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Smoothness-Constrained Face Photo-Sketch Synthesis Using Sparse Representation

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Abstract

Face photo-sketch and sketch-photo synthesis have important usages in law enforcement. It is challenging to synthesize face sketches from photos because the drawing techniques and styles of artists' depictions are hard to be learned. To synthesize face photos from sketches is also hard due to its ill-posed nature. In order to avoid mosaic effects in the existed photo-sketch methods, we propose a smoothness-constrained photo-sketch synthesis method via sparse representation. The work is an extension of the previous work[1]. The method is modeled as the minimization of an energy function, a large scale convex optimization problem with l_1-norm constraint. Since previous optimization methods are infeasible to solve our problem, we propose an iterative optimization approach, which decomposes the large scale optimization into a sequence of small scale optimizations and solve them iteratively to obtain the approximated optimal solution. The same synthesis strategy can be also used to synthesize photos from sketches. Experiments show its effectiveness.

1 Introduction

Face photo-sketch and sketch-photo synthesis have a wide range of applications for law enforcement [4, 8]. In many scenarios of law enforcement, traditional face recognition based on photos is infeasible because the face photo of a suspect is unavailable. Only the face sketch of the suspect is available according to the description of the wittiness [4]. Researchers proposed two approaches for identification: (a) sketch based face retrieval; (b) photo based face retrieval. In the first approach, face sketches synthesis provides an alternative to the sketch database collection; In the second approach, the synthesized face photo of the suspect is used for recognition. Compared with face photos, sketches are more concise and discriminative [8].

Several studies have been conducted on sketch synthesis. Tang [6] developed an eigentransform based algorithm, in which the transformation between photos and sketches is assumed to be linear. Liu [4] presented a method which is similar in the spirit to LLE [5]. This method needs a carefully chosen of the number of nearest neighbors. Wang [8] proposed a method using a multiscale Markov random field model, which is relatively time-consuming due to use an inference procedure with belief propagation as reported in [8]. Many other algorithms are proposed to synthesize face sketches, such as Zhang [11] proposed a sketch synthesis by using SVM. In recent years, sparse representation has been regarded as a breakthrough in signal processing and pattern recognition, it has been applied widely in various computer vision tasks [9][10]. In the previous work [1], we proposed to synthesis face sketch via sparse representation. Sparseness is desired due to its succinct representation ability and its discriminative nature. Another merit of the method is that it has smaller storage requirement due to the fact that it only requires a much smaller succinct dictionary by sparse coding.

In this paper, we propose a smoothness-constrained face photo-sketch synthesis method, which has the advantage that it alleviates mosaic effects of synthesized sketches. The method can be outlined as: firstly, the training photos and sketches are divided into overlapped patches. In each patch, photo and sketch patch pairs are used to built a coupled dictionary[3]; Secondly, for each image patch in the test photo, we compute its sparse representation coefficient with respect to the photo bases in coupled dictionary. The sketch patch is recovered with the same coefficient and the sketch bases in coupled dictionary (Section 2). The coefficient is used as the initialization of the sketch synthesis results; Thirdly, smoothness-constrained face photo-sketch synthesis is modeled as minimization of an energy function (Section 3), which is usually a large-scale convex optimization problem with l_1-norm constraint, and then we propose an efficient decomposition algorithm to solve it by using a series of small scale convex optimizations. Experiments show that the results with our method and a state-of-the-art method [8] resemble the sketches by artists well.

2 Initialization of Face Photo-Sketch Synthesis

Face photo-sketch synthesis is initialized via sparse representation[1]. Given a face photo $\mathbf{P}$ as input, in this section, we give an initialization to its corresponding face sketch $\mathbf{S}$ using sparse representation.

2.1 Dictionary Preparation

We use sparse coding to build the local coupled dictionaries for sketch patches and photo patches. Denote $\mathbf{p}_i$ to be the i-th photo patch in the test photo, $\mathbf{s}_i$ to be the desired sketch patch. Since the same face component is roughly in the same region of photos and sketches due to geometry alignment, we divide the training face photos and sketches into a set of overlapping patches $\{\mathbf{p}_i\}_{i=1}^n$ and $\{\mathbf{s}_i\}_{i=1}^n$ by scanning the whole image (See Fig. 1). For each image patch, a coupled dictionary is built using image patches within the local region of the training photo and sketch set. Instead of building dictionaries on raw image patches, we use the sparse coding [3] to get a succinct dictionary. We assume that the sparse linear relationship of a given photo patch with respect to the photo bases of the coupled dictionary are maintained for the corresponding sketch patch with respect to sketch bases.

