ENHANCING KIN RELATIONSHIP IN IMAGES USING GABOR FILTER

Deepak Ahire[1], Prof. Devidas Dighe[2]

[1] *Department of Electronics and Telecommunication, Savitribai Phule Pune University, Matoshri College of Engineering and Research Centre, Nashik, India*

[2] *Associate Professor and Head in E&TC at Matoshri College of Engineering and Research Centre, Nashik105,india*

ABSTRACT

In this paper work it is possible to detect the parent by given in their children images. Initially filter the image noise is removed from the image. And then detect the face from the image Viola john methods are used for face detection. For the detected faces extract the Gabor features. Gabor features based on the frequency and orientation. The method used as a shape representation. The Extracted feature will classified by the k-NN Classifier. The input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression. Both for classification and regression, it can be useful to weight the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. The trained classifier will predict about the images.

Keyword: Gabor features, k-NN Classifier, face recognition, face detection, Transfer subspace learning…..

---

1. INTRODUCTION

Familial relationships are based on blood and marriage. They include primary relationship (children, parents, grandparents and great-grandparents), secondary relations (siblings, cousins, nieces and nephews, and aunts and uncles), and ties with in-laws All human beings are connected to others by blood or marriage. Connections between people that are traced by blood are known as consanguineal relationships. Relationships based upon marriage or cohabitation between collaterals (people treated as the same generation) are affinal relationships. We can manage images of people automatically on Web in general and in social media in particular. Instead of just face detection and face recognition. We can study what are the relationships between them Even made distinction is that original family member and other family members. People generally refer to as immediate family, and the latter are generally labeled "extended family. Marriage, as a principle of kinship ,differs from blood in that it can be terminated. Along With the development of technology in modern multimedia society, image acquisition and storage by digital devices have never been easier than today. Storage unit like GB or TB is not qualified already in storing images from the Internet. For example, as the most popular social network website around the world, Facebook has already hosted over 20 billion images, with more than 2.5 billion new photos being added each month. However, how to successfully and automatically manage the substantial images captured by people is a real challenge since it pushes the computer to its limit of image understanding it requires both large-scale data analysis and high accuracy[1].

In most cases, people are the focus of images taken by consumers and managing or organizing them essentially raises two problems:

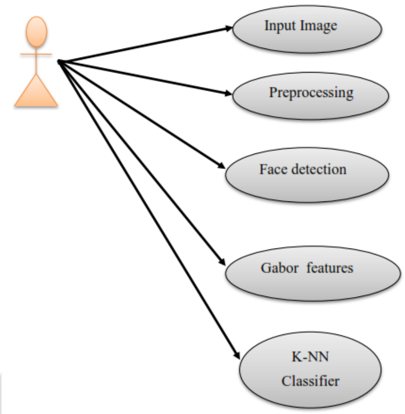
1) who these people are?
2) what their relationships are?

