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Age Estimation Using Fixed Rank Representation (FRR)

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***Abstract*—** As it is an important and challenging problem in computer vision, face age estimation is typically cast as a classification or regression problem over a set of face samples with several ordinal age labels which have intrinsically cross-age correlations across adjacent age dimensions. As an outcome, these such correlations normally lead to age label ambiguities of face samples. Each face sample is associated with a latent label distribution that encodes the cross-age correlation information on label ambiguities. As we propose a totally data-driven distribution learning, approach to adaptively learn the latent label distributions. The proposed approach is capable of effectively discovering the intrinsic age distribution patterns for cross-age correlation analysis on the any prior assumptions on the forms of label distribution learning, this approach is able to flexible model of sample-specific context aware label distribution properties by solving a multi-task problem which jointly optimizes the tasks of age-label distribution learning and age prediction for individuals. Experimental outcomes demonstrate effectiveness of our approach.

Keywords — Age estimation, subspace learning, label distribution learning.

I. INTRODUCTION

The face age estimation has recently attracted considerable attentions as it has a wide range of applications such as face identification and human-computer interaction. The approaches of age estimation focus on the following three-issue face feature representation, face context structure construction, age prediction modeling. The face appearance is usually represented by various visual features such as face texture features (LBP, Garbor, and AAM), biologically inspired features (BIF) and deep learning features. The face context structure is often modeled by constructing a face affinity graph for subspace analysis which aims to capture the intrinsic interactions among face samples in the face-related image feature or attribute space (gender and race).The problem of age prediction modeling is to effectively learn the mapping function (e.g. non-linear and hierarchical function) from low-level image features to high-level age labels.

For cross age correlations by introducing the concept of label distribution which gives ambiguity properties of age labels. So based on these we focus on designing a data-dependent label distribution model, which is capable of adaptively learning the cross-age correlations from context-structure-preserving face data. We first discover its context affinity structure through subspace learning, and then incorporate the context structure into the process of constructing a data dependent label distribution model for modeling the cross-age correlations. It is obvious that our label distribution model is sample-specific, that is, different face samples have different label distributions determined by the face samples themselves as well as their associated context structures.

Specifically, this propose a novel age estimation approach called "Age Estimation with Data-Dependent Label Distribution Learning" (D2LDL). Compared the existing efforts to data-dependent label distributions are automatically learned by the real face data samples and this preserve the underlying manifold structure information with respect to different but correlated face samples. Based on the local context structures of face samples. Since learning the local structure is helpful in understanding the relationship among the face samples our label distribution of face sample considers both the aging degree of itself and the external influence of its neighboring face samples. Typically, several existing approaches to label distribution learning enforce particular prior assumption on the distribution forms (eg.Gaussian) which often restrict the flexibility of model learning for learning the age ambiguity. In Contrast, our learning scheme is capable of adaptively capturing the sample-specific context-aware label distribution properties by jointly optimizing the tasks of age-label distribution learning and age prediction for individuals.

II. LITERATURE SURVEY

Face age estimation is considered as a label prediction problem [1]. It follows review the literature of face age estimation in the following three aspects face feature representation, face context structure construction and age prediction model. Face Feature Representation on the face region has the regular texture information the earlier approaches build the texture features to represent the face appearance. Compared with these efforts directly using the face region image to extract the feature recent studies consider the correlations among the face organs. Proposed System the biologically inspired features. The first segment the face image into many local regions and then extract the face features by the strategy of "spatial pyramid model". In this paper, efforts of face identification design various deep neural networks to extract face features. The main advantage is that the extracted deep learning features capture much discriminative visual information.

This paper a good distance metric for the input data is crucial in many pattern recognition and machine learning applications [2]. Past studies have demonstrated that learning metric from labeled samples can significantly improve the performance of classification and clustering algorithms. In this paper, we investigate the problem of learning a distance metric that measures the semantic similarity of input data for regression problems. The particular application we consider is Human age estimation. Guiding principle for learning the distance metric is to preserve the local neighborhood based on a specially designed distance as well as to maximize the distances between data that are not in the neighborhood. In the Semantic space without any assumption about the structure and the distribution of the input data, we show that this could be done by using semidefinite programming. Furthermore the low-level feature space can be mapped to the high-level semantic space by a linear transformation with very low computational cost. Experimental results on the publicity available FG-NET Database show that 1)The learned metric correctly discovers the semantic structure of the data even when the amount of Training data is small and 2) significant improvement over the Traditional Euclidean metric for regression can be obtained.