Sparse coding is an unsupervised learning algorithm for discovering concise high-level basis vectors using a large number of unlabeled data[3]. For an input data $\mathbf{a}_i$, sparse coding discovers basis vector set $\{\mathbf{b}_1, \ldots, \mathbf{b}_m\}(i = 1...m)$. Thus $\mathbf{a}_i$ can be represented approximately as linear combination of basis vectors, i.e. $\mathbf{a}_i \approx \mathbf{b}_1 t_1 + \ldots + \mathbf{b}_m t_m$, in which $\mathbf{a}_i$ relies on a few basis vectors, and many linear coefficients are equal to zero. Then the basis vectors are learned by minimizing an energy function, which consists of two items: the reconstruction error and l_1-norm penalty which can guarantee that the coefficients to be sparse. The problem is solved by an iterative strategy of two convex optimization problems.

Denote $(\hat{\mathbf{D}}_P^i, \hat{\mathbf{D}}_S^i)$ to be an local coupled dictionary of the i-th patches in photo and sketch. $\hat{\mathbf{D}}_P^i$ is composed of basis vectors of the i-th photo patch, and $\hat{\mathbf{D}}_S^i$ is composed of corresponding basis vectors of the i-th sketch patch. For each photo patch $\mathbf{p}_i$, we find its sparse representation with respect to local photo dictionary $\hat{\mathbf{D}}_P^i$ as $\mathbf{p}_i = \hat{\mathbf{D}}_P^i \alpha_i$. According to the assumption, with the sparse coefficient α_i and local sketch dictionary $\hat{\mathbf{D}}_S^i$, we can initialize the sketch patch as $\mathbf{s}_i = \hat{\mathbf{D}}_S^i \alpha_i$.

2.2 Sparse Representation

Given the photo patch $\mathbf{p}_i$, the sparse representation of $\mathbf{p}_i$ with respect to the local dictionary $\hat{\mathbf{D}}_P^i$ can be formulated as a constrained l_1-norm optimization problem as follows:

$$\alpha_i = \arg\min \|\alpha_i\|_1 \quad s.t.\ \hat{\mathbf{D}}_P^i \alpha_i = \mathbf{p}_i, \qquad (1)$$

The minimization problem has the same formulation as Lasso for linear model estimations in statistics[2], thus α_i can be solved easily with Lasso. Sparseness is desired due to its succinct representation ability and its discriminative nature.

We reconstruct an initialized face sketch by stitching the estimated sketch patches $\mathbf{s}_i = \hat{\mathbf{D}}_S^i \alpha_i$, and use the obtained α_i as the initial value of following face sketch refinement.

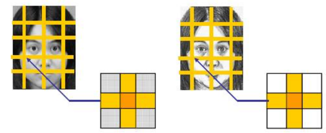

Figure 1. The overlapped image patches of the image patch and its adjacent image patches.

3 Face Photo-Sketch Synthesis Method

In this section, we use the texture smoothness constraint of sketch to refine the initialized results by the method in Section 2, which can alleviate mosaic effects of the initialized sketch.

3.1 Face Sketch Refinement

The synthesized sketch in Section 2 usually has mosaic effects due to the fact that each local patch is independently synthesized and the local texture smoothness constraint is not enforced. We proposed a sketch synthesis approach via sparse representation, which is capable of enforcing local texture smoothness constraint and alleviating mosaic effects. An energy function is minimized to solve the problem. The energy function denoted as E (See Eq.(2)) consists of three parts: 1) E_1 measures the difference between the original face photo and the face photo synthesized by sparse coefficient; 2) E_2 measures the smoothness of the synthesized sketch patches with its adjacent patches; 3) E_3 is an l_1-norm regularization term to enforce the sparse representation. The coefficients $\alpha_1, \ldots, \alpha_n$ of the refined face sketches can be obtained by minimizing the energy function E:

$$E = E_1 + \beta^2 E_2 + \lambda E_3 \qquad (2)$$

$$\begin{aligned} E_1 &= \sum_{i=1}^{n} \|\mathbf{p}_i - \hat{\mathbf{D}}_P^i \alpha_i\|^2 \\ E_2 &= \sum_{i=1}^{n} \sum_{j \in \mathcal{N}(i)} \left\| \mathbf{T}_i \hat{\mathbf{D}}_S^i \alpha_i - \mathbf{T}_j \hat{\mathbf{D}}_S^j \alpha_j \right\|^2 \\ E_3 &= \sum_{i=1}^{n} \|\alpha_i\|_1 \end{aligned}$$

where β^2 and λ are regularization parameters to balance the weights of E_1, E_2, E_3, n is the number of image patches in each photo and sketch image, $\mathbf{p}_i \in R^d$ is the i-th photo patch, $\mathcal{N}(i)$ is the set of neighboring patches of $\mathbf{p}_i$, $\mathbf{T}_i$ and $\mathbf{T}_j$ are the matrixes which extract the overlapped regions of neighboring patches $\mathbf{p}_i$ and $\mathbf{p}_j$, and $\hat{\mathbf{D}}_S^i \alpha_i$ and $\hat{\mathbf{D}}_S^j \alpha_j$ to be the corresponding sketch patches of $\mathbf{s}_i$ and $\mathbf{s}_j$. Denote $\bar{\alpha} = [\alpha_1^T, \ldots, \alpha_n^T]^T$, then the energy function (2) can be transformed into the following equivalent problem:

$$E = \|\bar{\mathbf{X}} - \bar{\mathbf{D}}\bar{\alpha}\|^2 + \lambda\|\bar{\alpha}\|_1 \tag{3}$$

where $\bar{\alpha} \in R^{mn\times 1}$, m is the number of basis vectors by sparse coding, and n is the number of patches in an image. In our experiment, the number of image patches n is about 5000, m is 128, thus the dimension of $\bar{\alpha}$ is quite high. Optimization of the energy function, which is a large scale convex optimization problem with l_1-norm regularization, is a non-trivial task, and traditional methods for l_1-norm optimization problem is infeasible.

We propose a decomposition method to solve the problem. The energy function of (3) is decomposed into a series of small problems. We divide all the variables in the energy function to be the sets of working set and non-working set. In each iteration, variables in the working set is chosen and the corresponding subproblems are recomputed. The working set is selected by computing the difference of gray value of the overlapped regions between each image patch and its adjacent patches. The difference is measured by the l_2-norm difference. For a given threshold ε, if the i-th image patch and its adjacent image patches violates at least one of the following conditions

$$\begin{aligned} \|\mathbf{T}_d\mathbf{F}_{i_u} - \mathbf{T}_u\mathbf{F}_i\| &\leq \varepsilon, \|\mathbf{T}_u\mathbf{F}_{i_d} - \mathbf{T}_d\mathbf{F}_i\| \leq \varepsilon \\ \|\mathbf{T}_r\mathbf{F}_{i_l} - \mathbf{T}_l\mathbf{F}_i\| &\leq \varepsilon, \|\mathbf{T}_l\mathbf{F}_{i_r} - \mathbf{T}_r\mathbf{F}_i\| \leq \varepsilon \end{aligned}$$

where $\mathbf{F}_i = \hat{\mathbf{D}}_S^i\alpha_i$ is the feature vector of the i-th image patch, $\mathbf{F}_{i_u} = \hat{\mathbf{D}}_S^{i_u}\alpha_{i_u}, \mathbf{F}_{i_d} = \hat{\mathbf{D}}_S^{i_d}\alpha_{i_d}, \mathbf{F}_{i_l} = \hat{\mathbf{D}}_S^{i_l}\alpha_{i_l}, \mathbf{F}_{i_r} = \hat{\mathbf{D}}_S^{i_r}\alpha_{i_r}$ are the feature vectors of its up, down, left and right neighboring patches, respectively. Then we call the i-th image patch an ε-smooth violating image patch. Here, $\hat{\mathbf{D}}_S^{i_u}, \hat{\mathbf{D}}_S^{i_d}, \hat{\mathbf{D}}_S^{i_l}, \hat{\mathbf{D}}_S^{i_r}$ are the local sketch dictionaries of the up, down, left and right neighboring image patches.