In the first problem, identities are what we are most concerned with and intuitively faces are critical clues. Face recognition is therefore an important approach toward this problem. Basically, face recognition can be further categorized into two classes according to whether the contextual information is used. Face recognition without context information, namely, pair wise face recognition, has been extensively studied during the past decade by exploration of following techniques: face detection and alignment , subspace learning ,invariant feature extraction , metric learning method , attributes based classifier and face synthesis and hallucination . Nevertheless, it is still an ongoing problem due to several practical factors, e.g., illumination, pose, expression and aging. The performance of the face recognition algorithm is dramatically degraded when a large-scale database is considered. On the other hand, in practice, faces no longer appear alone due to the rapid development of multimedia.[1] What often accompany faces are text, video and many other metadata. Recently, research attention is shifting to contextual information involved in the people-centric images, including locations, capture time of images and patterns of co-occurrence and reoccurrence in images , social norm and conventional positioning observed , text or other linked information , and clothing . The relationship of people in a photo also deserves the research attention in that social connection has been the essence of modern society. The possible relationships in consumer images include “kinship,” people’s albums and successfully parsing or tagging those leads to better understanding of images. Among them, kinship is believed to be the most discriminative one since children naturally inherit gene from their parents. An intuitive way to annotate this relationship is by identities of individuals the images contain, and in theory, this can be achieved using automatic face recognition the first problem aforementioned. However, it is also possible that the relationship is still uncertain even if identities are known. Therefore, direct kinship verification is worth investigating. The pioneer work in attempted to discriminate kinship based on selected inheritance invariant features. When kin relationship, gender and age are known, a family tree can be automatically created given an family image. Moreover, kinship verification can be applied to both general computer vision problems, such as image retrieval or annotation, and some specific application scenarios, such as finding missing children[1]. In this paper, as an extension of our previous work,1 attempt to tackle the kinship discrimination problem based on faces as well as the semantics embedded in contexts. This is reasonable because both appearance and semantics are valuable for relationship inference. Recent research dis-covers that facial appearance is a cue for genetic similarity as children resemble their parents more than other adults of the same gender, and that there is differential resemblance between two parents, depending on the age and gender of the child. Analogously, a critical observation is that faces of parents captured while they were young closely resemble their children’s compared with images captured when they are old. This promising statistics inspires us to perform the following research. First, the UB Kin Face database is set up by collecting child, young parent and old parent face1 images from the Web. Through this database, aforementioned hypothesis based on genetics theory is preliminarily proved .Second, a transfer subspace learning based method is proposed, aiming at reducing the large divergences of distributions between children and old parents. The key idea is to utilize some intermediate data set close to both the source and target distributions and naturally the young parent set is suitable for this task. Third, to exploit the value of contextual information and semantics in kinship, a database called Family Face is built and its images are drawn from social network websites, such as Facebook and Flickr.

1.1 Enhancing Relationship

First, the User Based Kin Face database is set up by collecting child, young–parent and old–parent face images from the Web. Second, a transfer subspace learning based method is used to reduce the large difference between young parent and old parent. Young parents have more similar features as compared to old parent. Then we will use a technique to find most possible kin relation. Conducting both objective and subjective evaluations; a human based test is introduced for more verification .

1.2 METHODOLOGY:



2. Literature Review

Literature survey is able to critically summarize the current technology in the area of face detection for any potency and debilitation in precedent work. Identify the technique to eliminate the implicit wimpiness, whilst bringing to the fore the potential strengths.

As you wait for baby, you've probably tried to picture what he might look like. Will he be tall like his father? Will he have curly hair like yours? Or is he going to inherit his grandfather's sense of humor?[31]There are 60,000 to 100,000 genes (made up of DNA) in a human being's 46 chromosomes. A baby gets 23 chromosomes from his mother and 23 from his father. With all the possible gene combinations, one pair of parents has the potential to produce 64 trillion different children. This probably gives you an idea of how impossible it is to predict just what baby will look like As it turns out, most human traits are polygenic the result of many genes acting together. To complicate things even further, for some traits such as height, weight, and especially personality environment also has a significant influence on which genes are expressed and which remain muted. Certain facial characteristics such as dimples, widow's peak, and facial symmetry (a high eyebrow on one side of your face, for instance) are believed to be dominant and filter down through the generations. Hand shape, finger shape, toenail shape, and unusual traits such as hair with double cowlicks often appear over generations. Fingerprint patterns have been shown to run in families. And crooked teeth can be inherited too, because the configuration of the jaw and the tilt of the teeth are genetically determined. There's even a specific gene for "gap tooth" that's been discovered and is believed to be dominant. To get an idea of what quirks and facial features your child may inherit, examine photos of relatives over generations. If it turns out most family members have a prominent chin or a round face, these are fairly strong traits that are likely to be passed on.[30]

a) **Reviews on Face Recognition techniques:**
   i)Eigenfaces

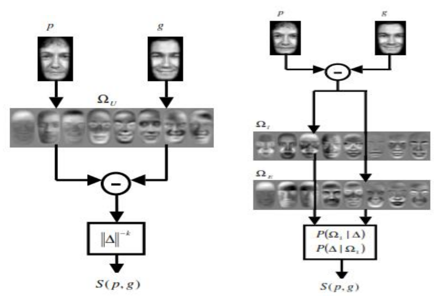


Fig.1 Appearance model Fig.2 Discriminative model[2]

