International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2017 IJSRCSEIT | Volume 2 | Issue 2 | ISSN : 2456-3307

2D-DCM Based Face Specific Markov Network for Face Sketch Synthesis

Iswarya Manoharan, Kavitha P

Department of Computer Science and Engineering, R.M.K Engineering College, Chennai, Tamil Nadu, India

ABSTRACT

A feature based two dimensional direct combined models for the proposed facial sketch synthesis is given by Markov network. The 2DDCM approach for the global module it presents the images to synthesis which creates an appearance of the surface as texture and global facial geometry of the input image. By using a parametric 2DDCM model and a non-parametric Markov random field, a part distinct from the whole texture is appended to the synthesized sketch in a local patch manner. As the outcome, the resemblance between the synthesized sketches and the input images is improved to the extended. At last by adding strong lines or curves to emphasize the lighting conditions to the post-processing operation. For the performance to improve the shadowed regions of the synthesized image. Pertaining to confirm that the synthesized facial images are in well quantitative and qualitative concord with the input images as the direct observation on condition by the same artist.

Keywords : Direct Combined Model (DCM), Canonical Correlation Analysis (CCA), Markov Random Field (MRF)

I. INTRODUCTION

The computer vision field in recent decades attracted growing interest for the automatic synthesis of facial sketches. Nowadays, automatic facial recognition interest can be attributed to emerging law enforcement to emphasize certain features to ridicule facial images in a better way. For that reason, this paper develops facial sketch synthesis system having the ability of reproducing the unique drawing style of the particular artist in a fully automated manner. Existing sketch synthesis methods can be generally divided as two divisions. It can be either exemplar-based or image-based. Input images with the gray value or edge information directly generate sketch strokes in the former methods. The proposed synthesis framework in [8] produce sketches using bilateral weights it decide firmly based with the color distribution of the input image. It utilizes predefined sketch and strokes directly from the input images. Therefore, it is unable to synthesize sketches in unique drawing style.

The current exemplar-based facial synthesis framework use profile- sketching style [2,3,12,20] consist of simple lines without shadow whereas shading sketching style [9,7,13,14] gives shadow effects and more detailed texture information. By comparing these two sketching styles, the recent style tends to produce more acceptable and distinguishable outcomes. It satisfies the need for heterogeneous face recognition framework.

II. METHODS AND MATERIAL

A. Related Work

This study describe an exemplar-based facial synthesis schemes, the correlation between the pair -wise facial images and sketches can be obtained by using fundamental kernel function to get the quality of synthesized outcome. Basically kernel approaches are given by two categories. They are either parametric-based [9,10,12,16] or non parametric-based [7,13,14]. The parametric-based approaches for the synthesis result are based on a coordinates of the kernel subspaces. For instance, in the Eigen transformation method proposed in [9,10] is impel forward onto a linear principal component analysis(PCA) subspace and the projection weights are then used to build a related facial sketch in facial subspaces. In the training samples the linear combination process is applied to get synthesized result.

Despite, such approach leads to blurring the synthesized images. As a consequence, the authors in [5],[6],[15] proposed two step based approaches. They are coarse-based and sparse-representation based enhancement techniques. Using non parametric-based MRF the blurring problems can be solved. For instance, the MRF approaches in [7,13] gather set of pair wise images and sketch samples to build the correlation and smooth the boundaries among neighboring patch markov random field graph is used. Moreover, in [18],[17],[19] the authors intended methods where the test sample was included in the learning process as a means of figure out texture inconsistency problem enclosed by test sample and the training sample.

B. Key Contribution

In a nutshell, exemplar based approach which illustrate the counterpart among the image and sketch in the parametric-based way, lead to accomplish images with a blurred and more imitative type appearance. By converse, non-parametric-based methods being as Markov random field networks lead to yield clear output images but are perceptive to texture fluctuation in the training dataset. The enhanced two dimensional direct combined model(2DDCM) kernel framework method has three assets over the existing kernel methods. First, correlation among the pairwise images and sketch samples is conserved better and represented in the form of one dimensional vectors[22] , when the 2DDCM combines in a single 2D matrix to obtain facial geometry. Second, examine with existing Markov random field synthesis framework the 2DDCM approach increase number of derivative candidates. Finally, the proposed synthesis scheme use Bayesian inference framework, to learn complex geometry and texture correlation. As a result, the proposed framework produce synthesis facial sketches with poses, gaze directions and expressions which are not displayed among the original training images.