Suppose patch i to be a randomly selected ε-smooth violating image patch. We update its sparse coefficient by minimizing the following small scale problem

$$\begin{aligned} &\min_{\alpha_i} \quad \|\alpha_i\|_1 \\ &s.t. \quad \begin{array}{l} ||\mathbf{p}_i - \hat{\mathbf{D}}_P^i\alpha_i||_2^2 \leq \widetilde{\varepsilon}^2 \\ ||\mathbf{T}_d\hat{\mathbf{D}}_S^{i_u}\alpha_{i_u} - \mathbf{T}_u\hat{\mathbf{D}}_S^i\alpha_i||_2^2 \leq \varepsilon^2 \\ ||\mathbf{T}_u\hat{\mathbf{D}}_S^{i_d}\alpha_{i_d} - \mathbf{T}_d\hat{\mathbf{D}}_S^i\alpha_i||_2^2 \leq \varepsilon^2 \\ ||\mathbf{T}_r\hat{\mathbf{D}}_S^{i_l}\alpha_{i_l} - \mathbf{T}_l\hat{\mathbf{D}}_S^i\alpha_i||_2^2 \leq \varepsilon^2 \\ ||\mathbf{T}_l\hat{\mathbf{D}}_S^{i_r}\alpha_{i_r} - \mathbf{T}_r\hat{\mathbf{D}}_S^i\alpha_i||_2^2 \leq \varepsilon^2 \end{array} . \end{aligned} \tag{4}$$

where $\alpha_{i_u}, \alpha_{i_d}, \alpha_{i_l}, \alpha_{i_r}$ are coefficients of the up, down, left and right neighboring patches of patch i in the previous iteration, and $\widetilde{\varepsilon}$ is the upper bound of the noise term. Here, the coefficients are initialized with the results Section 2.

The above constrained optimization can be solved by the following unconstrained optimization problem

$$\begin{aligned} \min_{\alpha_i} \quad & \|\mathbf{p}_i - \hat{\mathbf{D}}_P^i\alpha_i\|_2^2 \\ & + \beta_1^2\|\mathbf{T}_d\hat{\mathbf{D}}_S^{i_u}\alpha_{i_u} - \mathbf{T}_u\hat{\mathbf{D}}_S^i\alpha_i\|_2^2 \\ & + \beta_2^2\|\mathbf{T}_u\mathbf{D}_S^{i_d}\alpha_{i_d} - \mathbf{T}_d\hat{\mathbf{D}}_S^i\alpha_i\|_2^2 \\ & + \beta_3^2\|\mathbf{T}_r\hat{\mathbf{D}}_S^{i_l}\alpha_{i_l} - \mathbf{T}_l\hat{\mathbf{D}}_S^i\alpha_i\|_2^2 \\ & + \beta_4^2\|\mathbf{T}_l\hat{\mathbf{D}}_S^{i_r}\alpha_{i_r} - \mathbf{T}_r\hat{\mathbf{D}}_S^i\alpha_i\|_2^2 + \lambda\|\alpha_i\|_1 \end{aligned} \tag{5}$$

Here, we choose $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta$, the optimization (5) can be transformed into

$$\min_{\alpha_i} \|\tilde{\mathbf{X}} - \tilde{\mathbf{D}}\alpha_i\|_2^2 + \lambda\|\alpha_i\|_1 \tag{6}$$

where

$$\begin{aligned} \tilde{\mathbf{D}} &= [(\hat{\mathbf{D}}_P^i)^T, \beta(\mathbf{T}_u\hat{\mathbf{D}}_S^{i_u})^T, \beta(\mathbf{T}_d\hat{\mathbf{D}}_S^{i_d})^T, \\ &\quad \beta(\mathbf{T}_l\hat{\mathbf{D}}_S^{i_l})^T, \beta(\mathbf{T}_r\hat{\mathbf{D}}_S^{i_r})^T]^T \end{aligned}$$

$$\begin{aligned} \tilde{\mathbf{X}} &= [\mathbf{p}_i^T, \beta(\mathbf{T}_d\hat{\mathbf{D}}_S^{i_u}\alpha_{i_u})^T, \beta(\mathbf{T}_u\hat{\mathbf{D}}_S^{i_d}\alpha_{i_d})^T, \\ &\quad \beta(\mathbf{T}_r\hat{\mathbf{D}}_S^{i_l}\alpha_{i_l})^T, \beta(\mathbf{T}_l\hat{\mathbf{D}}_S^{i_r}\alpha_{i_r})^T]^T \end{aligned}$$