ii)Singular Value Decomposition Methods

Theorem: Let I_{pxq} be a real rectangular matrix Rank(I)=r, then there exists two orthonormal matrices U_{pxp}, V_{qxq} and a diagonal matrix Σ_{pxq} and the following formula holds:

$$I = U\Sigma V^T = \sum_{i=1}^{r} \lambda_i v_i v_i^T , \qquad (2.29)$$

where

$U=(u_1, u_2,..., u_r, u_{r+1},..., u_p)$

$V=(v_1, v_2,..., v_r, v_{r+1},..., v_q)$,

$\Sigma=diag(\lambda_1, \lambda_2,..., \lambda_r, 0,..., 0), \lambda_1>\lambda_2>...>\lambda_r>0,\ \lambda_i^2 , i=1,...,r$ are the eigenvalues of II^T and I^TI, $u_i, v_j, i=1,...,p, j=1,...,q$ are the eigenvectors corresponding to eigenvalues of II^T and I^TI.

iii)Hidden Markov Model Based Methods

Hidden Markov Models (HMM) are a set of statistical models used to characterize the statistical properties of a signal. Rabiner [2][8], provides an extensive and complete tutorial on HMMs. HMM are made of two interrelated processes:

- An underlying, unobservable Markov chain with finite number of states, a state transition probability matrix and an initial state probability distribution.
- A set of probability density functions associated to each state.

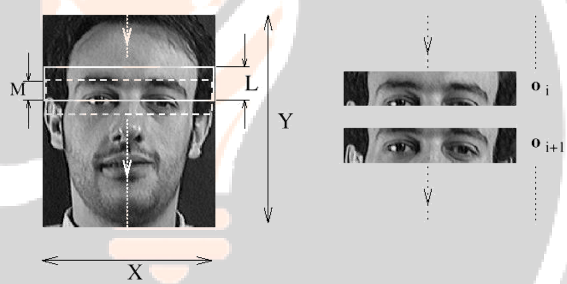


Fig.3 Image sampling technique for HMM recognition

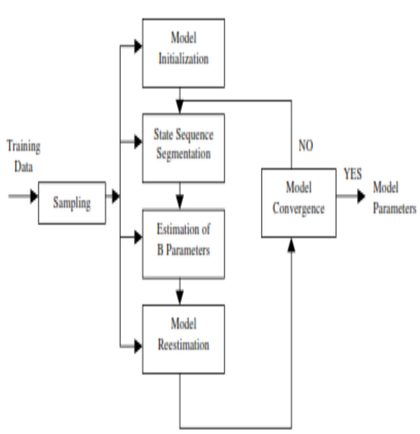


Fig.4 HMM training scheme

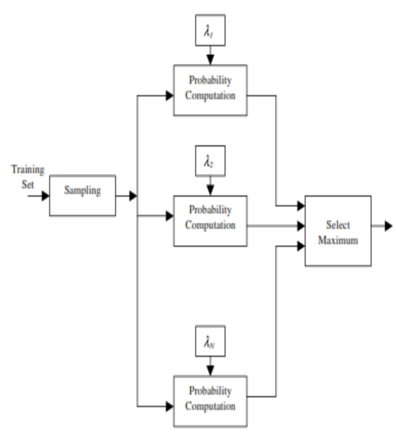


Fig.5 HMM recognition scheme[2]

Comparing recognition results of different face recognition systems is a complex task, because generally experiments are carried out on different datasets. However, the following 5 questions can help while reviewing different face recognition methods:

1. Were expression, head orientation and lighting conditions controlled?
2. Where subjects allowed wearing glasses and having beards or other facial masks?
3. Was the subject sample balanced? Where gender, age and ethnic origin spanned evenly?
4. How many subjects there in database? How many images were used for training and testing?
5. Were the face features located manually?

