A SURVEY ON: "FACE RECOGNITION USING SKETCH, THERMAL AND INFRARED IMAGES"

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Abstract : Heterogeneous face recognition aims to acknowledge faces across totally different sensor modalities. Typically, gallery images are normal visible spectrum pictures, and probe images are infrared images or sketches or thermal image. Recently vital improvements in face recognition are obtained by CNNs learned from very massive training datasets. In this paper, we are trying to find match between sketch with digital photograph, thermal image with digital photograph and infrared image with digital photograph. We explore totally different metric learning methods to reduce the discrepancies between the various modalities. In this paper we are making use of high level feature of deep convolutional neural network that are trained on digital photograph and these images do not belong to any type or any domain.CNN can also be used to encode the image that are taken from different media. A generic framework for Heterogeneous Face Recognition is planned by making use of Deep Convolutional Neural Networks low-level feature for each domain and it is called as Domain Specific Units. Domain Specific Units extract the shallow feature for every new image domain. Even, it handles its transformation to a generic face space shared between all image domains. Experiments carried out with four face databases i.e CUHK Face Sketch Database (CUFS) ,CASIA NIR-VIS face database(CASIA) ,Near Infrared And Visible Light(NIVL) dataset , Polarimetric And Thermal Database (Pola Thermal) covering 3 different image domains i.e sketch ,thermal image, infrared image and show improvements, in terms of matching ratio.

Index Terms **- Face Recognition , Heterogeneous Face Recognition, Reproducible Research, Domain Adaptation, Deep Neural Networks.**

I. INTRODUCTION

Face Recognition has become important aspect in every field. People from various field like psychology, pattern recognition , neuroscience, computer graphics and computer vision are trying to understand face recognition. Heterogeneous face recognition aims to recognize faces across completely different modalities. There may be many situations like no real face is available. The main problem working with heterogeneous face recognition is that face can be appear in different domain like sketch, infrared image, thermal image. In most cases, gallery of known people consists of normal visible spectrum images. Probe images could also be forensic or composite sketches, near-infrared (NIR) and shortwave-infrared pictures are less sensitive to illumination variation. Midwave-infrared and longwave-infrared (LWIR), additionally observed as "thermal infrared". Variations between the gallery and probe modality, build heterogeneous face recognition tougher than traditional face recognition, see for a sample of VIS and NIR pictures, furthermore as sketches. The main problem in matching faces from heterogeneous conditions is that images of an identical subject could differ in look because of changes in the image domain, e.g. between visual spectra images (VIS) and near-infrared pictures (NIR), between VIS images and sketches. This shift introduces a problem for comparison of images across these all domain (sketch, thermal, infrared) reduces the performance of recognition. we analyze the performance of Deep Convolutional Neural Networks (DCNN) trained for VIS images. This analysis creates a baseline for comparison. The domain specific units extract the feature of different domain. The application of such structure improves the recognition rates. This work is distributed in few steps that are: We have to analyze Deep Convolutional Neural Network (DCNN) Trained with VIS image. This analysis creates baseline for comparison. After that we have work with Domain Specific Unit. And at last we have to make everything publicaly available.

II. LITERATURE REVIEW

1) Heterogeneous face recognition exploitation kernel prototype similarities
B. F. Klare , A. K. Jain

Heterogeneous face recognition (HFR) consist of identified images of different domain such as infrared image to visual spectra image and sketch to a visual spectra images [1]. HFR has become very popular in recent days eg. forensic laboratory where the gallery images consist of criminal images or passport photos but the probe images consist of different domain such as sketch or infrared. Gallery and probe photographs are interpreted with non linear similarities [2]. The training set has images in each probe and gallery. The efficiency is enhanced by estimating the feature into a linear discriminant subspace [3].HFR uses random sampling to handle the tiny sample size downside [4].Wang and Tang proposed markov random field model for converting a sketch into a photograph. NIR to VIS face recognition by processing face images with a difference of Gaussian filter and encoding them using multi block : local binary pattern MB-LBP [5].