Using the learned metric most importantly, simple regression methods such as k nearest neighbors (kNN) combined with our learned metric become quite competitive in Terms of accuracy when compared with the state of the art Human age estimation approaches.

This paper considered that the human age difference is influenced by the face context structure [3]. In order to discover this structure use OLPP to embed the face samples into a low-dimensional manifold structure which preserves the original neighborhood among the face samples learn a distance metric to preserve the contextual correlation among the neighboring face samples. Propose RCA and LPP to extract the face features and the extracted face features both preserve the feature similarity and the label similarity between the neighboring face samples. Learn a mapping function and consider all the samples being related and propagating their labels in this mapping space. The other studies consider that the face-related attributes (e.g., gender and race) also play an important role in describing the face context relationships. They predict the human age through reclassifying the face samples with the face-related attributes and their experiments show the difference of aging pattern between male and female. Furthermore, propose a "cross-population" learning strategy, which embeds different aging patterns into a common space and enforces the face samples with the semantically close face-related attributes to be correlated.

In Age Prediction Modeling, the existing efforts focus on designing the various age label predictors through classification or regression learning [4]. Motivated by these studies propose a mixture approach combining the advantages from both Classification and regression approaches. Recently observe that the human age can be represented by a set of adjacent age labels. The proposed system of label-distribution to replace with original age label which improves the typical objective function of the age estimation problem. Specifically, they explicitly enforce 3848 a fixed-form prior assumption on the label distribution (Gaussian or Triangle) resulting in the inflexibility of adapting to complicated face data in practice. Furthermore, propose an adaptive label distribution learning approach, which considers that the label distribution varies with the temporal changes.

In Sparse Subspace Clustering (SSC) is a typical approach to cluster the high-dimensional data (e.g., images and videos) [5]. Its basic idea is that each sample reconstructed through a linear combination of a few other samples. Therefore, all the original samples are embedded into many local manifold subspaces and the SSC approach considers that there exist the context relationships among the samples in the same subspace. Many researchers improve the clustering performance by adding various constraints into the subspace learning, such as the low-rank constraint the trace Lasso constraint and the mixed Gaussian noise constraint Recently solve the SSC problem through combining the context structure discovery and the data clustering into a unified framework.

The SSC techniques are widely used to solve a variety of image or video processing problems. For example assume each video frame can be reconstructed by the temporal-neighboring video frames. Therefore, they segment the video by implementing SSC for all the video frames with adding the temporal smoothing constraint for the temporal-neighboring video frames. Recently, extend the SSC problem into the multi-view image clustering where they solve SSC for every view iteratively as well as use the "Hilbert-Schmidt norms" to constrain the correlation among the different views. Although the manifold learning methods and the subspace learning of our approach all are capable to capture the context structure, their roles in the age estimation are different these existing efforts use the manifold learning to extract the image features and our approach use the subspace learning to build the prediction objects.

In this paper multi-label learning can deal with many problems with label ambiguity [6]. It does not fit some real applications well where the overall distribution of the importance of the labels matters. These paper proposes a novel learning paradigm named as label distribution learning (LDL).This label distribution covers a certain number of labels representing the degree to each label describes the instance. The LDL is a more general learning framework this includes both single-label and multi-label learning as its special cases. These paper proposes six working LDL algorithms in three ways problem transformation, algorithm adaptation, and specialized algorithm design. In order to compare the performance of the LDL algorithms six representative and diverse evaluation measures are selected via a clustering analysis and the first batch of label distribution datasets are collected and made publicly available. Experimental results on one artificial and 15 real-world datasets show clear advantages of the specialized algorithms, which indicates the importance of special design for the characteristics of the LDL problem.

