Finger Knuckleprint based Recognition System using Feature Tracking

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Problem Definition

- Biometric based Personal authentication systems are in demand.
- Several biometric traits are studied such as face, iris, palmprint, ear, fingerprint etc.
- Biometrics based PAS:

  Authentication Problem One to One matching and decide using thresholding (Verification).

  Identification Problem One to Many matching and best matching scores and corresponding subjects are reported (Recognition problem)

Several Biometric Traits and Challenges

- FACE: Expression, Illumination, Pose, Occlusion, Ageing.
- IRIS: Occlusion, Specular reflection, User Co-operation, Difficult to acquire and Very expensive acquisition sensors.
- FINGERPRINT: Fail to acquire specially for cultivators and workers, low public acceptance as connected to criminals and Dirty.
- EAR: Occlusion, Illumination.
- PALMPRINT: Non-uniform illumination, Expensive acquisition and Require too much pressure.
- NEW TRAITS: Knuckleprint, Footprint, Vein Patterns etc.

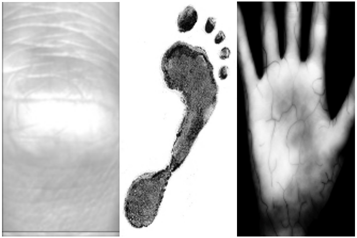


Figure: New Biometric Traits

Motivation

- Out of the all the traits listed in previous slide fingerprint is used and accepted widely worldwide. But stills cons are Fail to acquire specially for cultivators and workers, low public acceptance as connected to criminals and Dirty.

Pros of Knuckleprint

- No expression, pose and ageing.
- No occlusion, less cooperation an inexpensive sensors.
- Cultivators and workers have the equally good quality prints as others.
- Also never ever got connected to criminals.

PolyU Knuckleprint Database

- Total Distinct Subject = 165
- 4 finger per subject (LI,LM,RI,RM) = 165 x 4 (Total 660 distinct fingers)
- 12 images per subject = 660 x 12 (Total 7920 images)

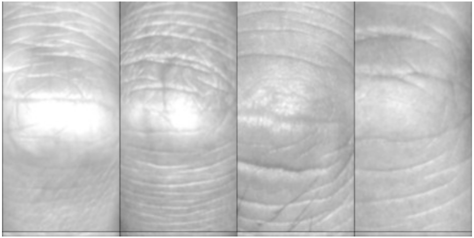


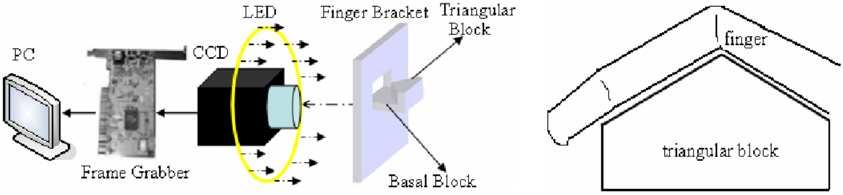
Figure: Original Database Sample Images

Previous knuckleprint based personal authentication system

- **Finger Knuckle-Print Verification Based on Band-Limited Phase-Only Correlation**
  Zhang, Lin, Zhang, Lei, and Zhang, David
  Computer Analysis of Images and Patterns, volume 5702, Springer Berlin Heidelberg, 141-148, Eds: Jiang, Xiaoyi, and Petkov, Nicolai, 2009.
- **Finger Knuckle Print**
  A New Biometric Identifier
  Zhang, Lin, Zhang, Lei, and Zhang, David.
- **Online finger-knuckle-print verification for personal authentication**
  Zhang, Lin, Zhang, Lei, Zhang, David, and Zhu, Hailong
  Pattern Recogn. 43, volume 43, Elsevier Science Inc., 2560 - 2571, July 2010.

KNUCKLE (Global Feature BLPOC - 2009) [3]

- Novel FKP acquisition device is used to capture FKP image.
- Local Convex Direction (LCD) map is computed to define a reference coordinate system to register images and to extract a ROI for feature extraction and matching.
- FKP images are matched using *BLPOC* method exploiting the global features.