Answering the above questions contributes to building better description of the constraints within each approach operated. This helps to make a more fair comparison between different set of experimental results. However the most direct and reliable comparison between different approaches is obtained by experimenting with the same database.

Using local features is a mature approach to face recognition problem[2] [11,14, 17, 18, 23, 35, 59, 36, 62]. One of the main motivations of feature based methods is due to: representation of the face image in a very compact way and hence lowering the memory needs. This fact especially gains importance when there is a huge face database. Feature based methods are based on finding fiducial points (or local areas) on a face and representing corresponding information in an efficient way. However, choosing suitable feature locations and the corresponding values are extremely critical for the performance of a recognition system. Searching nature for finding an answer has lead researchers to examine the behavior of human visual system (HVS).

Physiological studies found simple cells, in human visual cortex, that are selectively tuned to orientation as well as to spatial frequency. It was suggested that the response of a simple cell could be approximated by 2 D Gabor filters [2][119]. Over the last couple of years, it has been shown that using Gabor filters as the front-end of an automated face recognition system could be highly successful[2] [23, 36, 35, 27, 32]. One of the most successful face recognition method is based on graph matching of coefficients which are obtained from Gabor filter responses [2][83, 23]. However, such graph matching algorithm methods have some disadvantages due to their matching complexity, manual localization of training graphs, and overall execution time. They use general face structure to generate graphs and such an approach brings the question of how efficient the feature represents the special facial characteristics of each individual. A novel Gabor based method may overcome those disadvantages. 2D Gabor functions are similar to enhancing edge contours, as well as valleys and ridge contours of the image. This corresponds to enhancing eye, mouth, nose edges, which are supposed to be the main important points on a face. Moreover, such an approach also enhances moles, dimples, scars, etc. Hence, by using such enhanced points as feature locations, a feature map for each facial image can be obtained and each face can be represented with its own characteristics without any initial constrains. Having feature maps specialized for each face makes it possible to keep overall face information while enhancing local characteristics. Each member of this family of Gabor wavelets models the spatial receptive field structure of a simple cell in the primary visual cortex. The Gabor decomposition can be considered as a *directional microscope* with an orientation and scaling sensitivity. Due to the end-inhibition property of these cells, they response to short lines, line endings and sharp changes in curvature. Since such curves correspond to some low-level salient features in an image, these cells can be assumed to form a low level feature map of the intensity image (Figure 3.2).

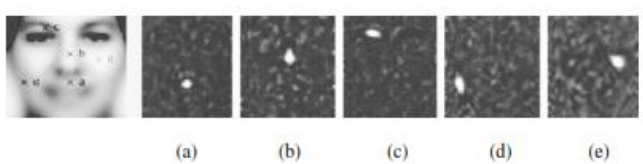


Fig.6 Small set of features can recognize faces uniquely, and receptive fields that are matched to the local features of the face (a) mouth, (b) nose, (c) yebrow, (d) jawline, (e) cheekbone.[2]

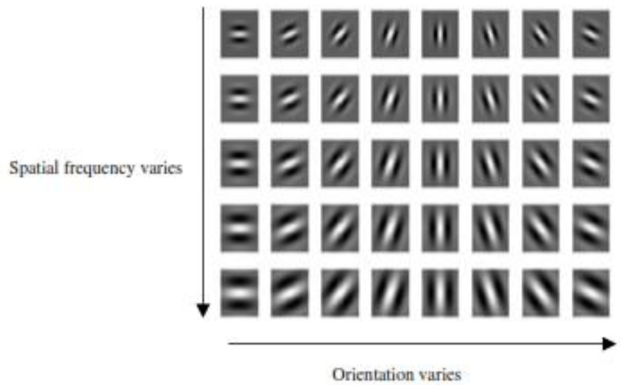


Fig.7 Gabor filters correspond to 5 spatial frequency and 8orientation.[2]

An image can be represented by the Gabor wavelet transform allowing the description of both the spatial frequency structure and spatial relations. Convolving the image with complex Gabor filters with 5 spatial frequency (v =0,…,4) and 8 orientation (μ = 0,…,7) captures the whole frequency spectrum, both amplitude and phase (Figure 3.3). In Figure 3.4, an input face image and the amplitude of the Gabor filter responses are shown.

