

Result Set On Reconsideration By Weakly Labeled Digital Human Face Images

Dhokchaule Sagar¹, Patare Swati², Patare Rushikesh³, Makahre Priyanka⁴

Computer Department, Shri Chhatrapati Shivaji College of Engineering, Rahuri Factory, Ahmednagar, MH, India^{1,2,3,4}

Abstract: A challenge in this system is to perform glossary by exploring the list of comparable facial photos and their weak tag that are much noisy and deficient. On face model, we are using unsupervised face alignment into the Lucas-Kanade image registration approach [3][4]. We are using efficient optimization technique to handle appearance variations. The method is full automatic and can cope with pose variations and expressions in photos, all in an unsupervised manner. Experiments on a more number of images showed that the approach is efficient. We are using search-based face annotation (SBFA) by mining weak labeled facial photos are freely available on the World Wide Web (WWW). Challenging problem for search-based face annotation technique is how to efficiently perform annotation by the index of similar facial photos and their no correct labels that are noisy or incomplete. We are developing powerful optimization techniques to solve the large-scale learning task efficiently. To increase the speed of the proposed system, we also based a clustering-based algorithm this can improve the scalability and performance. We have conducted an extensive set of empirical studies on a large-scale web facial image testbed, in which encouraging results showed that the developed ULR algorithms can boost the performance of the SBFA scheme.

Keywords: Face annotation, content-based image retrieval, machine learning, label refinement, search-based face annotation, weak label.

I. INTRODUCTION

Data mining refers to extracting or “mining” knowledge from large amounts of data stored either in data warehouses or other information repositories like database. Data mining has mostly get an important area for research. The term is actually defined misnomer. It is a process of identifying valid, novel, potentially and ultimately understandable patterns in data mining. It can be view as the result of the natural evolution of information technology. The database has witnessed an evolutionary path in the development of the following functionalities. Processing of database creation and data management and advanced data analysis.

It has attracted a deal of attention in the industry and in society as a whole in recent days, due to the range of database availability of amounts of data and the imminent need for turning such data into useful information. The reason for this present interest in the data mining area arises its applicability to a wide variety of problems arises, including not only databases containing consumer and transaction information but also advanced data bases on multimedia, storage, spatial and temporal information. In imaging science, image processing is of for which the input is an image, such as a photograph; the output of image processing is either an image or a set of characteristics or parameters related to the image. Generally image-processing techniques are treating the photos as a two-dimensional and apply it signal-processing techniques. Image processing generally refers to digital image processing, but optical and analog image processing is also possible. We are study general techniques that apply to all of them. The sorting of images (producing the input image in the first place) is referenced to as imaging.

Closely related to image processing is computer vision technique. In computer graphics, photos are generally made from models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras, mobiles) from natural scenes, as in most animated movies. Computer vision, on the other way, is often considered high-level image processing out of which a machine/computer/software intends to depher the physical contents of an image or a list of images (e.g., videos or 3D full-body magnetic resonance scans). In science and technologies, photos also very much scopes due to the grow importance of scientific visualization (of often large-scale complex scientific or experimental data). Examples such as microarray data in genetic research, or real-time multi-asset portfolio trading in finance. The popularity of various digital cameras and the speedy growth of social media tools for internet-based photo sharing, In recent years have an explosion of the varios photos captured and stored by constmers.

A hugenumber of photos shared by users on the Internet are human facial images. Such of these facial photos are tagged with names, but some users of them are not tagged properly. This isproblem has to study of automatic face annotation, an easy technique that to annotate facial photos automatically. Auto face annotation can be beneficial to many realworld applications. For example, with auto face annotation techniques, online photo-sharing sites (e.g., Facebook) can automatically annotate users’ uploaded photos to facilitate online photo search. Besides, face annotation can also be applied in news video domain to detect important persons appeared in the videos to facilitate news video retrieval and summarization tasks. Recently, some emerging study have to explose a pro search-based annotation paradim for facial photos

annotation by mining the World Wide Web (WWW), where a more number of weakly labelled facial photos are freely available.

