similar architecture and ReLU as the activation function without applying data augmentation.

![Fig. 3](image_url)

**Fig. 3.** Sample image pairs from the Celebrities in Frontal-to-Profile dataset [29] where our method is able to successfully verify the pairs whereas both FV and DCNN-based methods fail.

![Fig. 4](image_url)

**Fig. 4.** The ROC curves corresponding to (a) Frontal-Profile matching and (b) Frontal-Frontal matching on the CFP dataset. The evaluation results and the ROC curves are shown in Table 2 and Figure 4, respectively. From the figure, even though there exists the large performance drop in the frontal-to-profile setting, the proposed FV-DCNN approach still perform comparable to the human performance and better than pool5 features and other approaches, including the DCNN algorithm using ReLU. Since FV-DCNN encodes the spatial and appearance information contained in conv52 features.
Table 1. Performance comparison of different methods on the LFW dataset.

<table>
<thead>
<tr>
<th>Method</th>
<th>#Net</th>
<th>Training Set</th>
<th>Metric</th>
<th>Mean Accuracy ± Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>DeepFace [18]</td>
<td>4</td>
<td>4.4 million images of 4,030 subjects, private</td>
<td>cosine</td>
<td>95.92% ± 0.82%</td>
</tr>
<tr>
<td>DeepFace</td>
<td>7</td>
<td>4.4 million images of 4,030 subjects, private</td>
<td>unrestricted, SVM</td>
<td>97.35% ± 0.25%</td>
</tr>
<tr>
<td>DeepID2</td>
<td>25</td>
<td>202,595 images of 10,117 subjects, private</td>
<td>unrestricted, Joint-Bayes</td>
<td>99.19% ± 0.15%</td>
</tr>
<tr>
<td>FaceNet [8]</td>
<td>59</td>
<td>202,595 images of 10,117 subjects, private</td>
<td>unrestricted, Joint-Bayes</td>
<td>98.15% ± 10%</td>
</tr>
<tr>
<td>Yi et al. [9]</td>
<td>1</td>
<td>494,414 images of 10,575 subjects, public</td>
<td>cosine</td>
<td>96.13% ± 0.30%</td>
</tr>
<tr>
<td>Yi et al.</td>
<td>8</td>
<td>494,414 images of 10,575 subjects, public</td>
<td>unrestricted, Joint-Bayes</td>
<td>97.73% ± 0.31%</td>
</tr>
<tr>
<td>Wang et al. [27]</td>
<td>1</td>
<td>494,414 images of 10,575 subjects, public</td>
<td>cosine</td>
<td>96.95% ± 1.02%</td>
</tr>
<tr>
<td>Wang et al.</td>
<td>7</td>
<td>494,414 images of 10,575 subjects, public</td>
<td>cosine</td>
<td>97.52% ± 0.76%</td>
</tr>
<tr>
<td>Wang et al.</td>
<td>1</td>
<td>494,414 images of 10,575 subjects, public</td>
<td>unrestricted, Joint-Bayes</td>
<td>97.45% ± 0.99%</td>
</tr>
<tr>
<td>Wang et al.</td>
<td>7</td>
<td>494,414 images of 10,575 subjects, public</td>
<td>unrestricted, Joint-Bayes</td>
<td>98.53% ± 0.68%</td>
</tr>
<tr>
<td>Ding et al. [26]</td>
<td>8</td>
<td>471,592 images of 9,000 subjects, public</td>
<td>cosine</td>
<td>99.02% ± 0.19%</td>
</tr>
<tr>
<td>Human, funneled [27]</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>99.20%</td>
</tr>
<tr>
<td>Pool5 cosine</td>
<td>1</td>
<td>494,414 images of 10,575 subjects, public</td>
<td>cosine</td>
<td>97.82% ± 0.59%</td>
</tr>
<tr>
<td>FV-DCNN</td>
<td>1</td>
<td>494,414 images of 10,575 subjects, public</td>
<td>unrestricted, Joint-Bayes</td>
<td>97.79% ± 0.61%</td>
</tr>
<tr>
<td>FV-DCNN + pool5 cosine</td>
<td>1</td>
<td>494,414 images of 10,575 subjects, public</td>
<td>unrestricted, Joint-Bayes</td>
<td>98.13% ± 0.40%</td>
</tr>
</tbody>
</table>

Table 2. Performance comparison of different methods on the CFP dataset where pool5 means "pool5 + cosine distance".