III. SYSTEM DESIGN

The age estimation is completed in five module *III.I.* Face Feature Representation, *III.II.* Face Context structure Construction, *III.III.* Age Prediction Modelling, *III.IV.* Sparse Subspace Clustering and *III.V.* Fixed Rank Representation

III.I Face Feature Representation

The face region has the regular texture information, the earlier approaches build the texture features (e.g.LBP, Garbor and AAM) to represent the face appearance. Compared with these Efforts directly using the face region image to extract the feature, recent studies consider the correlations among the face organs. The biologically inspired features. They first segment the face image into many local regions and then extract the face features by the strategy of "spatial pyramid model". In the related field, many efforts of face identification design various deep neural networks to extract face features. The main advantage of these efforts is that the extracted deep learning features capture much discriminative visual information.

III.II Face Context Structure Construction

These studies consider that the human age difference is influenced by the face context structure. In order to discover this structure, Guo use OLPP to embed the face samples into a low-dimensional manifold structure, which preserves the original neighborhood among the face samples. learn a distance metric to preserve the contextual correlation among the neighboring face samples. Chao propose lsRCA and lsLPP to extract the face features and the extracted face features both preserve the feature similarity and the label similarity between the neighboring face samples. Learn a mapping function and consider all the samples being related and propagating their labels in this mapping space. It consider that the face-related attributes (e.g. gender and race) also play an important role in describing the face context relationships. They predict the human age through reclassifying the face samples with the face-related attributes and their experiments show the difference of aging pattern between male and female. Furthermore propose a "cross-population" learning strategy, which embeds different aging patterns into a common space and enforces the face samples with the semantically close face-related attributes to be correlated.

III.III Age Prediction Modeling

The existing efforts focus on designing the various age label predictors through classification or regression learning. Motivated by these studies, propose a mixture approach combining the advantages from both classification and regression approaches. It observe that the human age can be represented by a set of adjacent age labels. Therefore, they propose "label-distribution" to replace the original age label, which improves the typical objective function of the age estimation problem. Specifically, they explicitly enforce.

III.IV. Sparse Subspace Clustering (SSC)

SSC is a typical approach to cluster the high-dimensional data (e.g. images and videos). Its basic idea is that each sample can be reconstructed through a linear combination of a few other samples.

Therefore, all the original samples are embedded into many local manifold subspaces and the SSC approach considers that there exist the context relationships among the samples in the same subspace. Many researchers improve the clustering

Performance by adding various constraints into the subspace learning, such as the low-rank constraint the trace Lasso constraint and the mixed Gaussian noise constraint. Recently solve the SSC problem through combining the context structure discovery and the data clustering into a unified framework.

III.V Fixed Rank Representation

Subspace clustering and feature extraction are two of the most commonly used unsupervised learning techniques in computer vision and pattern recognition. State-of-the art techniques for subspace clustering make use of recent advances in sparsity and rank minimization. The techniques are computationally expensive and may result in degenerate solutions that degrade clustering performance in the case of insufficient data sampling. To partially solve these problems, and inspired by existing work on matrix factorization, this fixed-rank representation (FRR) as a unified framework for unsupervised visual learning. FRR is able to reveal the structure of multiple subspaces in closed-form when the data is noiseless. Furthermore, we prove that under some suitable conditions, even with insufficient observations, FRR can still reveal the true subspace memberships. To achieve robustness to outliers and noise, a sparse regularizes is introduced into the FRR framework. Beyond subspace clustering, FRR can be used for unsupervised feature extraction. As a non-trivial byproduct, a fast numerical solver is developed for FRR. Experimental results on both synthetic data and real applications validate our theoretical analysis and demonstrate the benefits of FRR for unsupervised visual learning.

III.V.I SSC ALGORITHM:

Input: face image features X and age labelsY;
D2LDL Model Learning
- Initialization
  -Initialize the subspace representation C by SSC.
  -Initialize the regression matrix W by the linear regression.
- Optimization

While the convergence condition are not met do
  -Update the subspace representation C via NMF
  -Compute the affinity graph A according to equation
    $A=½(|C| + |C^T|)$
  -Update the label distribution P according to equation
    $P=\mu Y+(1-\mu)YA$
  -Update the regression matrixW:
    #solve the linear regression
    while the value of W are not convergent do
For each Wt (the t-th column of W)do
    $Wt= (XX^T + M_t)^{-1} XP(t,:)^T$
Update the auxiliary matrix M_t ,t=1,…..,T'
Age Prediction in the testing dataset
Obtain the predicted age y_q,q ϵ testing samples,

III.V.II FRR ALGORITHM:

- FRR for Subspace Clustering.