Instead of explicit classification models by the general model-based face annotation techniques, the search-based face annotation (SBFA) scheme aims to remove the automated face annotation task by exploiting content-based image retrieval (CBIR) tools in mining massive weakly labeled facial images on the web.

Challenge by SBFA is to effectively extract the short list of exact facial images and their weak labels for the face name annotation task. To resolve the above problem, we are implementing a search-based face annotation scheme. In particular, we also used an unsupervised label refinement (URL) scheme by exploiting machine learning techniques to enhance the name of photos to purely from the weakly labelled photos without human efforts.

II. RELATED WORK

In this paper, we propose a novel scheme that exploits both semi-supervised kernel learning and batch mode active learning for relevance feedback in CBIR. In particular, a kernel function is first learned from a mix of labelled and unlabeled examples.

The kernel will then be used to effectively identify the informative and diverse examples for active learning via a min-max framework.

An empirical study with relevance feedback of CBIR showed that the proposed scheme is significantly more effective than other state-of-the-art approaches.

Learning with user's interactions is crucial to many applications in computer vision and pattern recognition. One of them is content-based image retrieval (CBIR) where users are often engaged to interact with the CBIR system for improving the retrieval quality.

Such an interactive procedure is often known as relevance feedback, where the CBIR system attempts to understand the user's information needs by learning from the feedback examples judged by users.

Due to the challenge of the semantic gap, traditional relevance feedback techniques often have to repeat many runs in order to achieve desirable results.

To reduce the number of labeled examples required by relevance feedback, one key issue is how to identify the most informative unlabeled examples such that the retrieval performance could be improved most efficiently.

Active learning is an important technique to address this challenge.

III. SYSTEM ARCHITECTURE

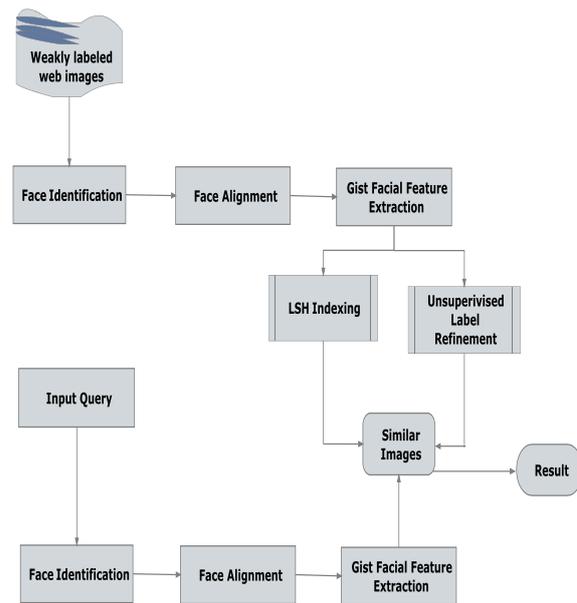


Fig: System Architecture

IV. EXISTING SYSTEM

The first work is on the topics of face recognition and verification, which are classical research problems in computer vision and pattern recognition scheme and have been extensively studied for many years. Recent years have observed some emerging benchmark studies of unconstrained face detection and verification techniques on facial images or photos that are collected from the web, such as the LFW benchmark studies. Some recent study had also attempted to extend classical face recognition techniques for face annotation tasks. Comprehensive reviews on face recognition and verification topics can be found in some survey papers, and books. The second group is about the studies of generic image annotation. The classical image annotation Approaches usually apply some existing object recognition techniques to train classification models from human-labeled training photos or to infer the correlation/probabilities between images and labelled keywords.

Given limited training data, semi-supervised learning tools have also been used for image annotation. For example, Wang et al. proposed to refine the model-based annotation results with a label similarity graph by following random walk principle. Although semi-supervised learning approaches have leverage both labeled and unlabeled data of photos, it remains fairly time-consuming to collect enough well-labelled training data to achieve good performance in large-scale scenarios. Early, the search-based image annotation paradigm has attracted more and more attention. For example, Russell et al. built a large collection of web images with ground truth labels to facilitate object recognition research. However, most of these works were focused on the indexing, search, and feature extraction techniques.

