Human age-group estimation using Curvelet features

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***Abstract*—In this paper we investigate whether human digital fingerprints can be used to estimate human age-groups. To our knowledge,human age-group estimation using digital fingerprints have not been addressed formally. Human age-group estimation can be applied in the areas of online child protection, age based access control or customized services based on estimated age-groups. Motivated by the fact that human digital fingerprint vary in width ranging from birth to adulthood but pattern remains the same, we have developed a procedure to extract discriminating features using Curvelet Transform to classify fingerprints into three age groups. Experimental results show the feasibility of our method which can be used to protect children over cyberspace by automatically customizing their access according to their age-group.**

Keywords:Digital Fingerprints;Biometric;Age-group Estimation; Online child Protection;Curvelet features

I. INTRODUCTION

Cyber - the world of applications and services over computer networks or internet is prone to security issues. Tools that are used for attacks are easily available over the internet and can be downloaded free of cost. This ease of access and usability, and anonymity that is easily achievable by the attacker are the root causes of the problem. This makes researchers give more impetus to the field of cyber security and give significant attention to remove the obstacles that come their way to secure the current and future users of internet. Cyber security itself is a vast area covering security of everything that relies on internet and computers. Out of the number of issues, child protection over cyber world is one of the important aspects.

Immature users, usually children, who are unknown to dark side of the cyber world, are easy targets for attackers. This means thereby that children who are active on internet can become easy prey to attackers. Therefore several countries around the globe have cyber security standards and mechanisms to make their cyber space a secure space. Ubiquitous availability of wireless communications devices and internet is increasing manifold in India and so are the related cyber security issues. When taking into consideration the particular geographical region for the present study (India), Internet penetration level has climbed with 0.1 percent penetration rate since 1998 to 8.5 percent in 2010[1]. The United Nations General Assembly in the year 1989 has given its mandate and approved the UN convention on the Child Rights. Particularly Article 17 gives significant attention to the protection of children from the material and information which might be injurious to their well being[2].

With the advancement in the field of pattern recognition and computer vision, computer-based automatic age estimation has become a particularly interesting research topic recently because of its applicability in various real world applications, such as surveillance monitoring and security control [3], [4], electronic customer relationship management (ECRM)[5], [6] , biometrics[7], [8] and entertainment.

Age group estimation by automated systems has been deemed to be a challenging problem by existing methods since people from different races have varying rates of aging process [3], [9]. This is not only governed by the peoples' race and genes but by many other factors such as working environment, living style, sociality and health condition [10], [11] to name a few. Existing age group estimation methods use facial images for estimation and analysis[12], [13], [14]. In a situation when we require age group estimation and authentication, fingerprints are the most suited biometric modality to achieve this task. Age-group estimation through fingerprints can be of great use in areas where we are not actually concerned about the identity of a particular individual, but we want to know under which age group his or her age lies. It has been reported in a study done in the area of paleontology that fingerprints contain discriminative features based on which we can differentiate between children and adults[15].

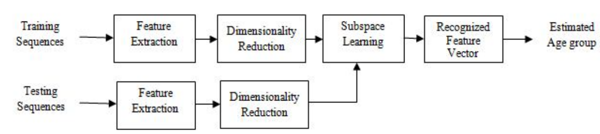

Fig. 1. Flowchart of proposed fingerprint-based age group estimation

Based on these findings we have used digital fingerprints in this work for age-group estimation. Our foremost objective is to identify children's fingerprints and differentiate them from those of an adult. The definition of the age of child is adopted according to Indian law that is up to 14 years for fixing criminal responsibility. [16]. Our experimental results clearly showcased the feasibility of digital fingerprints in estimating human age group so that we can easily classify fingerprints by differentiating child's fingerprints from that of an adult.

The paper is organized as follows: In Part II, we have discussed about the Curvelet transform based feature extraction and our proposed approach for age-group estimation. Part III describes our experimental setup Part IV deals with Results and discussion and Part V concludes the paper.

II. Proposed Approach

The approach we followed for estimating human age-group using fingerprints is shown in the flow chart depicted in Fig.1.We extracted the discriminating features of fingerprints for training and testing sequences using Curvelet coefficients.The features so extracted were having very high dimensionality.So to remove this high dimensionality we projected the extracted features into principal component (PCA) subspace[17].At last we performed child identification or age group estimation using *K*-nearest neighbour(KNN)[18]classifier and arrive at the fingerprint age-group.