Input: Let $X \epsilon R^{d\times n}$ be a set of data points sampled from k subspaces
Step 1: To obtain (Z*, L*, R*)
Step 2: Construct a graph by using $(|Z^*| + |(Z^*)^T|)$ or $(|L^*R^*| +|(L^*R^*)^T|)$ as the affinity matrix.
Step 3: Apply Ncut to this graph to obtain the clustering.

- FRR By ADM-type Algorithm:

Input: Observation Matrix $X \epsilon R^{d\times n}$,m > 0,ϵ1,ϵ2 > 0
parameters β >0 and p > 1

Initialization: Initialize $Z_0 \epsilon R^{n\times n}$,$L_0 \epsilon R^{n\times m}$,$R_0 \epsilon R^{m\times n}$,$E_0 \epsilon R^{d\times n}$ $\Lambda_0 \epsilon R^{d\times n}$ and $\pi_0 \epsilon R^{1\times n}$
while not converged do
Step 1: Update (Z,L,R,E,Λ,π)
Step 2: check the convergence condition:
$||X-XZ_+ - E_+|| \leq \epsilon 1$ and $||1_n^T Z + -1_n^T|| \leq \epsilon 2$
end while
output:Z*,L*,R*and E*

IV. RESULT - PERFORMANCE ANALYSIS

Performance analysis evaluated by applying SSC and FRR algorithm. Age estimated using FRR algorithm with less time to calculate feature extraction, precision of FRR algorithm is very close to SSC algorithm. Below steps are to illustrate FRR algorithm as a performance booster for age estimation over SSC algorithm.

Select image as an input for processing to SSC and FRR algorithm.

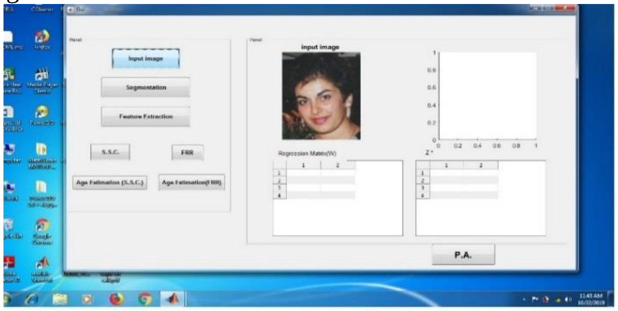

Figure 1. Input images

Process segmentation to discrete face part like eyes, nose, lips.

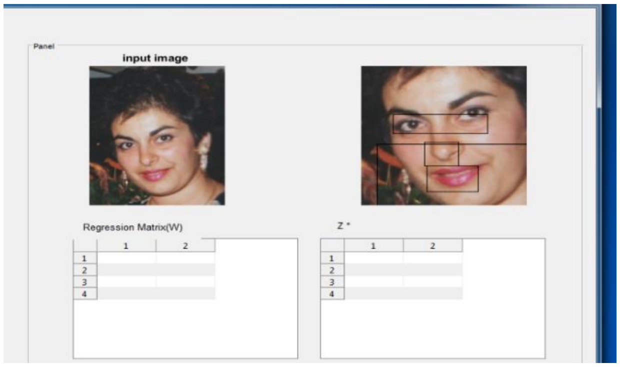

Figure 2. Segmentation

Feature extraction to analysis the sizes, length, width, thickness and edge between them of this face part like nose, eyes, lips part.

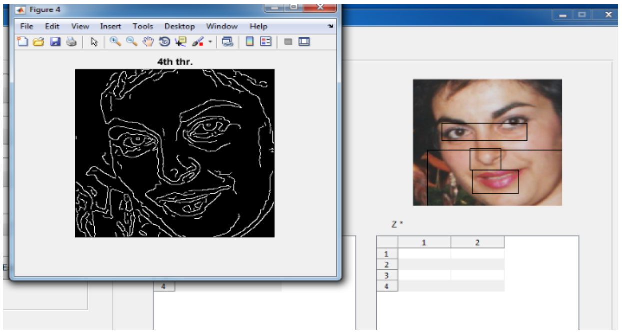
Figure 3. Feature Extraction

After the feature extraction, SSC algorithm is applied for optimization.