DISADVANTAGES

- The number of persons/classes is generally quite tiny, creating such annotation tasks are demands.
- Duplicate name can be a practical issue in real-life schemes.
- The facial picture is not a well-known person, there may not occur many suitable facial images on the WWW.
- The computation cost high.
- The evaluation time and data storing memory consumption level also high in existing model.

V. PROPOSED SYSTEM

- 1) Facial image data collection;
- 2) Face detection and facial feature extraction;
- 3) high-dimensional facial feature indexing and learning;
- 4) Learning to purify weakly labeled data;
- 5) Similar face retrieval; and
- 6) Face annotation by majority voting graph on the matches faces photos with the refined labels.

The first four steps are usually conducted before the test phase of a face annotation task, while the last two steps are conducted during the test phase of a face annotation task, which usually should be done vary efficiently. We briefly Describe each step below. The first step is the data gathered of facial images in which we crawled a gatheted facial images from the WWW by an any web search engine (i.e., Google) according to a name list that contains the names of persons to be collected.

As the output of this crawling process, we shall obtain a data of facial images, each image is associated with some human names. Given the nature of web images, these facial images are often noisy, which do not always correspond to the right human name. Thus, we call such kind of web facial images with incorrect names as weakly labeled facial image data. The second step is to preprocess web facial images to extract face-related information, including face detection and alignment, facial region extrction, and facial feature representation. For face detection and aligment, we used the unsupervised face alignment technique proposed in For facial feature representation, we collect the GIST texture features to represent the extracted faces. As a result, each face of photos can be represented by a d-dimensional feature vector.

ADVANTAGES

- Propose a clustering-based alikness algorithm which can develop the scalability appreciably
- An powerful algorithm a correlative descent-based approach to improve the extensibility.
- This can take advantages of the power of latal calculation when clear up a very large-scale problem.
- The soft-regularization production, we can also adopt the cordinate plunge scheme to further improve the quality.
- The ULR algorithm, which could much improve the accuracy of search-based face annotation structure.

MODULES

- Image Preprocessing
- Indexing
- Labeling
- Web Crawler
- Search

VI. MODULES DESCRIPTION

1. IMAGE PREPROCESSING

Human faces play an important role in efficiently indexing and accessing video contents, especially in large scale broadcasting news video databases. It is due to faces are associated to people who are related to key events and key activities happening from all over the world. There are many applications using face information as the key ingredient. face appearance in real environments exhibits many variations such as pose changes, facial expressions, aging, illumination changes, low resolution and occlusion, making it difficult for current state of the art face processing techniques to obtain reasonable retrieval results. Preprocessing the image involves series of steps. Firstly, identify the face in the given image based on Viola-Jones algorithm.

Then Face is aligned / Registered based on Deformable Lucas Kanade Algorithm .Finally the image's GIST features are extracted for indexing. The extracted GIST features are high dimensional data of the image.

2. INDEXING:

The indexing of high dimensional data is done. These data are indexed and a hash table is generated. Locality Sensitive Hashing (LSH) a proved algorithm in indexing is employed. LSH based indexing is done upon the extracted GIST features. human face processing techniques whose target is to efficiently apply to a general framework for large scale video mining and indexing.

In this framework, faces firstly are extracted, filtered and normalized from video sequences by using a fast and robust face detector. Next, similar faces are grouped into clusters. Then, these face clusters are labeled by the person names extracted from the transcripts. Therefore, effective and scalable tools for indexing, manipulating and retrieving video contents are strongly needed.

3. LABELLING:

A novel ULR(Unsupervised Label Refinement) scheme is employed. The quality of the labels are enhanced via a graph based operation. The low-rank graph based learning approach refines the label quality. The refined label are mapped for helping the search operation.