C. Facial sketch synthesis adopting 2DDCM

The 2DDCM-based face specific Markov network is given with the objective function of the Bayesian framework. To examine the global pairwise sample of the testing input in global module, the global 2DDCM model U^g is composed. The final local synthesized sketch is provoked by using MRF graph. The cognition layer is consonant to the geometry and advent prior knowledge of the global and local 2DDCM models, used to withhold the screened layer for the purpose of final result propagation. The screened layer consist of two various types of nodes, they are immotile node (p^{th} node) and flexile node (q^{th} node). The candidates for the immotile nodes chosen from the 2DDCM synthesize patches, although for the flexile nodes are selected directly from the training sample patches. The afterward sections explains the elaborate processing steps in three modules. They are especially global module, local module and the enhancement module.

D. Global Structure Synthesis Module

The study of the 2DDCM global module associate N pairwise training samples, where every sample $(I_{i,}S_i)$ is expressed as two dimensional combined matrix. Foremost, the joined formulation greater conserves the correlation within the images and sketches. In the present study, the 2DDCM approach is used to search for the optimal feature space U, it can be buckled down by using singular value decomposition (SVD).

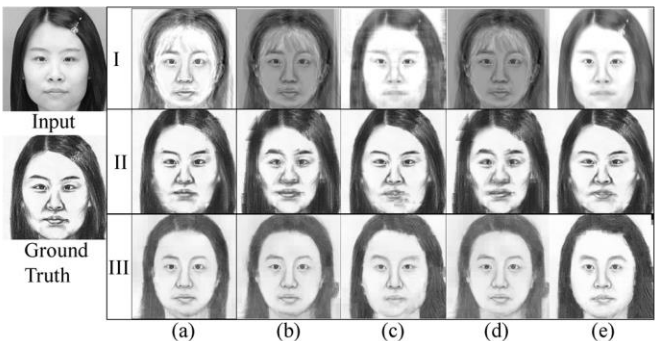

Figure 1. Global synthesized results. (a) Eigen transformation method [9]; (b) Canonical Correlation Analysis (CCA) [24]; (c) two dimensional CCA [1]; (d) Direct Combined method (1DDCM) [12]; (e) two dimensional DCM (2DDCM) [21];

Using different kernel approaches the results obtained for global structure synthesis given by five method. It is monitored that the synthesis results acquired by employing 2DDCM approach and 2DCCA approach are qualitatively better than others. Furthermore, the image synthesized by employing 2DDCM method are obsolete than those obtained using 2DCCA approach.

B. Local module with detailed structured synthesis

The target of the local module is to model the given pairwise global sample (I^g,S^g) and its antecedent probability $P(S^l|S^g)$. The aspiration function of the local module is carry out by using a 2DDCM-Based face specific Markov network, which incorporate both the parametric-based 2DDCM approach and non parametric-based MRF method.

1. 2DDCM Bi-Transformation for the images and sketch residual generation
2. 2DDCM based face specific Markov network for sketch residual complementation
3. Residual sketch subspace for the adaptive candidate selection process.

Effect of sample number for training local 2DDCM model, the synthesized results for the above subjects use K^{DCM}=30 and K^{DCM}=300.It is used to train patches the local 2DDCM model.

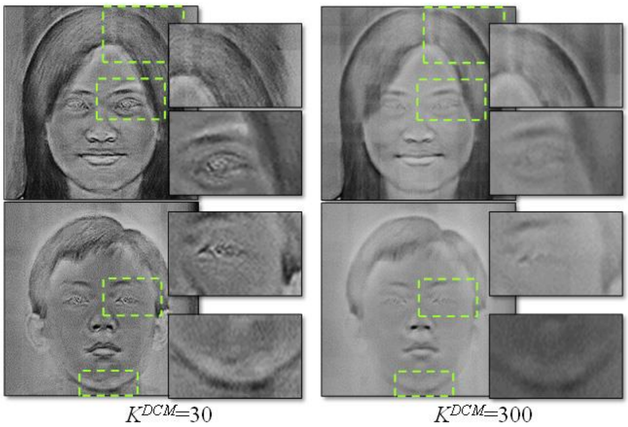

Figure 2. Local 2DDCM model with generated local component image i.e., using different values of K^{DCM}

The synthesize results conserves the approximate local geometry, but are noticeably blurred. By contrary, for center value of K^{DCM} the synthesized results consist of bounteous texture, but also append noise.