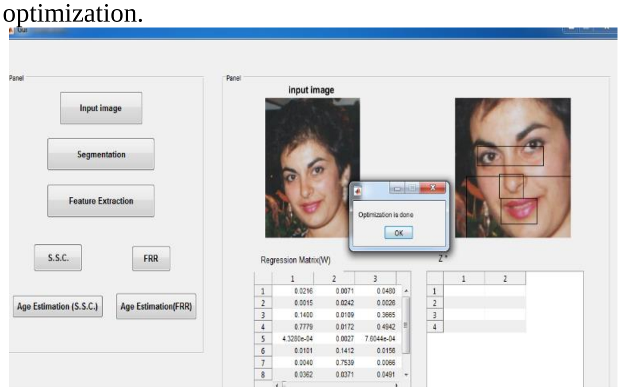

Figure 4. SSC Algorithm

SSC algorithm estimates age of that input images.

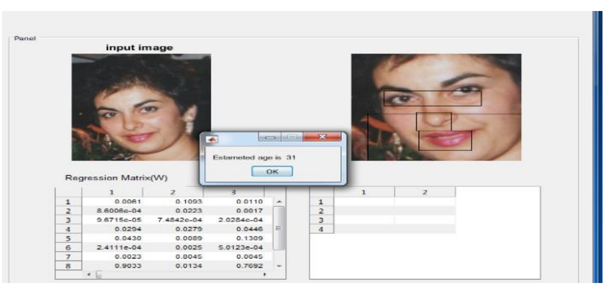

Figure 5. SSC - Age Estimation

FRR algorithm apply on that image and find the result

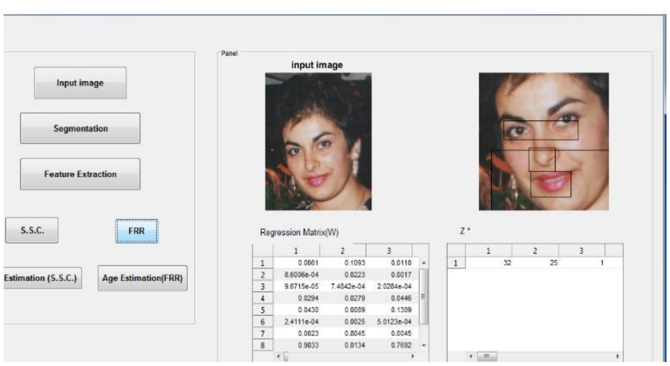

Figure 6. FRR Algorithm

FRR algorithm is fast numerical solver and find age estimation

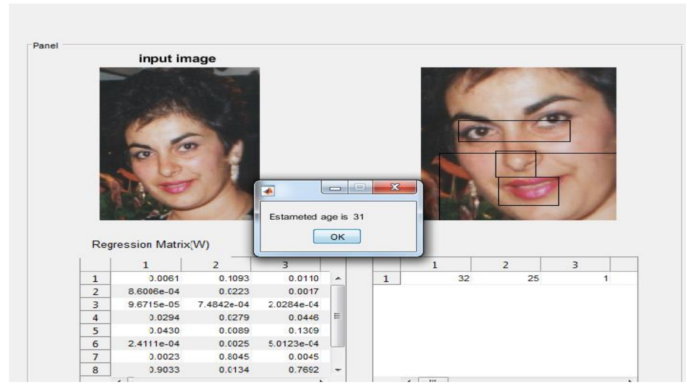

Figure 7. Age Estimation

Time complexity for SSC and FRR algorithm

Table 1. Time Complexity

Algorithm	Execution Time
SSC Algorithm	0.76698ms
FRR Algorithm	0.18694ms

Table representing the value of recall, precision

Table 2. Recall, precision

Algorithm	RECALL	PRECISION	SPECIFICITY
SSC	0.8043	0.8362	0.9984