Labeling faces by corresponding names, image databases can be organized by presence of individuals. As a result, large and realistic face databases can be built from many semi-supervised datasets available on the Internet. These databases are very useful in developing robust face detection and identification systems.

4.WEB CRAWLER:

The query entered by the user usually the names is processed. The search operation is done over the web based on the given query. The results of the search query is streamed and downloaded from the web. The downloaded images can be viewed for further processing. Supervised validation of the result images can be done. Large number of weakly labeled facial images are freely available. Instead of training explicit classification by the regular model-based face annotation approaches, the search-based face annotation (SBFA) aims to overcome the automated face annotation task by exploiting content-based image retrieval (CBIR) scheme in massive weakly labeled facial images on the web. Besides the indexing step, another key step of the framework is to engage an unsupervised learning scheme to enhance the label quality of the weakly labeled facial photos. This process is very important to the entire search-based annotation framework since the label quality plays a difficult factor in the final annotation performance.

5.SEARCH :

The given input image is preprocessed before entering the search phase. The preprocessing involves face identification, face registration and extracting the GIST features. The extracted GIST features are used for recognizing the similar images in the dataset. The high dimensional data of the input image is compared with the dataset hash table and labels. The Top K results are provided for user validation/annotation. The second step is to preprocess web facial images to gather face-related information, including face detection and alignment, facial region extraction, and facial feature representation.

For face detection and alignment, we use unsupervised face alignment technique proposed. For facial feature representation, we extract the GIST texture features to represent the extracted faces. As a result, each face can be represented by a d-dimensional feature vector. The main scheme of SBFA is to assign correct name labels to a given weakly facial image. In particular, given a facial image for annotation, we first retrieve a short list of top M most similar facial photos from a weakly labeled facial photos database, and then annotate the facial image by performing voting on the labels associated with the top M similar face images.

VIII. ALGORITHM DESCRIPTION

1.Viola-Jones object detection framework:

The Viola-Jones object detection framework is the first object detection framework to provide competitive object detection rates in real-time proposed in 2001 by Paul Viola and Michael Jones. Although it can be trained to detect a variety of object classes, it was motivated primarily by the problem of face detection. This algorithm is implemented in OpenCV as `cvHaarDetectObjects()`. The features employed by the detection framework universally involve the sums of image pixels within rectangular areas. As such, they bear some resemblance to Haar basis functions, which have been used previously in the realm of image-

based object detection. However, since the features used by Viola and Jones all rely on more than one rectangular area, they are generally more complex. The figure at right illustrates the four different types of features used in the framework. The value of any given feature is always simply the sum of the pixels within clear rectangles subtracted from the sum of the pixels within shaded rectangles.

Learning algorithm

The speed with which features may be evaluated does not adequately compensate for their number, however. For example, in a standard 24x24 pixel sub-window, there are a total of $M = 162,336$ possible features, and it would be prohibitively expensive to evaluate them all when testing an image. Thus, the object detection framework employs a variant of the learning algorithm AdaBoost to both select the best features and to train classifiers that use them. This algorithm constructs a "strong" classifier as a linear combination of weighted simple "weak" classifiers.

$$h(\mathbf{x}) = \text{sign} \left(\sum_{j=1}^M \alpha_j h_j(\mathbf{x}) \right)$$

Each weak classifier is a threshold function based on the feature f_j .

$$h_j(\mathbf{x}) = \begin{cases} -s_j & \text{if } f_j < \theta_j \\ s_j & \text{otherwise} \end{cases}$$

The threshold value θ_j and the polarity $s_j \in \pm 1$ are determined in the training, as well as the coefficients α_j . Here a simplified version of the learning algorithm is reported:^[5]

Input: Set of N positive and negative training images with their labels (\mathbf{x}^i, y^i) . If image i is a face $y^i = 1$, if not $y^i = -1$.