C. Enhancement module with synthesized result

It is an post-processing module. Commonly, the composer finish a facial sketch by including less number of heavy lines on curves to the obscurity regions of the images to dramatize the lighting effects. To train the enhancement subspace, the 2DDCM approach is used. The enhancement images consist of dark lines and curves enunciate the shadowed areas.

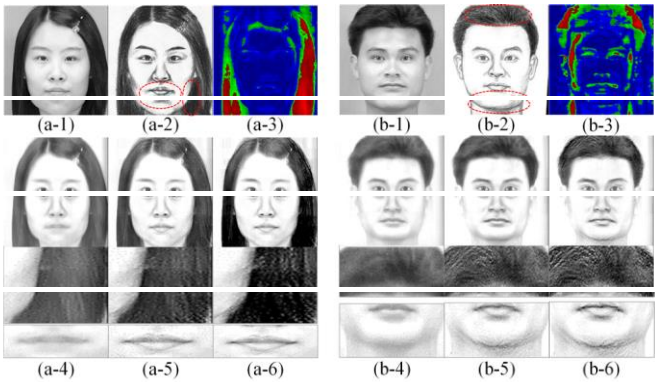

Figure 3. Synthesized sketch with all three module

(a~b-1) and (a~b-2) input test images and ground truth; (a~b-3) learned enhancement maps; (a~b-4) Global module for synthesized sketch; (a~b-5) Global and local module for synthesized sketch; (a~b-6) proposed with 3 modules.

The synthesis sketch compared with local module and global module, the result shows that the local module consist of distinct sketch lines and curved strokes. The enhancements images indicates its scaling value 1~1.5 in blue; values of 1.5~2 in green and values of 2~3 are indicated in red. The focused enhancement area in images is partaken in the hair regions and over the facial contours.

III. RESULTS AND DISCUSSION

Observational Results

A. Observational Setting

It can proceed with the experimental settings.

1. Sketch Datasets and parameter settings

Using CUHK face sketch database [7], the AR dataset [15], the sketch samples and pair-wise image were obtained. To access a detailed comparison of the synthesis performance of the proposed framework with the existing methods, two different observation settings were used. The first case was consistent and involved two databases, they are CUHK and AR and the training set, testing subjects were obtained from the same database. In CUHK database each sketch has a form of frontal view image and it has 188 subjects.

On computing performance of the proposed synthesis framework, for training 88 subjects is used and the left 100 subjects used for testing. The AR database consist 123 pair-wise samples and adopt leave-one-out strategy. Based on the position of eyes corner and mouth center, this two databases normalized to an image size of 200×200 pixels using affine transformation process. In the second observation setting case the training dataset contained 134 males and testing case 54 female subjects from the CUHK databases.

2. Techniques for comparison purposes

Based on the SSD approach, Synthesis method is proposed, the synthesized patch based on K-NN training patches and take out the noise using post processing operation from the synthesis images. On the same time, the CUHK method [7] processes the facial sketch synthesis using MRF graph model with a pyramid structure. At last, MWF approach is used to generate MRF candidates via linear combinational training samples. In [25], the sketch synthesis process can be applied to image with complex background and non portrait images and also based on a sparse representation scheme. Moreover, this technique achieved a good efficiency as it exploits prior knowledge and information regarding the image intensity and image gradient.

B. Experimental Results

1. Comparison with Existing Methods

The overall Information regarding the existing methods can given by the comparison.

a. Synthesize sketch images results in first observational setting case

Fig 4 , examine the synthesis result get from the proposed model with those obtained from the MRF[27], MWF[34], SSD[17] randomly chosen from CUHK testing database.

Fig 4(a) shows the ground truth sketches

Fig 4(b) shows the synthesis results obtained using MRF framework. By comparing with other synthesis method, it contains more local detailed texture information. Therefore, no assurance that the MRF model can always find the suitable candidate patches with which to synthesize facial sketch.