A. Curvelet Transform

According to mazundar et al. that any image representation as per human visual system should have properties of scaling, multi-resolution, localization, critical sampling, anisotropy and directionality[19].Wavelet transform provides localization,multi-resolution and critical sampling but lacks in capturing the features pertaining to directionality and anisotropy .

1) Directionality means image can be represented in terms of orientation in different directions.
2) Anisotropy means representation of image of different elongated shapes of varying aspect ratio.

These features are very well captured by curvelet transform[20] [21].The curvelet transform was carried out by performing multi-scale filtering in the continuous domain thereafter block ridgelet transform is carried out on each image[22].

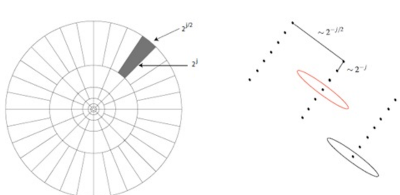

Fig. 2. Curvelet frequency and space tiling

In figure 2, Left part of the figure shows the frequency space tiling while the shaded area depicts the generic wedge whereas right part shows the grid formation at the given scale and direction[20].

Curvlets transforms provide us multi-scale and multi-resolution transformation but for human age-group classification problem using fingerprint biometric we only use multi-resolution properties of curvelets transform.Next we will discuss Ridgelet transform and its interplay in implementing the curvelet transform.

B. Ridgelet Transform

The Ridgelet transform is equivalent to applying 1D wavelet transform to the slices of Radon transform. Since in Ridgelet Transform the lines depicted in the original image is represented at peak position in transformed image at the corresponding line parameter, this is the basic reason why this transform is used in many line detection applications.A block diagram of the flow graph of Discrete Ridgelet Transform is shown in figure 3 below.

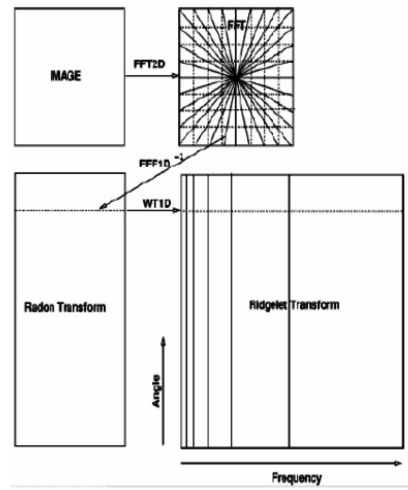

Fig. 3. Basic working of Discrete Ridgelet Transformations

The Radon transform is given as:

$$R : L^2(R^2) \longrightarrow L^2([0, 2\pi]), L^2(R) \quad (1)$$

$$R_f(\theta, t) = \iint f(x_1, x_2)\delta(x_1 cos\theta + x_2 sin\theta - t)dx_1 dx_2 \quad (2)$$

where δ is the Dirac delata.

The ridgelet transformation coefficients R_f (a,b,θ) of an image are given by:

$$R_f(a, b, \theta) = \int Rf(\theta, t)a^{1/2}\psi(t - b/a) \quad (3)$$

Here variable t is varying while the angular variable θ is constant.

C. The Fast Discrete Curvelet Transform(FDCT):Feature Extraction

The FDCT follows a parabolic scaling relation, which depicted at a scale of 2^{-j},having an envelope which is positioned along a sides of length $2^{-j/2}$and width 2^{-j}.In this paper a faster, simpler and less redundant method is used as fast 2D discrete curvelet transform (FDCTs).Its takes the Cartesian array as input in the form $f[t1, t2], 0 \leq t1, t2 < n$ and the coefficients $c^D(j, l, k)$, which is defined as below

$$c^D(j, l, k) = \sum_{0 \leq t1, t2 < n} f[t1, t2]\psi^D_{j,l,k}[t1, t2] \quad (4)$$

Here $\psi^D_{j,l,k}$ depicts a curvelet transformation(digital) and D means digital.Emmanuel Candes et al. reported two novel methods for fast discrete curvelet transform FDCTs.