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy</th>
<th>EER</th>
<th>ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>HoGrSub-SML</td>
<td>85.53 ± 1.33%</td>
<td>11.45 ± 1.35%</td>
<td>94.83 ± 0.80%</td>
</tr>
<tr>
<td>LBPrSub-SML</td>
<td>84.54 ± 2.70%</td>
<td>16.00 ± 1.74%</td>
<td>91.40 ± 1.52%</td>
</tr>
<tr>
<td>FV+Sub-SML</td>
<td>88.47 ± 1.51%</td>
<td>38.54 ± 1.59%</td>
<td>96.47 ± 2.02%</td>
</tr>
<tr>
<td>Deep features</td>
<td>84.91 ± 1.82%</td>
<td>14.97 ± 1.98%</td>
<td>93.00 ± 1.55%</td>
</tr>
<tr>
<td>Human</td>
<td>94.57 ± 1.10%</td>
<td>5.02 ± 1.07%</td>
<td>98.92 ± 0.46%</td>
</tr>
<tr>
<td>pool5</td>
<td>90.41 ± 1.16%</td>
<td>9.63 ± 1.21%</td>
<td>96.53 ± 0.99%</td>
</tr>
<tr>
<td>FV-DCNN</td>
<td>93.94 ± 1.88%</td>
<td>13.40 ± 1.95%</td>
<td>96.37 ± 0.79%</td>
</tr>
<tr>
<td>Human</td>
<td>91.97 ± 1.70%</td>
<td>8.00 ± 1.68%</td>
<td>97.70 ± 0.82%</td>
</tr>
</tbody>
</table>

Visualized of the Learnt GMM: Figure 5 shows an image in the LFW dataset along with the last two dimensions (which are the spatial coordinates) of the Gaussians learnt by our method. Gaussians are learnt from the original 320-dimensional conv52 features plus two dimensional spatial features without dimension reduction, from the images in the LFW split 1. We only choose Gaussians whose corresponding energy in the learnt projection matrices are among the top eight or bottom eight, which corresponds to the discriminative power of these Gaussians. Figures 5(a) and 5(b) are Gaussians learnt after we apply square root and $L_2$ normalization on the conv52 features. Figures 5(c) and 5(d) are Gaussians learnt without any normalization. From Figures 5(a) and 5(b), the top eight features into the high-dimensional feature vector, it is robust to large pose variations than other approaches. Also notice that by fusing FV-DCNN and pool5, we improve the performance for frontal-to-profile setting. But frontal-to-profile setting is not as good as single FV-DCNN. This is because under extreme poses, global features are not robust and will degrade the overall performance.

Labeled Face in the Wild Dataset (LFW)[30]: We also evaluate our approach on the LFW dataset using the standard protocol for the face verification task which defines 3,000 positive pairs and 3,000 negative pairs in total. The pairs are further split into 10 disjoint subsets for cross validation, and each subset consists of 300 same and 300 different pairs. It contains 7,701 images of 4,281 subjects. We show the mean accuracy of the proposed FV-DCNN representation with the other state-of-the-art deep learning-based methods on the "funneled" LFW images: DeepFace [18], DeepID2 [11], DeepID3 [31], FaceNet [8], Yi et al. [9], Wang et al. [27], and human performance. The results are summarized in Table 1. As can be seen from this table, the proposed FV-DCNN method performs comparable to many other deep learning-based methods. In addition, it also shows that the error reduces when we fuse the similarity scores of both FV-DCNN representation (local descriptor) and normal pool5 representation (global descriptor). Note that some of the deep learning-based methods compared in Table 1 use millions of data samples for training the model that typically has tens of millions of parameters or fuse multiple DCNN models together. In contrast, we use only the CASIA dataset which has less than 500K images to train a single DCNN model with about five million parameters.

Fig. 5. (a) Top eight Gaussians using square root and $L_2$ normalization. (b) Bottom eight Gaussians using square root and $L_2$ normalization. (c) Top eight Gaussians without normalization. (d) Bottom eight Gaussians without normalization.

Gaussians are located near eyes, nose and mouth after normalization. The bottom eight Gaussians are out of the face region in general. But in Figures 5(c) and (d), without pre-normalization, the top eight Gaussians are everywhere in the image with large variations in spatial location. Also, the bottom eight Gaussians are all located in the center of the face, which should not be the case. Comparison of these four figures shows that the spatial information is not encoded into Gaussians if we do not apply normalization before learning the Gaussians.

5. CONCLUSIONS

In this paper, we proposed a FV-DCNN model for unconstrained face verification which combines FV with DCNN features. We demonstrated the effectiveness of the proposed method on the standard LFW and the challenging CFP datasets with large pose variations, respectively. It was shown that the FV-DCNN method can capture the local variations and the original DCNN pool5 features characterize the global variations. Performance gains were obtained by simply fusing their similarity scores without training another new DCNN model.

In future, we plan to incorporate hard positive and hard negative mining to perform metric learning, including joint Bayesian metric or triplet loss.
6. REFERENCES