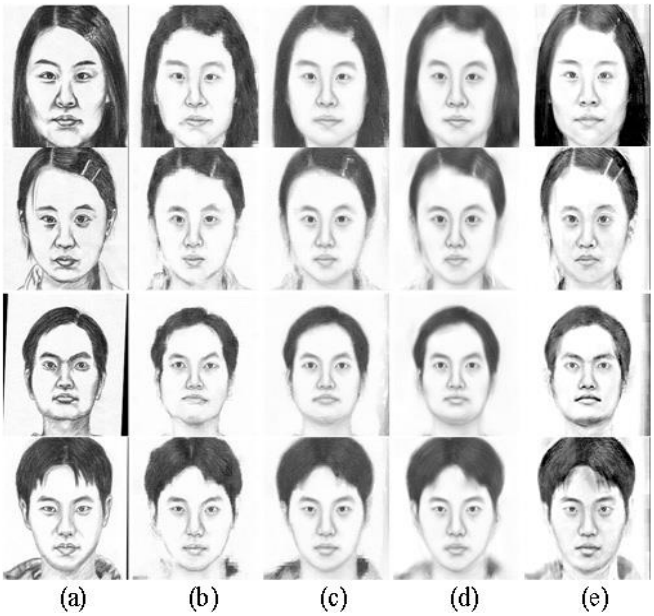

Figure 4. CUHK testing and training Databases for Synthesized results. (a) Ground-truth sketches; (b) MRF; (c) MWF; (d) SSD; (e) proposed method.

Fig 4(c) shows the synthesis images obtained using the MWF approach. The synthesis result conserves the facial geometry of the input images. The MWF framework is similar to MRF graph structure which synthesis candidate patches for the facial sketch based on a linear combination of the training samples. The synthesis output obtained using this approach instead blurred and lack clearly different sketch stroke.

Fig 4(d) shows the synthesis images obtained using SSD method. The sketches conserved the facial geometry structure of the input images. Anyhow, while comparing the results obtained using MRF and MWF methods, the SSD results are overly smooth obtain result as image de-noising process.

Fig 8(e) presents the synthesis results obtained using the method which is proposed in all three modules. Furthermore, the detailed facial features such as eyelid curves, nostril contours and so on, have clear separate edges.

At last, comparing the other methods with the images synthesized, the eyebrow features are far more similar to those in ground-truth images.

b. Synthesized sketch results in second observational setting case

It is given by cross database evaluation. Fig (5) shows the synthesized results get from MWF [14], SSD [17], and the sparse-representation-based method [21].

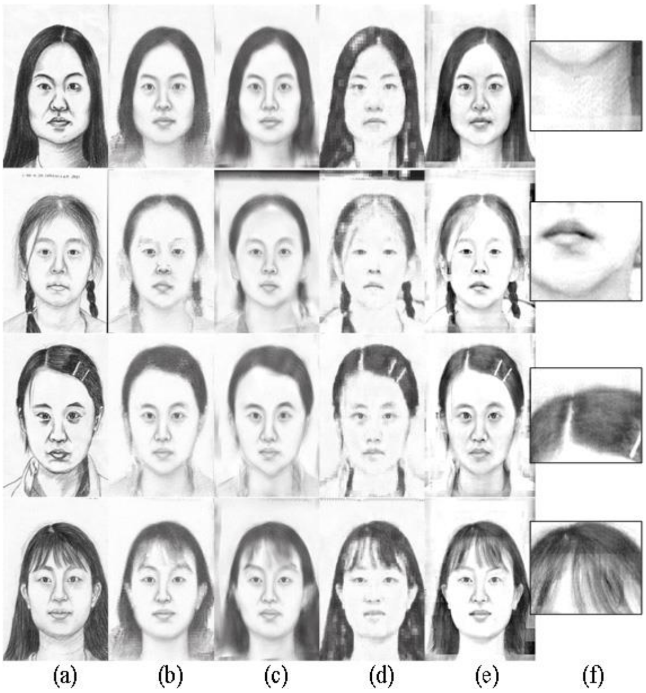

Figure 5. CUHK testing database using CUHK training database for the second setting case. (a) Ground-truth sketches; (b) MWF [14]; (c) SSD [17]; (d) method [21]; (e) proposed method; (f) specified region of (e).

The gray values of each synthesized sketch are scaled to the range 0~1. For the CUHK database, Fig (5) shows that the sparse-representation-based method. The synthesis performance of the proposed approach is insensitive to difference of appearance of training samples. For a case, the synthesis images should have their own unique feature which is based on both the structure of the face and property of the system input images.

c. Performance of Facial recognition

The two experimental setting cases was evaluated by means of automated face recognition tasks for the proposed framework to the synthesis performances. The objective of the framework proposed in this study is to synthesize sketches which mimic the specific style of the artist in terms of the subject-specific geometry, the sketch texture, the shadow area and distinctive sketching strokes.