- 1) Initialization: assign a weight $w_1^i = \frac{1}{N}$ to each image i .
- 2) For each feature f_j with $j = 1, \dots, M$
- 3) Renormalize the weights such that they sum to one.
- 4) Apply the feature to each image in the training set,

then find the optimal threshold and polarity θ_j, s_j that minimizes the weighted classification error. That

$$\theta_j, s_j = \arg \min_{\theta, s} \sum_{i=1}^N w_j^i \epsilon_j^i$$

is

$$\epsilon_j^i = \begin{cases} 0 & \text{if } y^i = h_j(\mathbf{x}^i, \theta_j, s_j) \\ 1 & \text{otherwise} \end{cases}$$

where

5) Assign a weight α_j to h_j that is inversely proportional to the error rate. In this way best classifiers are considered more.

6) The weights for the next iteration, i.e. w_{j+1}^i , are reduced for the images i that were correctly classified.

7) Set the final classifier

$$h(\mathbf{x}) = \text{sign} \left(\sum_{j=1}^M \alpha_j h_j(\mathbf{x}) \right)$$

to

8) alternatives such as steerable filters. Although they are sensitive to vertical and horizontal features, their feedback is considerably coarser.



9) Haar Feature that looks similar to the bridge of the nose is applied onto the face

11) Haar Feature that looks similar to the eye region which is darker than the upper cheeks is applied onto a face



12)

13) 3rd and 4th kind of Haar Feature



2. Deformable Lucas-Kanade:

We formulate the face alignment problem as a Deformable Lucas-Kanade (DLK) fitting task, employing a 2D nonrigid face model directly parameterized by the mesh vertex coordinates. Secondly, we adapt it further to our face problem, through an alignment algorithm which can handle outliers effectively and an efficient dual inverse compositional method to address lighting variations. Thirdly, we suggest a joint face alignment approach that employs multiple template images to improve the performance by incorporating more information. For simplicity, our proposed image-to-image face alignment method is denoted by “DLK” for short, and the proposed joint face alignment approach is denoted by “JDLK”, resp. To evaluate them, we conduct an extensive comparison with several state-of-the-art approaches, incl. the congealing algorithm, CMU’s face alignment method, and the direct face alignment method.

The Lucas–Kanade method assumes that the displacement of the image contents between two nearby instants (frames) is small and approximately constant within a neighborhood of the point p under consideration. Thus the optical flow equation can be assumed to hold for all pixels within a window centered at p . Namely, the local

image flow (velocity) vector (V_x, V_y) must satisfy

$$\begin{aligned} I_x(q_1)V_x + I_y(q_1)V_y &= -I_t(q_1) \\ I_x(q_2)V_x + I_y(q_2)V_y &= -I_t(q_2) \\ \vdots \\ I_x(q_n)V_x + I_y(q_n)V_y &= -I_t(q_n) \end{aligned}$$

Where q_1, q_2, \dots, q_n are the pixels inside the window, and $I_x(q_i), I_y(q_i), I_t(q_i)$ are the partial derivatives of the image I with respect to position x, y and time t , evaluated at the point q_i and at the current time.

These equations can be written in matrix form $Av = b$, where

$$A = \begin{bmatrix} I_x(q_1) & I_y(q_1) \\ I_x(q_2) & I_y(q_2) \\ \vdots & \vdots \\ I_x(q_n) & I_y(q_n) \end{bmatrix}, \quad v = \begin{bmatrix} V_x \\ V_y \end{bmatrix}, \quad \text{and } b = \begin{bmatrix} -I_t(q_1) \\ -I_t(q_2) \\ \vdots \\ -I_t(q_n) \end{bmatrix}$$

This system has more equations than unknowns and thus it is usually over-determined. The Lucas–Kanade method obtains a compromise solution by the least squares principle. Namely, it solves the 2×2 system

$$A^T Av = A^T b \text{ or } v = (A^T A)^{-1} A^T b$$

where A^T is the transpose of matrix A . That is, it computes

$$\begin{bmatrix} V_x \\ V_y \end{bmatrix} = \begin{bmatrix} \sum_i I_x(q_i)^2 & \sum_i I_x(q_i)I_y(q_i) \\ \sum_i I_y(q_i)I_x(q_i) & \sum_i I_y(q_i)^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_i I_x(q_i)I_t(q_i) \\ -\sum_i I_y(q_i)I_t(q_i) \end{bmatrix}$$

where the central matrix in the equation is an Inverse matrix. The sums are running from $i=1$ to n .