3. PROPOSED SYSTEM

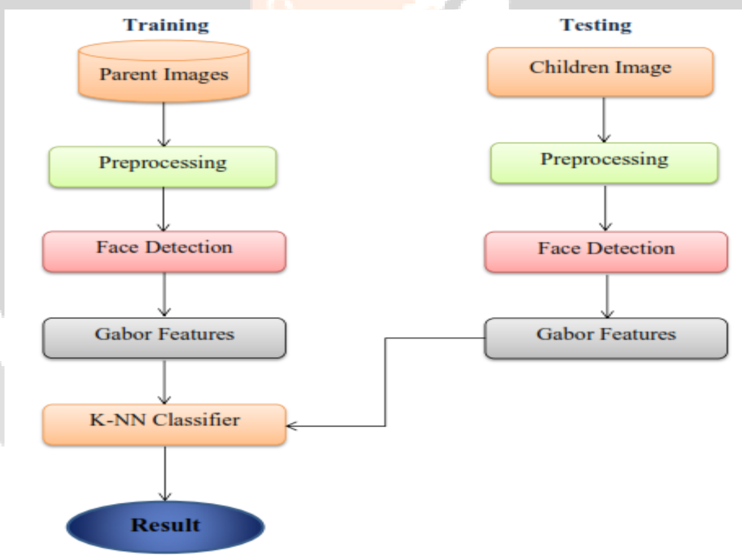


Fig. 8 General Block Diagram of the Proposed System

In the existing system there is a huge work carried out database model which contains images but it consists of optimization problem. Manual segmentation included most of the system so there is problems, noise and errors. Face Recognition and detection provided are not robust to the noise. Also recognition methods is not computed previously which is an important parameter for filtration rate calculation. Acute Detection and Face Recognition classification is not possible. There is no cleared approach toward of face Recognition in the past.

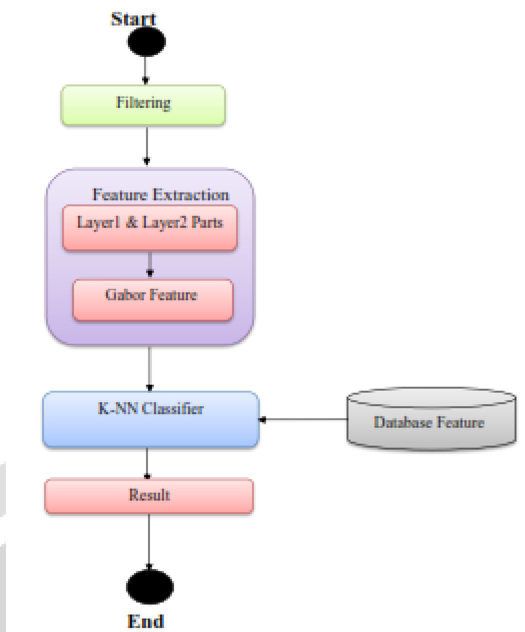


Fig.9 Activity Diagram

I. Preprocessing Using Relaxed Median Filters: In preprocessing method median filter is used to remove noise from the input test images. It is often desirable to be able to perform some kind of noise reduction on an image or signal. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing.

Let $\{X_i\}$ be a*m*-dimensional sequence, where the index i$\in Z^m$ A sliding window is defined as a subset W$\subset Z^m$ of odd size 2*N* C 1. Given a sliding window *W*, define $W_i = \{X_i : r \in W\}$ to be the window located at position **i**.

If we let *X***i** and *Y***i** be the input and the output at location **i**, respectively, of the filter, then we have for the standard median (SM) filter .