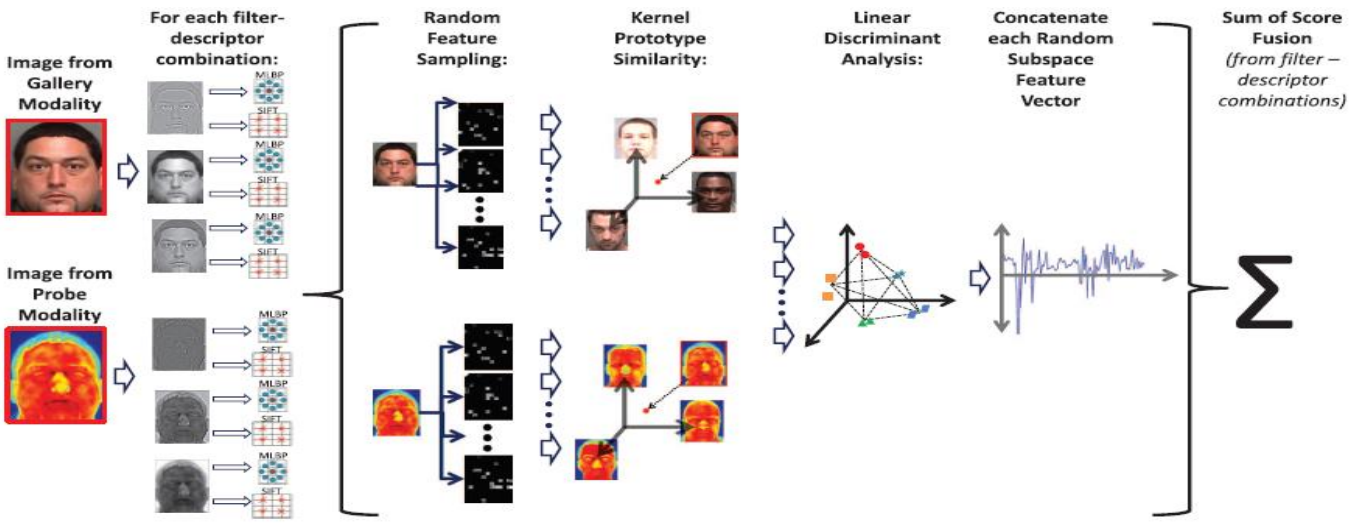

fig. 2.1 heterogenous face recognition using prototype similarities [31]

Working of heterogeneous face recognition starts with gallery and probe images . The comparison of two images is calculated by kernel function. The training set consists of gallery and probe images. For gallery and probe medium 2 positive semi definite kernel matrices are composed during training . Kernal prototypes similarities make the use of cosine kernel function. Cosine kernel is selected because it is devoid of parameter also it consistently gives higher accuracy on all tested scenarios. Making use of prototype similarities it degenerates to minimum kernel i.e 0 if we are making use of cosine kernel. Because of this it is possible for system to remain stable.

2)Memetically Optimized MCWLD for Matching Sketches With Digital Face pictures
H. S. Bhatt, S. Bharadwaj

One way to finding crimes and arrested criminals is matching sketches with visual spectra images [6]. With this work they are making use of automated algorithm to extract discriminating information from sketch and visual spectra images [7]. Such information is encoded using multiscale circular webers local descriptor [8]. Further, an evolutionary memetic improvement algorithm is projected to assign optimal weight to each native facial region to boost the identification performance [9]. Forensic sketches or digital face pictures may be of poor quality, hence a preprocessing technique is employed to enhance the standard of pictures and improve the identification performance. Wang and Tang proposes a new approach i.e Eigen transformation to transform a digital photo into sketch before matching. Uhl and Lobo proposed photometric standardization of sketches to compare it with visual spectra images. Sketches and photos were

normalized and Eigen analysis is used for matching. Yuen and Man used local and global feature measurements for identifing sketches and mug-shot images.