The matrix $A^T A$ is often called the structure tensor of the image at the point p .

3. Locality-Sensitive Hashing:

Locality-Sensitive Hashing (LSH) is a promising approach to similarity search in high-dimensional spaces, it has not been considered practical partly because its search quality is sensitive to several parameters that are quite data dependent. The K Nearest Neighbor (K-NN) problem is as follows: given a metric space M , d and a set $S \subseteq M$, maintain an index so that for any query point $v \in M$, the set $I(v)$ of K points in S that are closest to v can be quickly identified. We assume the metric space is the D-dimensional Euclidean space R^D , which is the most commonly used metric space. Indyk and Motwani introduced LSH as a probabilistic technique suitable for solving the approximate K-NN problem. The original LSH hash function families were suitable only for Hamming space, but more recent families based on stable distributions and suitable for L_p , $p \in (0, 2]$ have been devised. LSH, though obtained interesting asymptotic results, provides little guidance on how these parameters should be chosen, and tuning parameters for a given dataset remains a tedious process.

In this paper, we propose a novel scheme that exploits both semi-supervised kernel learning and batch mode active learning for relevance feedback in CBIR. In particular, a kernel function is first learned from a mixture of labeled and unlabeled examples. The kernel will then be used to effectively identify the informative and diverse examples for active learning via a min-max framework. An empirical study with relevance feedback of CBIR showed that the proposed scheme is significantly more effective than other state-of-the-art approaches.

Learning with user's interactions is crucial to many applications in computer vision and pattern recognition. One of them is content-based image retrieval (CBIR) where users are often engaged to interact with the CBIR system for improving the retrieval quality. Such an interactive procedure is often known as relevance feedback, where the CBIR system attempts to understand the user's information needs by learning from the feedback examples judged by users. Due to the challenge of the semantic gap, traditional relevance feedback techniques often have to repeat many runs in order to achieve desirable results. To reduce the number of labeled examples required by relevance feedback, one key issue is how to identify the most informative unlabeled examples such that the retrieval performance could be improved most efficiently. Active learning is an important technique to address this challenge.

IX. EVALUATION AND RESULTS

First of all, it is clear that ULR which employs unsupervised learning to refine labels consistently performs better than the ORI baseline using the original weak label, the existing CL algorithm, MKM algorithm, and the LPSN algorithm. The promising result validates that the proposed ULR algorithm can effectively explore the data distribution of all data examples to refine the label matrix, and increase the performance of the search-based face annotation approach. Second, we note that the ULR algorithm outperforms its special case without the sparsity regularization in the SRF formulation, which validates the importance of the sparsity regularizer. Finally, when T is small, the hit rate gap, i.e., the hit rate difference between ORI and ULR is more significant, and the performance increases slowly when T is large. In practice, we usually focused on the small T value since users typically would not be interested in a long list of annotated names.

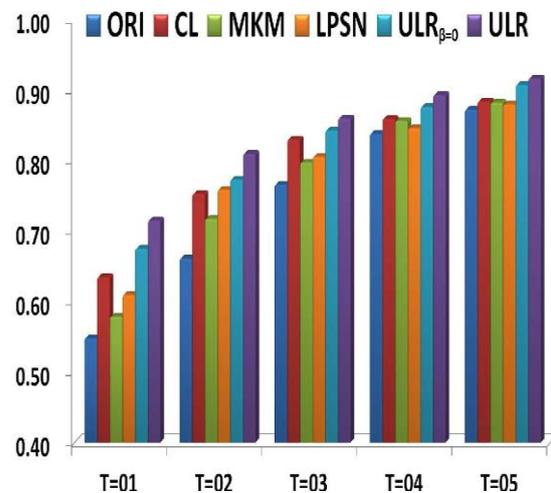


Fig. Evaluation of auto face annotation performance in terms of hit rates at top T annotated names