*Y***i** = med{*W***i**} = med{*X***i**+**r**: **r** $\in$ *W*}*;* where med*f:*g denotes the median operator Denote by [*W***i**]*.r /; r* = 1*; : : : ;*2*N*+1, the *r th order statistic* of the samples inside the window *W***i:**

$$[W_i]_{(1)} \leq [W_i]_{(2)} \leq \cdots \leq [W_i]_{2N+1)}$$

The relaxed median filter works as follows: two bounds and *u*—lower and upper, respectively—define a sub list inside the [W**i**].

The relaxed median filter with bounds ℓ and u is defined as

$$Y_i = RM_{\ell u}\{W_i\} = \begin{cases} X_i & \text{if } X_{i\in}[[W_i]_{(\ell)}, [W_i]_{(u)}] \\ [W_i]_{(m)} & \text{otherwise} \end{cases}$$

where [*W***i**]*.m/* is the median value of the samples inside the window *W***i**. As it can be easily seen, this new filter is at least as fast as the center weighted median filter, but slightly slower than the standard median filter It is worth noticing that the symmetric relaxed median filter (i.e. in the case where ℓ=2*N* +2-*u*) is the same as the rank conditioned median filter which is a subclass of RCRS filters.

II. Face Detection Using Viola-Jones face detector: The basic principle of the Viola-Jones algorithm is to scan a sub-window capable of detecting faces across a given input image. The standard image processing approach would be to rescale the input image to different sizes and then run the fixed size detector through these images.

This approach turns out to be rather time consuming due to the calculation of the different size images. Contrary to the standard approach Viola-Jones rescale the detector instead of the input image and run the detector many times through the image – each time with a different size. At first one might suspect both approaches to be equally time consuming, but Viola-Jones have devised a scale invariant detector that requires the same number of calculations whatever the size. This detector is constructed using a so-called integral image and some simple rectangular features reminiscent of Haar wavelets. The next section elaborates on this detector.

The first step of the Viola-Jones face detection algorithm is to turn the input image into an integral image. This is done by making each pixel equal to the entire sum of all pixels above and to the left of the concerned pixel.

1	1	1
1	1	1
1	1	1

Input image

1	2	3
2	4	6
3	6	9

Integral image

The integral image.

This allows for the calculation of the sum of all pixels inside any given rectangle using only four values. These values are the pixels in the integral image that coincide with the corners of the rectangle in the input image. This is demonstrated in Figure 3.

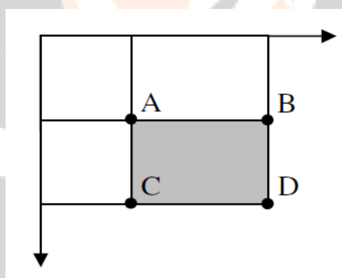


Fig.9 Sum of grey rectangle= D – (B+C) + A

Figure 4.4 - Sum calculation

Since both rectangle B and C include rectangle A the sum of A has to be added to the calculation. It has now been demonstrated how the sum of pixels within rectangles of arbitrary size can be calculated in constant time. The Viola-Jones face detector analyzes a given sub-window using features consisting of two or more rectangles. The different types of features are shown in Figure 4.

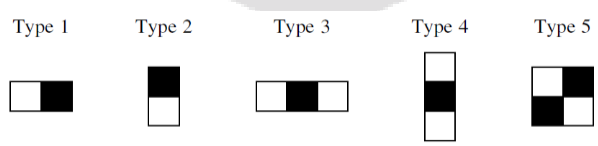


Fig.10 The different types of features

III. Feature Extraction: Extract the gabor feature forr the input image. Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for shape representation and discrimination.It is a linear filter used for edge detection.

Windowed Fourier Transform

$$F^{Fen}(\omega,\tau) = \int_{-\infty}^{+\infty} f(t)\, g(t-\tau)\, e^{-jwt}\, dt$$

- Gaussian function as windowing function

$$G_t(\omega, \tau) = \int_{-\infty}^{+\infty} f(t)\, g_{\propto}(t-\tau)\, e^{-jwt}\, dt$$

- Gabor Transformation :
- Orientation φ
- Frequency f
- Sigma **σ** (standard deviation of gaussian distribution)

IV. K-NN Classifier: The k-Nearest Neighbors algorithm (or k-NN for short) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression.