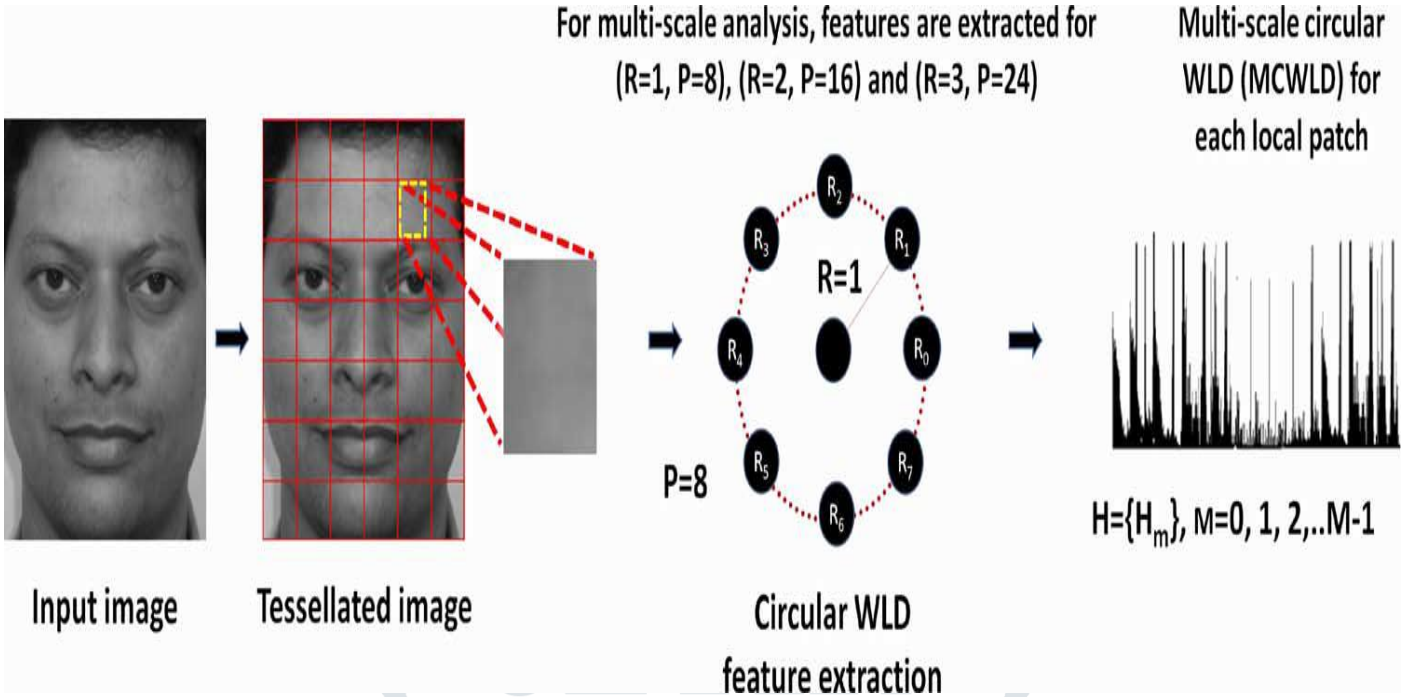

Fig. 2.2 Steps Involved For Matching Sketches With Digital Face Images [32]

As shown in figure Local Binary Descriptor (LBP) it is mostly used for face recognition. LBP is mostly used for calculating difference between grey color intensities between pixel neighbors and used for sketch recognition.LBP extracts the texture feature of the every input image. WLD calculates the micro patterns in a tiny area with fine granularity.WLD computes the multiscale descriptor in a circular manner for matching sketch with photograph. MCWLD is used for computing number of neighboring pixel.

3) On Matching Sketches with Digital Face pictures
H. S. Bhatt, S. Bharadwaj, R. Singh, and M. Vatsa

This work make use of an efficient algorithm for identifying sketches with digital face image [11]. The algorithm extracts discriminating information that are present in facial region at different level of granularity. Sketches and digital pictures are spoiled into multi-resolution pyramid to conserve high frequency information that forms the discriminating facial pattern [12]. Extended uniform circular native binary pattern based descriptors use these patterns to create a singular signature of the face image [13]. Further, for matching, a genetic improvement based approach is projected to search out the optimum weights corresponding to every facial region [14]. the knowledge obtained from completely different levels of Laplacian pyramid are combined to boost the identification accuracy. Experimental results on sketch-digital image pairs from the CUHK and IIIT-D databases show that the proposed algorithm will give higher identification performance compared to existing algorithms [15]. Robert and Niels proposed photometric standardization of sketches to compare it with the digital photos. They further geometrically normalized sketches and photos to match them through Eigen analysis. Wang and Tang proposed Eigen transformation based approach that transforms a digital image to sketch and then performs matching. In another approach, they presented an algorithm that separates shape and texture information and then applied Bayesian classifier for recognition.