1) Curvelets via wrapping ,
2) Curvelets via Unequispaced FFT

Both the above algorithms shows same running time complexity as $O(n^2 logn)$ for $n \times n$ Cartesian arrays,that is, n by n image.In comparison with FFT the computation time of FDCT via USFFT is 6-10 times more and also requires $O(n^2)$

storage,where n^2 is the total number of pixels in the image object.While doing curvelet transform initially the original image is decomposed into series of sub-bands to separate objects of different scales thereafter each and every sub-band is analyzed by using local block ridglet transform.The output of this algorithm is $J+1$ sub-band arryas of size nxn.

1) FDCT via USFFTs: The Algorithm:

1) At the onset we apply 2D FFT on an image object and obtain Fourier coefficients

$$\hat{f}[n1, n2], -\frac{n}{2} \leq n1, n2 < \frac{n}{2} \tag{5}$$

2) Afterwards for each pair of scale and angle (j,l) we resample the $\hat{f}[n1,n2]$ to obtain sampled values of form $\hat{f}[n1, n2 - n1tan\theta_l]$ for $(n1,n2)\epsilon P_j$
3) Then the parabolic window $\tilde{U}_j$ called Cartesian window (as shown in figure 4) is multiplied with the sheared object ˆ,this localizes ˆ close to the parallelogram with the orientation θ_l,which provides

$$\tilde{f}_{j,l}[n1, n2] = \hat{}[n1, n2 - n1tan\theta_l]\tilde{U}_j[n1, n2] \tag{6}$$

4) At last the discrete coefficients $c^D(j,l,k)$ are collected by taking the inverse 2D FFT of each $\tilde{f}_{j,l}$.

   $\tilde{U}_j[n1,n2]$ is the rectangular Cartesian window of length $L_{1,j}$ and width $L_{2,j}$.Further the length $L_{1,j}$ equals $L_{1,j} = 2^j$, because of the parabolic scaling, and width $L_{2,j}$ equals $L_{2,j} = 2^{j/2}$ as shown in figure 2.
   $P_j$is defined as

$$P_j = (n1, n2) : n_{1,0} \leq n1 < n_{1,0} + L_{1,j}, \\ n_{2,0} \leq n2 < n_{2,0} + L_{2,j} \tag{7}$$

   where $(n_{1,0}, n_{2,0})$ is the index value of the pixel found at the bottom-left of the $\tilde{U}_j[n1,n2]$, the rectangular Cartesian window. Thus with above steps of implementing FDCT using USFFT can simply be equated as

$$c^D(j,l,k) = \sum_{n1,n2\epsilon P_j} \hat{f}[n1, n2 - n1tan\theta_l] \\ \tilde{U}_j[n1,n2]e^{i2\pi(k1n1/L_{1,j})+k2n2/L_{2,j}} \tag{8}$$

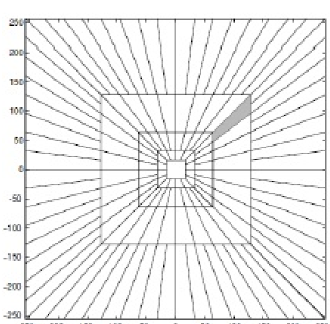

Fig. 4. The figure depicts the rectangular frequency tiling of an image at 5 level curvelet transform. The windows of $\tilde{U}_j[n1,n2]$ which precisely localize the fourier transform near the sheared edges obeying the parabolic scaling.

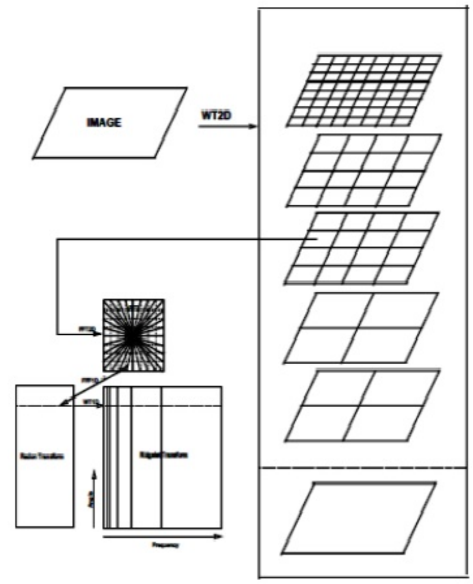

Fig. 5. Block diagram depicting the flow of Discrete Curvelet Transforms, the flow graph illustrates the image decomposition into various sub-bands which is then followed by spatial partitioning of each sub-bands.