2. Real-world images of synthesis sketches

i. **Lighting variation effect in image:** The proposed approach is more similar appearance in the photograph than a sketch. This scheme arises only at dark lighting conditions, where the global module overcomes the synthesized result.
ii. **Pose variation effect in image:** To pose variation the proposed approach is not sensitive because it is given by Eigen-face concept. Only the first few Eigen vectors induce to capture the pose variance.
iii. **Misalignment effect of images:** The images chosen from the CUHK testing dataset as in-plane rotation. Without considering in-plane rotation the obtained result in the facial contour can have ghosting effects around the images. Furthermore, the shapes of the eyes are destroyed. Using training candidate image patches in the facial local module at MRF stage is cropped from frontal view.

3. Computational Time

Using single-core Intel core 3.6 GHz CPU all the experiments are performed on a PC. For the training process the running time of the global module and enhancement module for first experimental setting case of CUHK databases was found to be 110.8 s. And for the AR databases it is 111 s. The second case setting for CUHK database is 218.8 s. In the second experimental case, the running for the three databases was 333.7 s and 30 s. It can also performed in offline for both the global module and enhancement module.

IV.CONCLUSION

This study has proposed facial sketch synthesis system based on a parametric 2DDCM approach and non-parametric MRF network. The new system is implemented using a Bayesian inference framework with three modules. Using a training dataset consisting of pair-wise images and the sketch samples, these modules are trained. The overview of the proposed framework has three advantages. First, the framework conserves the global geometry structure of the face and also the local detailed texture. At the same time, synthesized facial sketch image closely similar to the related ground-truth images. Second, the framework is able to accomplish diverse geometries and textures through the weighted linear combination of combined Eigen-spaces. Third, preserve the geometry structure of the input images not the detailed texture.

In the current method, this problem can be overcome by using 2DDCM based face specific Markov network. This network is used to chose the elaborated sketch strokes from the training images for the face regions but not easily obtained using parametric 2DDCM method. In the future work, the proposed framework will be elaborated to identify the heterogeneous face recognition problem. That is,Addressing the subspaces which maximise the discrimination between two subjects in two different domains. Moreover, variety of face related applications will be identified. It includes non-photorealistic rendering, super-resolution and facial expression synthesis.

V. REFERENCES

[1]. Anand B. Bhanu, “Face image super-resolution using 2D CCA, ”Signal Processing, 2013, pp. 184-194.

[2]. I. Berger, A. Shamir, M. Mahler, E. Carter, J. Hodgins, “Style and abstraction in portrait sketching,” ACM Transactions on Graphics (TOG), 2013, vol.32, issue 4.

[3]. H. Chan, Y. Xu, H. Shum, S. Zhu, N. Zheng, “Example-based facial sketch generation with non-parametric sampling,” 8th IEEE International Conference on Computer Vision (ICCV), 2001, vol.2, pp.433-438.

[4]. W.T. Freeman, E.C. Pasztor, and O.T. Carmichael, “Learning low-level vision,” Int’l J. Computer Vision, 2000, pp. 25-47

[5]. X. Gao, N. Wang, D. Tao and X. Li, “Face sketch-photo synthesis and retrieval using sparse representation,” IEEE Trans. Circuits Syst. Video Technol., 2012, vol.22, pp.1213-1226.

[6]. X. Gao, J. Zhong, J. Li and C. Tian, “Face sketch synthesis using E-HMM and selective ensemble,” IEEE Trans. Circuits Syst. Video Technol., 2008, vol.18, pp.487-496.

[7]. X. Gao, J. Zhong, D. Tao and X. Li, “Local face sketch synthesis learning,” Neurocomputing, 2008, vol.71, no.10-12, pp.1921-1930.

[8]. E. S. L. Gastal and M. M. Oliveira, “Domain transform for edge-aware image and video processing,” ACM Trans. Graph., 2011, vol.30, no.4, pp.69:1-69:12.

[9]. G. B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller, “Labeled faces in the wild: A database for studying face recognition in unconstrained environments,” Tech. Report 07-49, Univ. of Mass., 2007.

[10]. X. Huang, Z. Lei, M. Fan, X. Wang, and S. Z. Li. “Regularized discriminative spectral regression method for heterogeneous face matching”, IEEE Transaction on Image Processing, 2013, pp. 353-362.

[11]. B. F. Klare and A. K. Jain, “Heterogeneous face recognition using kernel prototype similarities,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2013, vol 35, no. 6, pp.1410-1422.

[12]. Q. Liu, X. Tang, H. Jin, H. Lu and S. Ma, “A nonlinear approach for face sketch synthesis and recognition,” Proc. IEEE Conf. Comput. Vis. Pattern Recognit. , 2005, pp.1005-1010.