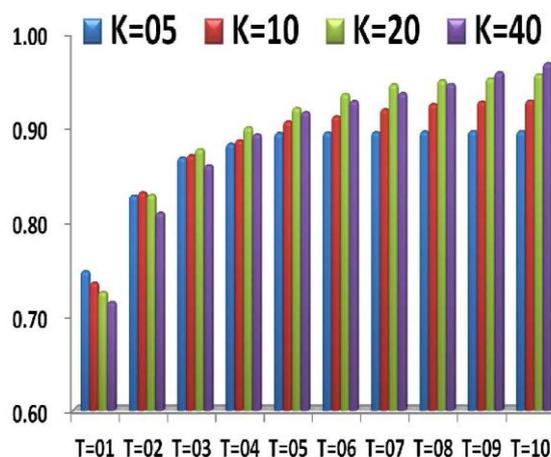


Fig. Annotation performance w.r.t. varied K and T values.

CONCLUSION

This paper investigated a promising search-based face annotation framework, in which we focused on tackling the critical problem of enhancing the label quality and

proposed a ULR algorithm. To further improve the scalability, we also proposed a clustering-based approximation solution, which successfully accelerated the optimization task without introducing much performance degradation. From an extensive set of experiments, we found that the proposed technique achieved promising results under a variety of settings. Our experimental results also indicated that the proposed ULR technique significantly surpassed the other regular approaches in literature. Future work will address the issues of duplicate human names and explore supervised/semi-supervised learning techniques to further enhance the label quality with affordable human manual refinement efforts.

Despite these promising results, some limitations and future directions should be addressed. Currently, our method was only tested on face images that have similar appearances. Besides, we have yet to carefully address the lighting issue in the joint face alignment scheme. For future work, we will address these issues and extend our technique to other objects by adopting appropriate metrics, such as mutual information.