The coefficient α_i can be updated by Lasso [2].

Proposition 1 If α_i is updated by Eq.(6), then the energy function (2) with the updated α_i decreases.

Proof. Denote E^t to be the energy function (2) at the t-th iteration, $\alpha_i^t, \alpha_{i_u}^t, \alpha_{i_d}^t, \alpha_{i_l}^t, \alpha_{i_r}^t$ are coefficients in the t iteration, E_i^t to be the following energy function

$$\begin{aligned} E_i^t &= \|\mathbf{p}_i - \hat{\mathbf{D}}_P\alpha_i^t\|_2^2 \\ &\quad + \beta^2\|\mathbf{T}_d\hat{\mathbf{D}}_S^{i_u}\alpha_{i_u}^t - \mathbf{T}_u\hat{\mathbf{D}}_S\alpha_i^t\|_2^2 \\ &\quad + \beta^2\|\mathbf{T}_r\hat{\mathbf{D}}_S^{i_l}\alpha_{i_l}^t - \mathbf{T}_l\hat{\mathbf{D}}_S{\alpha_i}^t\|_2^2 \\ &\quad + \beta^2\|\mathbf{T}_u\hat{\mathbf{D}}_S^{i_d}\alpha_{i_d}^t - \mathbf{T}_d\hat{\mathbf{D}}_S{\alpha_i}^t\|_2^2 \\ &\quad + \beta^2\|\mathbf{T}_l\hat{\mathbf{D}}_S^{i_r}\alpha_{i_r}^t - \mathbf{T}_r\hat{\mathbf{D}}_S\alpha_i^t\|_2^2 + \lambda\|\alpha_i^t\|_1 \end{aligned} \tag{7}$$

and $\bar{E}_i^t = E^t - E_i^t$. Since α_i^{t+1} is obtained by the minimization of (7) with respect to α_i^t, we have $E_i^{t+1} < E_i^t$. Note that $\overline{E}_i^{t+1} = \overline{E}_i^t$, we have $E^{t+1} = \overline{E}_i^{t+1} + E_i^{t+1} < E^t = \overline{E}_i^t + E_i^t$.

The optimization will be iterated for randomly selected ε-smooth violating image patches until no more such violating patches exist or it exceeds the predefined maximum iteration number.

3.2 Method Summary

Our smoothness-constrained face photo-sketch synthesis using sparse representation algorithm can be summarized in Algorithm 1, and the method can also synthesize a face photo given a sketch drawn by an artist, by simply switching roles of photos and sketches.

Remark 1: A simple method is adopted to enforce inter-patch relationships by averaging the gray values in the overlapped area between adjacent patches.

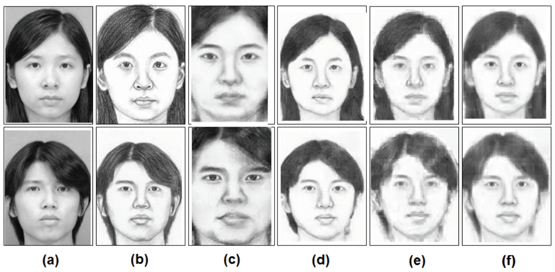

Figure 2. Comparison between the sketch synthesis results. (a) photos; (b) sketches drawn by artists; (c) sketches by method [4], which are copied from [8]; (d) sketches by method [8]; (e) initial sketches without smoothness-constraint[1]; (f) refined sketches by our method.