[13]. W. Liu, X. Tang and J. Liu, “Bayesian tensor inference for sketch-based face photo hallucination,” Proc. 20th Int. Joint Conf. Artif. Intell., 2007, pp.2141-2146.

[14]. C. Lu, L. Xu, and J. Jia, “Combining sketch and tone for pencil drawing production,” in Proceedings of the Symposium on Non-Photorealistic Animation and Rendering (NPAR '12), 2012, pp.6573.

[15]. A. R. Martinez and R. Benavente, “The AR face database,” Technical report, CVC Technical Report No.24, June 1998.

[16]. K. Messer, J. Matas, J. Kittler, J. Luettin, and G. Maitre, “XM2VTSDB: the extended of M2VTS database,” International Conference on Audio

and Video-Based Person Authentication, 1999, pp. 72-77.
[17]. Y. Song, L. Bao, Q. Yang, M. Yang, "Real-time exemplar-based face sketch synthesis," ECCV, 2014, pp.800-813.
[18]. M. Song, C. Chen, J. Bu, and T. Sha, "Image-based facial sketch-to-photo synthesis via online coupled dictionary learning," Information Sciences, 2012, pp. 223-246.
[19]. X. Tang and X. Wang, "Face sketch synthesis and recognition," Proc.IEEE Int. Conf. Comput. Vis., 2003, pp.687-694.
[20]. X. Tang and X. Wang, "Face sketch recognition," IEEE Trans. Circuits Syst. Video Technol., 2004, vol.14, pp.1-7.
[21]. C. T. Tu, K. H. Lin, and T. L. Liu, "A two-dimensional direct combined model for facial hallucination," IAPR International Conference on Machine Vision Application, 2013, pp.149-152.
[22]. C. T. Tu and J. J. Lien, "Automatic location of facial feature points and synthesis of facial sketches using direct combined model," IEEE Trans.on Systems, Man, and Cybernetics, Part B: Cybernetics, 2010, Vol.40,No.4, pp. 1158-1169, 2010.
[23]. N. Wang, J. Li, D. Tao, X. Li and X. Gao, "Heterogeneous image transformation," Pattern Recognit. Lett., 2013, vol.34, no.1, pp.77-84.
[24]. N. Wang, D. Tao, X. Gao, X. Li, J. Li, "Transductive face sketch-photo synthesis," IEEE Transactions on Neural Networks and Learning Systems, 2013, pp. 1364-1376.
[25]. N. Wang, D. Tao, X. Gao, X. Li, J. Li, "A comprehensive survey to face hallucination," International Journal of Computer Vision, 2014, pp. 9-30.
[26]. S. Wang, L. Zhang, Y. Liang and Q. Pan, "Semi-coupled dictionary learning with applications to image super-resolution and photo-sketch synthesis," Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2012,pp.2216-2223.
[27]. X. Wang and X. Tang, "Face photo-sketch synthesis and recognition, "IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 2009, vol.31, no.11, pp.1955-1967.
[28]. B. Xiao, X. Gao, D. Tao, Y. Yuan and J. Li, "Photo-sketch synthesis and recognition based on subspace learning," Neurocomputing, 2010, vol.73, no.4-6, pp.840-852.
[29]. B. Xiao, X. Gao, D. Tao and X. Li, "A new approach for face recognition by sketches in photos," Signal Process., 2009, vol.89, no.8, pp.1576-1588.
[30]. Z. Xu, H. Chen, S.C. Zhu and J. Luo, "A hierarchical compositional model for face representation and sketching," IEEE Trans. Pattern Analysis and Machine Intelligence, 2008, vol.30, no.6, pp.955-969.
[31]. W. Yang, D. Yi, Z. Lei, J. Sang, and S. Li, "2D–3D face matching using CCA," IEEE Conference on Automatic Face Gesture Recognition, 2008,pp.1-6.
[32]. W. Zhang, X. Wang, and X. Tang, "Lighting and pose robust face sketch synthesis," ECCV, 2010, pp.420-433.
[33]. S. Zhang, X. Gao, N. Wang, J. Li, and M. Zhang, "Face sketch synthesis via sparse representation-based greedy search," IEEE Transactions on Image Processing, 2015, vol. 24, no. 8, pp. 2466-2477.
[34]. H. Zhou, Z. Kuang and K. Wong, "Markov weight fields for face sketch synthesis," Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2012,pp.1091-1097.