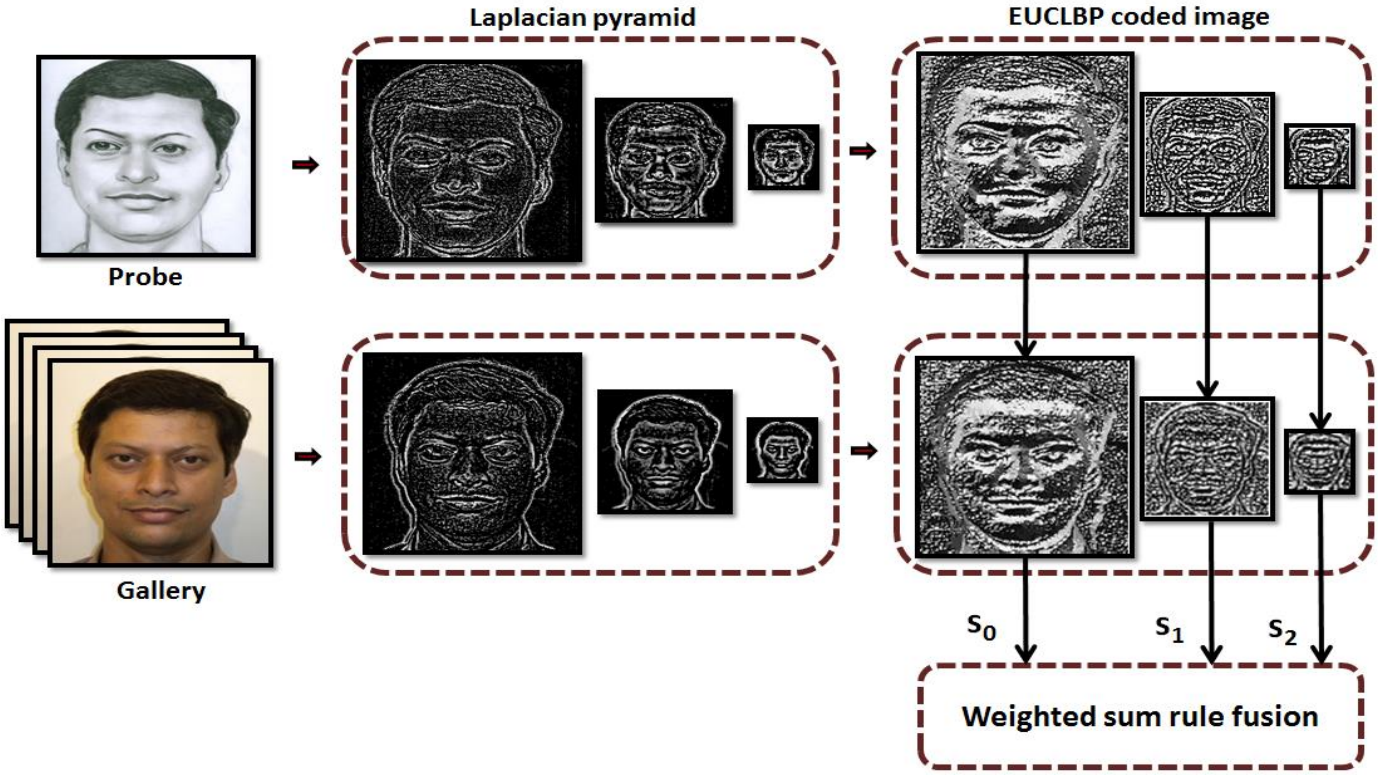

Fig. 2.3 Illustrating The Steps Involved In The Sketch To Digital Image Matching Algorithm [33]

Fig 2.3 shows the steps used for matching sketch with digital image. It stars with calculating Laplacian pyramid to preserve edges and frequency information that are available in image. Extended Uniform Circular Local Binary Pattern (EUCLBP) at each step of Laplacian pyramid. Matching is done with the help of genetic optimization. Identification rate at each level of Laplacian pyramid are joined using weighted sum rule fusion.