4. RESULT

Fig.11 (a) Original Image(b) Preprocessing (c) Face Detection (d)Face Patches (e) Result of KIN Relationship Detection After Gabor Extraction.
Fig.12 Enhancing Kin RelationshipResult.

5.CONCLUSION

This paper a novel method for Enhancing KIN Relationship and recognition, applicable to identify Kin relationship System or Kinship model by using face recognition technique splitting the face into subsets like forehead, eyes, nose, mouth, and cheek areas constitute through Gabor Filter on the available Real time Database. Enhancing Kin Relationship in an Images , envisioned as the next generation architecture of Kinship Image processing and Biomedical Enterprise is a talk of the town these days. Although it has revolutionized the computing social networking world, it is prone to manifold Kin relationship varying form Real-time Database in network level to application level Kin ship. In order to keep the Kinship secure and closely, this Kinship need to be controlled.

REFERENCES

[1]"Understanding Kin Relationship in Photo"Siyu Xia, Ming Shao, *Student Member, IEEE*,JieboLuo, *Fellow, IEEE*,and YunFu, *Senior Member*,IEEE TRANSACTIONS ON MULTIMEDIA, VOL. 14, NO. 4, AUGUST 2012.
[2]"FACE RECOGNITION USING GABOR WAVELETTRANSFORM" Kepenekci, Burcu M.S, Department of Electrical and Electronics Engineering Supervisor: A. Aydin Alatan Co-Supervisor: Gözde Bozda_i Akar September 2001, 118 pages.

[3]A. F. Abate, M. Nappi, D. Riccio, and G. Sabatino, "2D and 3D face recognition: A survey," *Pattern Recog. Lett., vol. 28, no. 14, pp. 1885–* 1906, Oct. 2007.
[4]T. Ahonen, A. Hadid, and M. Pietikainen, "Face recognition with local binary patterns," in *Proc. 8th ECCV, N. Sebe, M. S. Lew, and* T. S. Huang, Eds., 2004, pp. 469–481.

[5]T. Ahonen, A. Hadid, and M. Pietikäinen, "Face description with local binary patterns: Application to face recognition," *IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037–2041, Dec. 2006.*

[6]B. Becker and E. Ortiz, "Evaluation of face recognition techniques for application to Facebook," in *Proc. IEEE Int. Conf. Autom. Face Gesture Recog., 2008, pp. 1–6.*

[7]P. N. Belhumeur, D. W. Jacobs, D. J. Kriegman, and N. Kumar, "Localizing parts of faces using a consensus of exemplars," in *Proc. IEEE Conf. CVPR, 2011, pp. 545–552.*

[8]J. R. Beveridge, P. J. Phillips, G. H. Givens, B. A. Draper, M. N. Teli, and D. S. Bolme, "When high-quality face images match poorly," in *Proc. IEEE Int. Conf. Autom. Face Gesture Recog. Workshops, 2011,* pp. 572–578.

[9]V. Blanz and T. Vetter, "Face recognition based on fitting a 3D morphable model," *IEEE Trans. S Anal. Mach. Intell., vol. 25, no. 9, pp. 1063–* 1074, Sep. 2003.

[10]BURCU KEPENEKCI, "Face recognition using gabor wavelete transform"Sep 2001 *pp.118.*American Journal of Medical Genetics Part A 146A:2179–2202 (2008).
[11]A. Gallagher and T. Chen, "Clothing cosegmentation for recognizing people," presented at the IEEE Conf. Comput. Vis. Pattern Recognit., Anchorage, AK, Jun. 2008