REFERENCES

- [1]. Social Media Modeling And Computing, S.C.H. Hoi, J. Luo, S. Boll, D. Xu, And R. Jin, Eds. Springer, 2011.
- [2]. S. Satoh, Y. Nakamura, And T. Kanade, "Name-It: Naming And Detecting Faces In News Videos," *Ieee Multimedia*, Vol. 6, No. 1, Pp. 22-35, Jan.-Mar. 1999.
- [3]. P.T. Pham, T. Tuytelaars, And M.-F. Moens, "Naming People In News Videos With Label Propagation," *Ieee Multimedia*, Vol. 18, No. 3, Pp. 44-55, Mar. 2011.
- [4]. L. Zhang, L. Chen, M. Li, And H. Zhang, "Automated Annotation Of Human Faces In Family Albums," *Proc. 11th Acm Int'l Conf. Multimedia (Multimedia)*, 2003.
- [5]. T.L. Berg, A.C. Berg, J. Edwards, M. Maire, R. White, Y.W. Teh, E.G. Learned-Miller, And D.A. Forsyth, "Names And Faces In The News," *Proc. Ieee Cs Conf. Computer Vision And Pattern Recognition (Cvpr)*, Pp. 848-854, 2004.
- [6]. J. Yang And A.G. Hauptmann, "Naming Every Individual In News Video Monologues," *Proc. 12th Ann. Acm Int'l Conf. Multimedia (Multimedia)*, Pp. 580-587, 2004.
- [7]. J. Zhu, S.C.H. Hoi, And M.R. Lyu, "Face Annotation Using Transductive Kernel Fisher Discriminant," *Ieee Trans. Multimedia*, Vol. 10, No. 1, Pp. 86-96, Jan. 2008.
- [8]. A.W.M. Smeulders, M. Worring, S. Santini, A. Gupta, And R. Jain, "Content-Based Image Retrieval At The End Of The Early Years," *Ieee Trans. Pattern Analysis And Machine Intelligence*, Vol. 22, No. 12, Pp. 1349-1380, Dec. 2000.
- [9]. S.C.H. Hoi, R. Jin, J. Zhu, And M.R. Lyu, "Semi-Supervised Svm Batch Mode Active Learning With Applications To Image Retrieval," *Acm Trans. Information Systems*, Vol. 27, Pp. 1-29, 2009.
- [10]. X.-J. Wang, L. Zhang, F. Jing, And W.-Y. Ma, "Annosearch: Image Auto-Annotation By Search," *Proc. Ieee Cs Conf. Computer Vision And Pattern Recognition (Cvpr)*, Pp. 1483-1490, 2006.
- [11]. L. Wu, S.C.H. Hoi, R. Jin, J. Zhu, And N. Yu, "Distance Metric Learning From Uncertain Side Information For Automated Photo Tagging," *Acm Trans. Intelligent Systems And Technology*, Vol. 2, No. 2, P. 13, 2011.
- [12]. P. Wu, S.C.H. Hoi, P. Zhao, And Y. He, "Mining Social Images With Distance Metric Learning For Automated Image Tagging," *Proc. Fourth Acm Int'l Conf. Web Search And Data Mining (Wsdm '11)*, Pp. 197-206, 2011.
- [13]. D. Wang, S.C.H. Hoi, And Y. He, "Mining Weakly Labeled Web Facial Images For Search-Based Face Annotation," *Proc. 34th Int'l Acm Sigir Conf. Research And Development In Information Retrieval (Sigir)*, 2011.
- [14]. P. Belhumeur, J. Hespanha, And D. Kriegman, "Eigenfaces Versus Fisherfaces: Recognition Using Class Specific Linear Projection," *Ieee Pattern Analysis And Machine Intelligence*, Vol. 19, No. 7, Pp. 711-720, July 1997.
- [15]. W. Zhao, R. Chellappa, P.J. Phillips, And A. Rosenfeld, "Face Recognition: A Literature Survey," *Acm Computing Survey*, Vol. 35, Pp. 399-458, 2003.
- [16]. 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," *Technical Report 07-49*, 2007.
- [17]. H.V. Nguyen And L. Bai, "Cosine Similarity Metric Learning For Face Verification," *Proc. 10th Asian Conf. Computer Vision (Accv '10)*, 2008.
- [18]. M. Guillaumin, J. Verbeek, And C. Schmid, "Is That You? Metric Learning Approaches For Face Identification," *Proc. Ieee 12th Int'l Conf. Computer Vision (Iccv)*, 2009.
- [19]. Z. Cao, Q. Yin, X. Tang, And J. Sun, "Face Recognition With Learning-Based Descriptor," *Ieee Conf. Computer Vision And Pattern Recognition (Cvpr)*, Pp. 2707-2714, 2010.
- [20]. E. Hjelma'S And B.K. Low, "Face Detection: A Survey," *Computer Vision And Image Understanding*, Vol. 83, No. 3, Pp. 236-274, 2001.
- [21]. R. Jafri And H.R. Arabnia, "A Survey Of Face Recognition Techniques," *J. Information Processing Systems*, Vol. 5, Pp. 41-68, 2009.
- [22]. K. Delac And M. Grgic, *Face Recognition*, In-Tech, 2007.
- [23]. M.G. Kresimir Delac And M.S. Bartlett, *Recent Advances In Facerecognition*. I-Tech Education And Publishing, 2008.
- [24]. A. Hanbury, "A Survey Of Methods For Image Annotation," *J. Visual Languages And Computing*, Vol. 19, Pp. 617-627, Oct. 2008.
- [25]. Y. Yang, Y. Yang, Z. Huang, H.T. Shen, And F. Nie, "Tag Localization With Spatial Correlations And Joint Group Sparsity," *Proc. Ieee Conf. Computer Vision And Pattern Recognition (Cvpr)*, Pp. 881-888, 2011.