4) Shared illustration Learning for Heterogenous Face Recognition
D. Yi, Z. Lei, and S. Z. Li

After intensive analysis, heterogenous face recognition still remains a difficult problem. the most difficulties are in the heterogenous face image spaces[16]. The heterogeneity is usually tightly come with other variation, that makes the link of heterogenous face images extremely nonlinear [17]. several glorious strategies are proposed to model the nonlinear relationship, however they apt to overfit to the training set, because of small number of samples [18].Inspired by the unsupervised algorithms in deep learning, this paper proposes a unique framework for heterogeneous face recognition. We first extract the gabor feature of face with some localized point, and then use Restricted Boltzmann Machines (RBMs) for learning a shared representation natively to remove the heterogeneity of face around each facial point [19]. Finally , the shared representations of native RBMs are connected together and processed by PCA. Face recognition problem of Near infrared (NIR) to Visual Spectra Image (VIS) and two face database are selected to improve the performance of the proposed method. On CASIA HFB information, we tend to get comparable results to progressive strategies. On a harder database, CASIA NIR-VIS two.0, we tend to outstrip different strategies significantly [20]. The proposed system consist of 3 main steps: (1) extracting local Gabor features around facial points, as exiciting face recognition systems do; (2) learning a shared representation by RBM for each group of native features; (3) processing the whole RBM representations by PCA and matching by Cosine similarity. Among them the important step is (2), in which a 3-layer RBM is constructed and the central layer represents the shared properties of heterogeneous data.

