A Novel Approach of Fuzzy Based Semi-Automatic Annotation for Similar Facial Images

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Abstract— Auto face annotation is an important role for many real-world multimedia applications. Recently search based face annotation paradigm is one of the research challenge in computer vision and image analysis. In this paper, we present the problem is to annotate the most weakly labeled facial images are duplicate names, noisy and incomplete. To handle this problem we used an effective semi-automatic annotation methodology with unsupervised label refinement (ULR) approach for refining the labels in facial images by using some machine learning techniques and fuzzy clustering-based approximation algorithm is used to improve the scalability considerably. Finally to develop an optimization algorithm for solving a large scale learning task. The result of this proposed ULR algorithm can improve the performance than other ULR algorithms in weak label matrix.

Key words: Face annotation, weak label, optimization, ULR algorithms, fuzzy

I. INTRODUCTION
Due to the popularity of various digital cameras and the rapid growth of social media tools for internet-based photo sharing [7], by users on the Internet are human facial images. Some of these facial images are tagged with names, but many of them are not tagged properly. Recently search based annotation are used for facial image annotation by mining the World Wide Web (WWW), where large number of weakly labeled facial images are freely available. This has motivated the study of auto face annotation, an important technique that aims to annotate facial images automatically. 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 [6], [5]. Classical face annotation approaches are often treated as an extended face recognition problem, where different classification models are trained from a collection of well Labeled facial images by employing the supervised or semi-supervised machine learning techniques [6], [17].

The SBFA framework is data-driven and model-free, which to some extent is inspired by the search-based image annotation techniques [14], [15] for generic image annotations. The main objective of SBFA is assign to correct name labels to a given query facial image. In some cases, the additional information may be labels that are often incorrect. For example, these labels may come from an alternative classifier. In this case, the problem becomes how to incorporate these “noisy” or “weak” labels well. In particular, given a novel facial image for annotation, we first retrieve a short list of top K most similar facial images from a weakly labeled facial image database, and then annotate the facial image by performing voting on the labels associated with the top K similar facial images.

One challenging problem is most weakly labeled facial images are duplicate names, noisy and incomplete. To handle this problem we used an effective semi-automatic annotation methodology with unsupervised label refinement (ULR) approach for refining the labels in facial images by using some machine learning techniques and fuzzy clustering-based approximation algorithm is used to improve the scalability considerably. This can take advantages of the power of parallel computation when solving a very large-scale problem. A good approximation is expected to achieve a high reduction in running time with a small loss in annotation performance.

II. RELATED WORK
In earlier work, A. Nithya and K. Haridas [4] proposed a facial image annotation. It represents efficient automated image tagging and text based retrieval for visual identifications. Our work aims to solve the content-based face annotation problem using the search-based paradigm, where facial images are directly used as query images and the task is to return the corresponding names of the query images. Some recent work [16] mainly addressed the face retrieval problem, in which an effective image representation has been proposed using both local and global features. The other is CBSA [18], a content-based soft annotation tool that allows adding semantic labels to a small set of images. Machine learning algorithms extend the labels to larger image sets, based on the visual similarity between the new (unlabeled) images and previously labeled images. Among the most widely cited facial recognition systems in the literature are those based on Principal Component Analysis (PCA) of intensity images, better known as eigen-faces, presented by Sirovich et Kirby [8] and used for recognition by Turk et Pentland[10]. Wang et al. [6] proposed a search-based annotation system – This system requires an initial keyword as a seed to speed up the search by leveraging text-based search technologies.

In [20], Lei et al. proposed a semi-automatic approach to do face annotation. In their method, they proposed aBayesian framework to automatically calculate a candidate list of names for the face to be annotated. The purifying web facial images, which aims to leverage noisy web facial images for face recognition applications [1], [19]. Usually these works are proposed as a simple preprocessing step in the whole system without adopting sophisticated techniques. Zhao et al. [19] proposed a consistency learning method to train face models for the celebrity by mining the text-image co-occurrence on the web as a weak signal of relevance toward supervised face learning task from a large and noisy training set. Enhancing the label matrix over the
entire facial image database, the WLRLCC algorithm [11] is focused on learning more discriminative features for the top retrieved facial images for each individual query, which thus is very different from the ULR. The learning methodology for solving the unsupervised label refinement task are partially inspired by some existing studies in machine learning, including graph based semi-supervised learning and multilabel learning techniques [9].