[12]T. L. Berg, E. C. Berg, J. Edwards, M. Maire, R. White, Y. whye Teh, E. Learned-miller, and D. A.Forsyth, "Names and faces in the news," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2004, pp.848–854.
[13]J. Yagnik and A. Islam, "Learning people annotation from the web via consistency learning," in *Proc.Int. Workshop Multimedia Inf. Retrieval*,2007, pp. 285–290.
[14]G.Wang, A. Gallagher, J. Luo, and D. Forsyth, "Seeing people in Social context:reconition people and social relationships ,"in proc.Eur.conf.comput vis.,2010,pp.169-18.
[15]S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Trans. Knowledge Data Eng.*, vol. 22, no.10, pp. 1345–1359, Oct. 2010
[16]A.Gallagher and T. Chen, "Understanding images of groups of people," in *Proc. IEEE Conf. Comput.Vis. Pattern Recognit.*, 2009, pp. 256–263.
[17]Ruogu Fang, Kevin D Tang, Noah Snavely, and Tsuhan Chen, "Towards computational models of kinship verification," in Image Processing(ICIP), 2010 17th IEEE International Conference on. IEEE, 2010,pp. 1577–1580.
[18]Siyu Xia, Ming Shao, and Yun Fu, "Kinship verification through transfer learning," in Proceedings of the Twenty-Second international joint conference on Artificial Intelligence-Volume Volume Three. AAAI Press, 2011, pp. 2539–2544.
[19]M. Turk and A. Pentland, "Eigenfaces for recognition," *J. Cognitive Neurosci.*, vol. 3, no. 1, pp. 71–86,1991.
[20]M. Bartlett, J. Movellan, and T. Sejnowski, "Face recognition by independent component analysis,"*IEEE Trans. Neural Netw.*, vol. 13, no.6, pp. 1450–1464, Nov. 2002.
[21]S. Si, D. Tao, and B. Geng, "Bregman divergence-based regularization for transfer subspace learning,"*IEEE Trans. Knowl. Data Eng.*, vol. 22, no. 7, pp. 929–942, Jul. 2010.
[22]A.Gallagher and T. Chen, "Understanding images of groups of people," in *Proc. IEEE Conf. Comput.Vis. Pattern Recognit.*, 2009, pp. 256–263.
[23]R. E. Galper, "Recognition of faces in photographic negative",*Psychonomic Science*, vol. 19, pp. 207-208, 1970.
[24]D. Beymer, "Face recognition under varying pose," *Proc. of 23 Image understanding Workshop*, vol.2, pp. 837-842, 1994.1
[25]S. Carey, R. Diamond, and B. Woods, "The development of face recognition- A maturational component?" *Develop. Psych.*, vol. 16, pp.257-269, 1980.
[26]S. Lin, S. Kung, and L. Lin, "Face Recognition / Detection by Probabilistic Decision-Based Neural Network," *IEEE Trans. Neural Networks*, vol.8, pp.114-132, 1997.
[27]P. Belhumeur, J. Hespanha, and D. Kriegman, "Eigenfaces vs. Fisherfaces:
Recognition using class Specific linear projection," *IEEE Trans. on PAMI*,vol.19, no.7, 1997.
[28]B. Duc, S. Fisher, and J. Bigün, "Face Authentication with Gabor Information on Deformable Graphs," *IEEE Trans. On Image Proc*., vol.8,no.4, pp.504-515, 1999.
[29]Human Reproduction Vol.21, No.7 pp. 1918–1924, 2006 Advance Access publication March 3, 2006.
[30]The ethics of creating children with three genetic parents 1472-6483/$ - see front matter ª 2013, Reproductive Healthcare Ltd. Published by Elsevier Ltd. All rights reserved.http://dx.doi.org/10.1016/j.rbmo.2013.03.006

BIOGRAPHIES

Deepak M Ahire has completed Diploma E & TC From Govt. Polytechnic Nasik and B. E. Electronics from Savitribai Phule Pune University and pursuing M. E. E&TC (VLSI and Embedded System) from Matoshri College of Engineering and Research Centre, Nasik-105.His Field of interest are signal processing, image processing.

Devidas D. Dighe has completed BE Electronics from Savitribai Phule Pune University and ME Electronics (Digital Systems) from Government College of Engineering, Pune, currently pursuing PhD from Amravati University. His Major field of studies are Digital Systems, Signal Processing, Image processing. He is working as Associate Professor and Head in E&TC at Matoshri College of Engineering and Research Centre, Nashik-105.