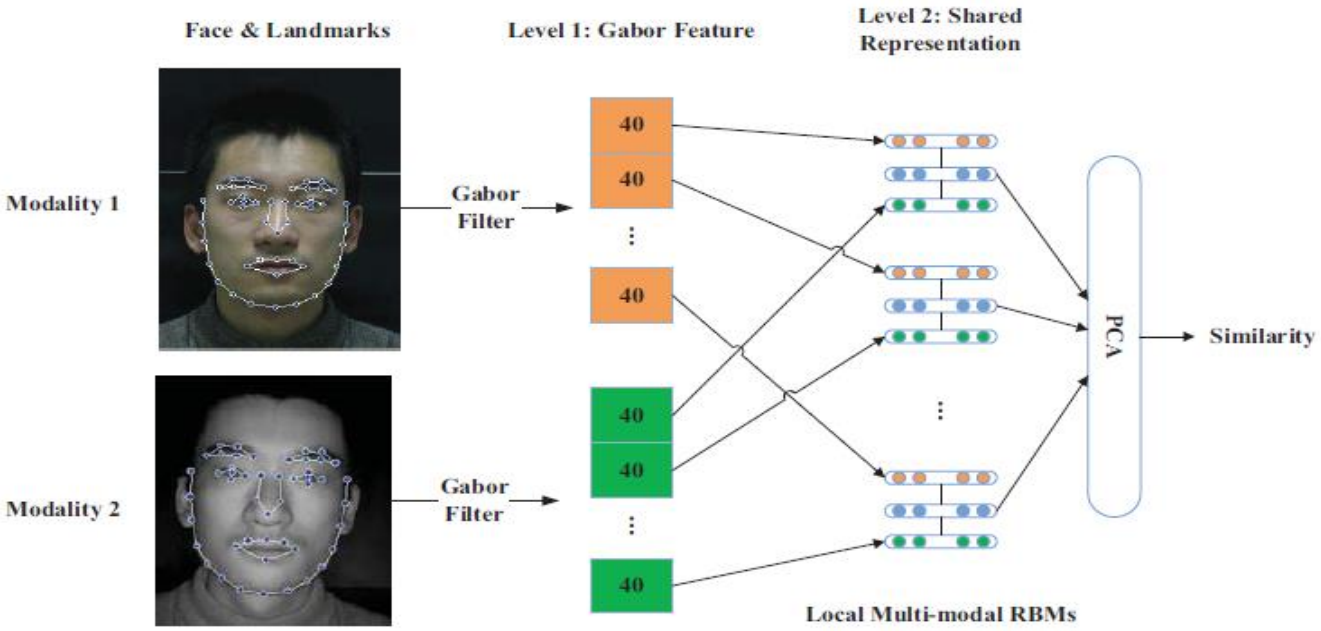

Fig. 2.4. The Proposed Framework For Heterogeneous Face Recognition By Combining Traditional Face Recognition Modules And Local Rbms [34]

As shown in figure it consist of two modalities i.e NIR and VIS. Initially Gabor feature of NIR and VIS image are extracted with many facial points. With the help of this gabor feature a series of RBM used for learning the shared representation of NIR and VIS for each facial points. Later PCA process and concatenate all local shared representations. At last similarity of NIR and VIS features are evaluated by cosine metric. In case of level 1 we extract discriminant feature for each domain i.e NIR and VIS. The task of level 2 is that make relationship between this 2 domain. Local relationship is easy that's why we are making use of local RBM for learning shared representation. For each facial point.

5) Local-Gravity-Face (LG-face) for Illumination-Invariant and Heterogeneous Face Recognition H. Roy, D. Bhattacharjee

The transition paper Local-gravity-face proposes a unique technique referred to as Local- Gravity-Face (LG-face) for illumination-invariant and heterogeneous face recognition (HFR)[21].LG-face introduces a concept called as the Local Gravitational Force Angle (LGFA) [22].The LGFA is the direction of the gravitational force that the middle pixel exerts on the opposite pixels at a local neighborhood[23]. Theoretical knowledge tells that LGFA is an illumination-invariant feature, that considers the reflectance part of the local texture effect of the neighboring pixels. It preserves the edge information. CMU-PIE database gives rank 1 with identification rate of 97.78% and Extended Yale B database are achieved under varying illumination, It shows that LG-face is the best technique of illumination-invariant face recognition. For HFR, once faces seem in several modalities, LG-face produces a standard feature illustration [24]. Rank one recognition rates of 99.96% on the CUFS database, 98.67% on the CUFSF database, and 99.78% on the CASIA-HFB database show that LG-face is also an efficient technique for HFR. The Local-gravity-face method performs consistently even it consists of noise and complicated variations [25].

6) The HFB Face information for Heterogeneous Face biometrics analysis
S. Z. Li, Z. Lei, M. Ao

A face database is a combination of visual (VIS), near infrared (NIR) and three-dimensional (3D) face images[26].It is referred to as the HFB Face database, it's discharged currently to market analysis and development of Heterogeneous image processing[27].Here we are going to make use of PCA (Pricipal Component Analysis) and LDA (Linear Discriminant Analysis) strategies on the database [28,29].Image

Processing by and image matching of different type of face is done using Biometric Methods and it is called as HBF means heterogeneous face biometrics. Six experiment carried out for better performance on the HFB database. Tang and many other people evaluate a method for matching sketch with digital photograph using PCA. Author developed inter-modality face matchching (CDFE)for inter-modality face matching[30].

III. CONCLUSION

According to the this survey, DCNN high level options trained with VIS face images give discriminative power within the Heterogeneous Face Recognition task. Tests carried out in 3 completely different image domains have shown that such DCNNs are terribly correct for VIS-NIR task. The VIS-Sketch task they're less correct, however still higher than a random guess and higher than some baselines during this dataset. The VIS-Thermal task is that the most difficult one, however these DCNNs are still higher than a random guess. So as to improve these recognition rates exploitation the discriminative capabilities of such DCNNs already trained for VIS, we tend to introduced a technique for HFR referred to as Domain Specific Units. Such units learn low level feature detectors that are domain specific and share a similar set of high level options from the supply domain while not re-train them. Future work can target the analysis on what such feature detectors are learning for every image domain.

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