Algorithm 1 Smoothness-Constrained Face Photo-Sketch Synthesis Using Sparse Representation

Input: the training set of face photos and the face sketches, and a test face photo.
Output: a synthesized sketch for the test face photo.
For each patch i in the training set of photo and sketch, construct the local coupled dictionary $\{\hat{\mathbf{D}}_P^i, \hat{\mathbf{D}}_S^i\}$ by sparse coding[3].
Initialize the sketch image via sparse representation(Section 2). For each photo patch i, compute its sparse representation coefficient α_i with respect to $\hat{\mathbf{D}}_P^i$ by Eq. (1), and initialize the sketch patch $\mathbf{s}_j$ by $\hat{\mathbf{D}}_S^i \alpha_i$.
while no ε-smooth violating patch exists or it exceeds the predefined maximum iteration number **do**
    At iteration t, select for ε-smooth violating image patches in the sketch.
    if the j-th patch is ε-smooth violating **then**
        we update α_j^t and $\mathbf{s}_j = \hat{\mathbf{D}}_S^j \alpha_j^t$ by solving the minimization problem (6);
    else
        the sparse representation of $\mathbf{s}_j$ keeps unchanged.
    end if
end while
Reconstruct the sketch by stitching the estimated sketch patches.

4 Experiments

In our experiments, a face photo-sketch database from the CUHK student database was used [7]. The database contains 88 faces for training and 100 faces for testing. For each face, a sketch by an artist and a photo taken in the front pose are given. The feature vectors of the photos and sketches are represented by the gray values inside the corresponding photo and sketch patches.

4.1 Face Sketch Synthesis

In our experiments, the size of all the face and sketch images are 160×120. The size of image patch is 7×7, and the overlapping area for adjacent patches is 5×7. The regularization parameters β and λ in l_1 minimization are set to be 1.0 and 0.1 respectively, and the maximum iteration number in Algorithm 1 is set to 100. In Fig. 2, we compare our method with our previous method [1] and the state-of-the-art methods in [4][8]. The results by our method are close to the sketches drawn by the artist. Although the synthesis of human hair is challenging due to the variation in the hair style, our method based on local dictionaries can synthesize the hair region well. Our synthesized sketches are less blurred and cleaner than the methods [4], and the face structure as well as details in sketches are synthesized well. In Fig.2 (e)(f), we compare the synthesized sketches with and without the smoothness-constraint. The results without the smoothness constraint [1] are noisy and have mosaic effect. The results are improved greatly with the smoothness-constraint, and our synthesize sketches are cleaner and have much less mosaic effects. In Fig. 2 (d)(f), the results with our method are compared with the results by the state-of-the-art method [8]. We give more synthesized face sketch results in Fig. 3. Moreover, our method can synthesize a face photo with a sketch by switching roles of photos and sketches.

5 Conclusion

We propose a face photo-sketch and sketch-photo synthesis method that exploits the nature of sparse representation as well as the smoothness prior of sketches and photos. Efforts have been taken to build succinct coupled dictionaries for local image regions and compute the sparse representation coefficient. In order to exploit the local smoothness of synthesized face sketches and photos, we propose an efficient convex optimization approach to refine the initialized sketches and photos by solving a sequence of small scale l_1-norm optimizations. Our method has advantages in that the face sketches and photos can be synthesized by using sparse representation as well as the smoothness prior of synthesized images. Experiments show that the obtained sketches and photos resemble the true sketches and photos well.

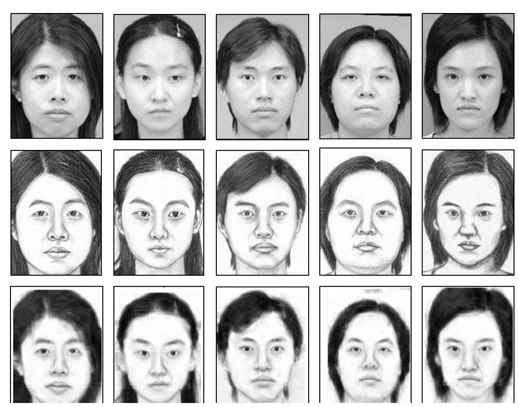

Figure 3. Face sketch synthesis results using smoothness-constrained face sketch synthesis method. The first row is the face photos, the second row is the face sketches drawn by artists, the third row is the synthesized face sketches.

6 Acknowledgement

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