Curvelets coefficients thus extracted is taken as feature vector of that image which is stored for later training and testing purpose.

2) ***Learning Algorithm***:

Input: fingerprint images X_i with known age class A_i
Output: Dimensionally reduced Training and Testing sequence matrix
Algorithim:
Step 1(Initialization): Let X_i be the image in Age class A_i.
Step 2(Feature Extraction):

- Generate Curvelet coefficients using ridgelet transform for different orientation and scales .These coefficients will form the feature vector C_i for our image X_i .

Step 3: Repeat above steps for each image X_i corresponding to age class A_i

Step 4(Dimension reduction & partition):

- After every Curvelet feature vector C_i of every image X_i in class A_i is collected as feature matrix.

- We partition the feature matrix into training sequence matrix and testing sequence matrix.

- Project both training sequence matrix and testing sequence matrix into PCA subspace.

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*3) **Classification Algorithim**:*

Input: Training and Testing sequence matrix .
Output: Estimated Age class A_i for the test image sequence T_i.
Algorithim:
step 1(Initialization): Let T_i be the test vector of image X_i and M be the learned feature Matrix.

step 2(Classification

- Feed test vector T_i and learning sequence matrix M into K-NN classifier

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III. EXPERIMENTAL RESULT

Though there are various fingerprint databases available,they do not contain age varying discriminating features.For training and testing purpose we have developed inhouse database of digital fingerprints in three age groups:

- 6-10 $\longrightarrow$ (360 fingerprints of 600 dpi each)
- 10-14$\longrightarrow$ (360 fingerprints of 600 dpi each)
- 14-18$\longrightarrow$ (360 fingerprints of 600 dpi each)

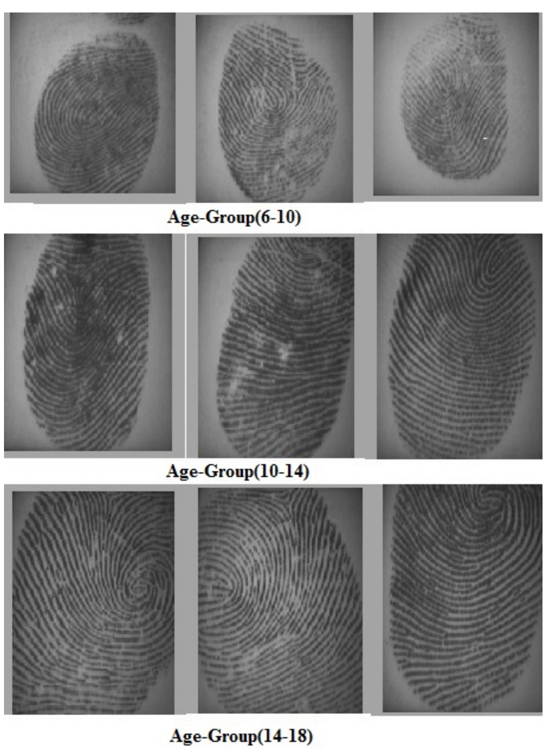

Fig. 6. Fingerprint image dataset for different age-group

360 fingerprint images are taken(180 males+180 females)for each age group.Fingerprints are numbered on the basis of following numbering scheme shown in Fig.7.

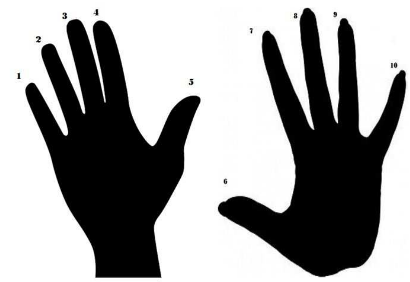

Fig. 7. Numbering used to store the fingerprints

Descriptice Statisticsl	**Age groups**		
	6-10	**10-14**	**14-18**
Mean Age	7.171429	10.36363636	15.08
Standard Error	0.198675	0.162859325	0.148021
Median	7	10	15
Standard Deviation	1.175378	1.080286549	1.046666
Sample Variance	1.381513	1.167019027	1.09551
No of Images	360	360	360

TABLE I. STATISTICS OF THE SAMPLES.