III. PROPOSED WORK

We propose a multistep gradient algorithm for Convex-constraint formulation and introduce the sparsity is formulate the optimization. We compute Euclidean for gradient iterations. Another method is fuzzy clustering; it is discover nonlinear relations among data. We used multiple kernel fuzzy algorithm for new embedded map features.

IV. ALGORITHMS

A. Multi-Step Subjective Gradient Algorithm For ULR

The sparsity constraints are trivial to solve since the objective function is separable and each decision-maker could simply minimize its loss independently of the others. Hence, it is the existence of constraints (must labeled or unlabeled) that makes challenging. In the optimization, mining facial annotation there are essentially two ways of dealing with constraints. One way is to project iterations onto the constraint set to maintain feasibility at all times; other way is to use dual decomposition to eliminate couplings between decision-makers and solve the associated dual problem.

Computing the Euclidean projection onto the constraint of typically requires the full decision vector \( x \), which is not available to the decision-makers in our research setting. An alternative, method is to consider weighted gradient methods which use a linear combination of the information available to nodes to ensure that iterates remain feasible.

The weighted gradient method takes the form

\[
x(k+1) = x(k) - \alpha W \nabla f(x(k))
\]  

(1)

Here, \( W \in \mathbb{R}^{n \times n} \) is a distance matrix that should satisfy the following three conditions:

- The locality of information exchange between the decision makers should be preserved;
- Provided that the initial point \( x(0) \) is feasible, the iterates generated by (1) should remain feasible;
- The fixed-points of (1) should satisfy the optimally condition;

The multi-step weighted gradient iteration as follows,

\[
x(k+1) = x(k) - \alpha W \nabla f(x) + \beta (x(k) - x(k-1))
\]  

(2)

Under the sparsity constraint on \( W \) detailed above, these iterations can be implemented by individual decision-makers.

The proposed multi-step methods have significantly improved convergence factors compared to the gradient iterations, and particularly so when the Hessian of the loss function and/or the graph Laplacian of the network is ill-conditioned. The results of equation (2) specify sufficient conditions for the convergence of multi-step iterations in terms of the design parameters \( \alpha, \beta \) and \( W \).

However, these parameters are determined based on upper and lower bounds on the Hessian and the largest and smallest non-zero eigenvalue of \( W \).

In our research framework, following the terminology of shared nearest neighbors; we proposed co-occurrence likelihood to compute the similarity value

B. Fuzzy Clustering Based Approximation

The facial annotation plays a vital role in numerous data mining applications, and fuzzy c-means (FCM) is one of the most well-known cluster based approximation algorithms. FCM assigns pixels to \( c \) partitions by using fuzzy memberships. Let \( X = \{x_1, x_2, x_3, \ldots, x_n\} \) denote an facial image with \( n \) pixels to be portioned into \( c \) clusters, where \( x_i \) (\( i = 1, 2, 3, \ldots, n \)) is the label intensity. The Objective function is to discover nonlinear relationships among data, kernel methods use embedding mappings that map features of the data to new feature spaces. The KFCM is an iterative clustering technique that minimizes the objective function. Given a dataset, \( p X = \{x_1, \ldots, x_n\} \subset \mathbb{R}^p \), the original Multi kernel Fuzzy cluster (MKFC) algorithm partitions \( X \) into \( c \) fuzzy subsets by minimizing the following objective function

\[
J(w, U, V) = \sum_{i=1}^{c} \sum_{k=1}^{n} \mu_{ik}^m \| x_k - v_i \|^2
\]  

(3)

Where \( c \) is the number of clusters and selected as a specified value, \( n \) the number of data points, \( \mu_{ik} \) the membership of \( x_k \) in class \( i \), satisfying the \( \sum_{i=1}^{c} \mu_{ik} = 1 \), \( m \) the quantity controlling clustering fuzziness, and \( V \) the set of cluster centers or prototypes \( \{v_i \in \mathbb{R}^p\} \).