FRR	0.8069	0.8994	0.9994

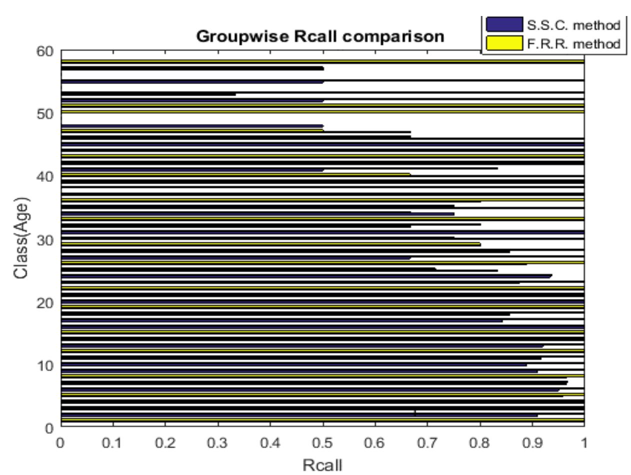

Figure 8. Recall Graph

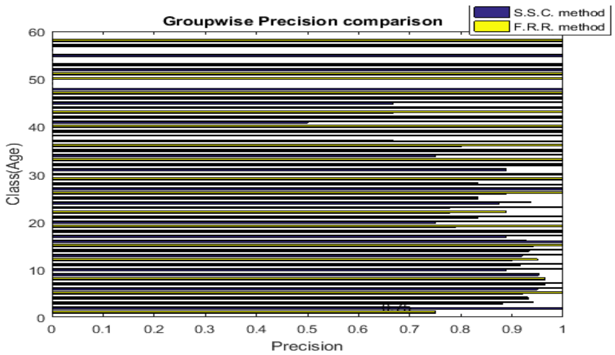

Figure 9. Precision Graph

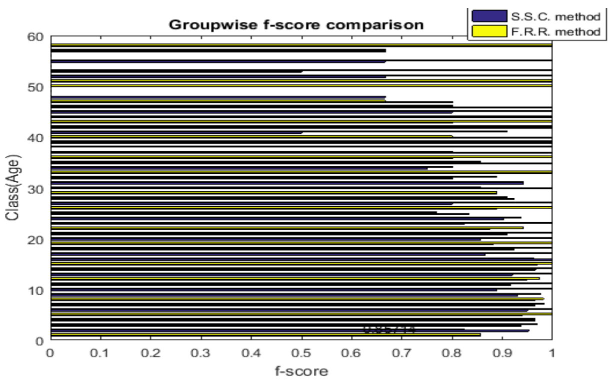

Figure 10. Fscore graph

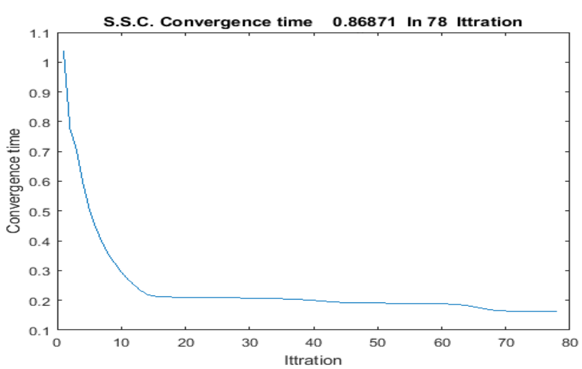

Figure 11. SSC Execution time

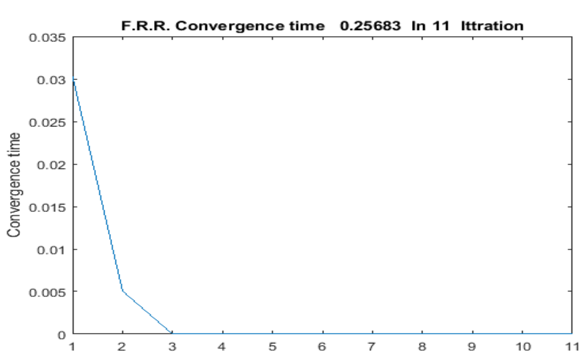

Figure 12. FRR Execution time

V. CONCLUSION

The age estimation using fixed rank representation (FRR) using subspace clustering and feature extraction gives better result concerning less computational cost and precision over SSC algorithm. FRR algorithm thus can be applied for feature extraction and age estimation.

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