Table I shows the descriptive statistics of our sample data collected. 250 fingerprints were used for learning sequence and 100 for training sequence.The database so collected contains the fingerprints of both the genders in equal proportions so that there is no age distribution bias. we have checked our approach on following 8 criteria:

1) When all fingers are used for learning and testing sequence.
2) When only the little fingers are used for learning and testing sequence.
3) When only ring finger is used for learning and testing purpose.
4) When only middle finger is used for learning and testing purpose.
5) When only index fingers are used for learning and testing purpose.
6) When only thumbs are used for learning and testing purpose
7) When all the fingers except thumbs are used for learning and testing purpose.
8) When we use only cropped fingerprints($128 * 128$ pixels)for learning and testing purpose.

Fig 8 shows recognition rates for all the three classes and when all the classes are taken together.From the fig 8 we conclude that little finger gives the best result for all the three classes taken together.For all the three classes we get the best result for the age-group of 6-10 and for this age group we get the best results when we use thumb only for learning and testing sequence.

Fig 9 shows the cluster diagram for all the three age groups when taking all the fingerprints together.Cluster encircled within the ellipse is the cluster for the age group 6-10 which clearly shows that fingerprints in this age-group is more identifiable than other age groups.

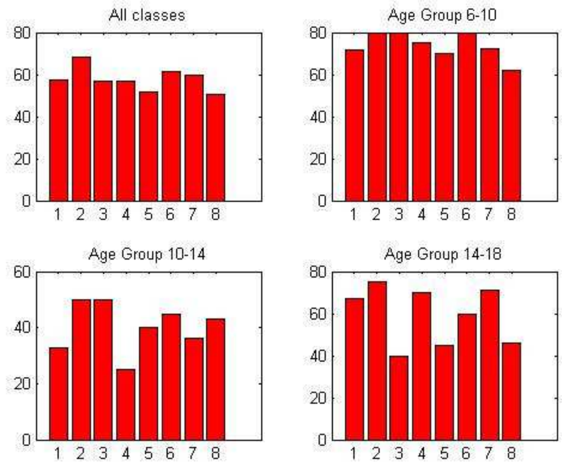

Fig. 8. Recognition rates for all classes jointly as well as separately on all 8 criteria

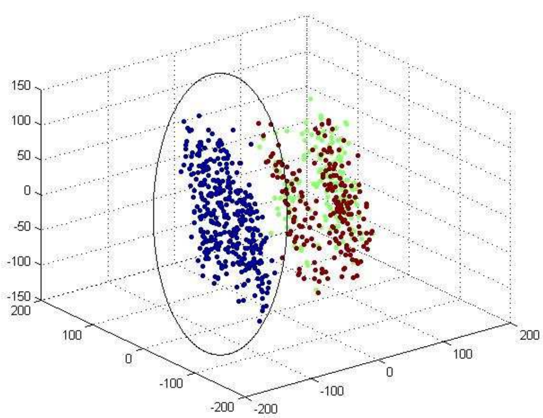

Fig. 9. Clusters for all three age groups when all fingerprints taken together.

IV. Result and Discussion

From the above experimental results we have following observations:

1) Fingerprints can be used to estimate age-groups.
2) We have designed our algorithm mainly to save on computational complexity which is quite practical .Our algorithm's time complexity is linear with number of images in each age-group.We consider a local run of our database of 250 images for training and 100 images for testing.Total classification computation time is **2.1928** seconds on a common PC(Intel Core 2 duo at 2.4GHz)
3) If we divide our age-group into just two classes, one below 14 and one above 14, Fig 9 depicts that if there would have been only two classes, the data points would have been linearly separable.Thus higher classification rates would have been achieved.

V. Conclusion

Above experimental results have proved beyond doubt the efficacy of using digital fingerprints to estimate age-groups.This methodology can be extended further for precise age estimation techniques.With more number of samples of different geographical locations the results can be improved.This result also proves the fact that fingerprints can be used to identify children in an automatic fashion.This methodology can be developed further to identify children online through their fingerprints as fingerprints scanner are getting embedded into user computer system as a measure for biometric passwords.Thus this methodology can be applied so that children online risk exposure can be limited as far as possible.

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