C. Optimizing Memberships

The MKFC is to find combination weights \( w \), memberships \( U \), and cluster centers \( V \), which minimize the objective function. The first fix the weights and cluster centers to find the optimal memberships. For brevity, we use \( D_{ic} \) to denote the distance between data \( x_i \) and cluster center \( v_c \).

\[
J(w, U, V) = \sum_{i=1}^{c} \sum_{k=1}^{n} \mu_{ik}^m D_{ic}^2
\]  

(4)

Where \( D_{ic}^2 = (u(x_i) - v_i)^T (u(x_i) - v_i) \), when the weights and cluster centers are fixed, the distances are constants Similar to FCM.

D. Optimizing Weights

The weights \( w \) and cluster centers \( V \) are fixed; the optimal memberships \( U \) can be obtained. Now, let us assume that the memberships are fixed. We seek to derive the optimal centers and weights to combine the kernels. By taking the derivative of \( J(w, U, V) \) in (3) with respect to \( v_c \) and setting it to zero,

\[
\frac{\partial J(w, U, V)}{\partial v_c} = -2 \sum_{i=1}^{n} \mu_{ik}^m (u(x_i) - v_c) = 0
\]  

(5)

The cluster centers are in the kernel-induced distance feature space which might be implicit or even have an infinite dimensionality. Therefore, it may be impossible to directly evaluate these centers.

The optimized ULR on each duplicate name subset has been reduced to number of pixels, which is much
smaller than the original number of variables on the entire database. As a result, each small sub-problem (duplicate names) could be solved efficiently. Besides, as the sub-problems on different subsets are independent, a parallel computation framework could also be adopted for further acceleration.

V. RESULTS AND DISCUSSION

In evaluation web facial annotation is one of the challenging factors in research area. The most weakly facial images noisy, incomplete and duplicate images. To take this problem we built an artificial dataset randomly and we introduce some noise into the label matrix and randomly half of them mislabeled of the whole dataset. We refer the algorithm for Convex-constraint formulation (CCF) solved by the multistep gradient algorithm (MGA) and coordinate descent approach is solve the optimization for improve the scalability. This can take advantages of the power of parallel computation when solving a very large-scale problem. Fuzzy clustering is achieving a high reduction in running time with a small loss in annotation performance.

According to the algorithm in fig-1 describes all data points person1-9 and fig-2 describes the half of them mislabeled dataset for the nine persons.

![Fig. 1: dataset for nine persons](image)

![Fig. 2: Mislabeled image](image)

In fig-3 the original noisy label matrix is shown and refined by using algorithms are MKM, CL, LPSN, ULR and optimized fuzzy ULR. We have measured the refining distance for $Y_{true}$ value. The algorithms of MKL and CL[3] good for the less noise but failed for the mislabeled and LPSN and ULR handle the class better.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Origin Y</th>
<th>MKM</th>
<th>CL</th>
<th>LPSN</th>
<th>ULR</th>
<th>Fuzzy ULR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y_{true}</td>
<td>12.96</td>
<td>9.70</td>
<td>8.12</td>
<td>8.65</td>
<td>4.70</td>
<td><strong>3.20</strong></td>
</tr>
</tbody>
</table>

Table 1: performance of algorithms

From table 1 we measured the $Y_{true}$ result of fuzzy ULR algorithms and other algorithms.

![Fig. 3: The original noisy label matrix and the refined ones](image)

As a result of proposed optimized fuzzy ULR can highly refine the label matrix comparing other algorithms. From fig-3 we achieved the highest $Y_{true}$ value of fuzzy is 3.20.

VI. CONCLUSION

In this paper focused a most challenging problem of annotation by similar facial images are duplicate names and weak labels that are often mislabeled, noisy, and incomplete. The proposed work is to improve the scalability using coordinate descent approach to solving the optimization iteratively. This can take of the power of parallel computation when solving a very large-scale problem. Convex-constraint formulation is solved by the multistep gradient algorithm.

REFERENCES