(a) (b)

KNUCKLE (Global Feature BLPOC - 2009) [3]

- For feature extraction POC and BLPOC are used exactly in the same manner as in IRISCODE.
- Phase Only Correlation is defined as:

$$P_{gf}(m,n) = \frac{1}{MN} \sum_{u=-M_0}^{M_0} \sum_{v=-N_0}^{N_0} R_{GF}(u,v) e^{j2\pi(\frac{mu}{M}+\frac{nv}{N})} \quad (1)$$

- Band Limited Phase Only Correlation is defined as:

$$P_{gf}(m,n) = \frac{1}{L_1 L_2} \sum_{u=-k_1}^{k_1} \sum_{v=-k_2}^{k_2} R_{GF}(u,v) e^{j2\pi(\frac{mu}{L_1}+\frac{nv}{L_2})} \quad (2)$$

- BLPOC exhibits a higher correlation peak than that of the original POC function hence provides much higher discrimination capability than the original POC function.

KNUCKLE (Local Feature Gabor - 2009)

- Competitive code [1] is used for feature extraction and rest remained to be the same.
- Orientation information is extracted using a bank of gabor filters sharing same parameter except the orientations.
- Only real part of filter is used for feature extraction.

$$Compcode(x, y) = ArgMin_j(I_{ROI}(x, y) * G_R(x, y, \omega, \theta_j)) \tag{3a}$$

where

$$G_R = Real\ part\ of\ filter\ G \tag{3b}$$

$$\theta_j = \frac{j\pi}{6}\ is\ the\ orientation\ of\ the\ filter\ \{j \in (0 \ldots 5)\} \tag{3c}$$

- Angular matching is used for matching on extended dataset so as to achieve robustness towards translation.

KNUCKLE (ImCompcode and Magcode- 2010)[4]

- They combined both orientation and magnitude information for feature extraction using bank of gabor filters.
- Compcode is modified to ImCompCode and used along with MagCode.
- Angular distance is used for matching.
- Final score is obtained by fusing the results obtained by both *ImCompcode* and *MagCode* using weighted sum rule .
- Pixels on plain areas does not have a dominant orientation. Hence do not provide robust features.
- Such pixels do not have much variation in their gabor responses. They are detected and are not considered while coding the magnitude.

Proposed System : STEPS

- Image Enhancement: Edge based local binary pattern (ELBP).
- Feature Extraction: Good corner features are extracted (Shi and Tomasi features).
- Feature Matching: A measure features tracked successfully (FTS) is proposed that can estimate how many features are tracked correctly by estimating how well Lucas Kanade tracking algorithm is working.

Proposed System - Enhancement (ELBP)

- Apply horizontal direction sobel edge operator on A to obtain its vertical edge map.
- ELBP value for every pixel $A_{j,k}$ in the vertical edge map is evaluated, defined as a 8 bit binary number S whose i^{th} bit is

$$S_i = \begin{cases} 0 & \textbf{if} \quad (Neigh[i] < threshold) \\ 1 & \textbf{otherwise} \end{cases} \tag{4}$$

where $Neigh[i], i = 1, 2, ...8$ are the horizontal gradient of 8 neighboring pixels centered at pixel $A_{j,k}$.

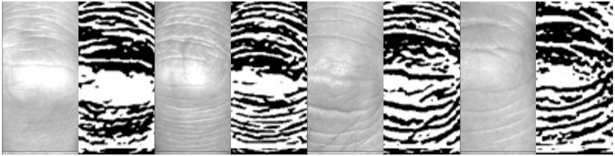


Figure: Original and Transformed (*edgecodes*) knuckleprint Images

Proposed System - Feature Extraction (Good Corner Features)

- Corners have strong derivative in two orthogonal directions and can provide enough information for tracking.
- Eigen values of autocorrelation matrix M is used to calculate good corner features.
- Matrix M can be defined for any pixel at i^{th} row and j^{th} column of *edgecode* as:

$$M(i,j) = \begin{pmatrix} A & B \\ C & D \end{pmatrix} \tag{5}$$

such that

$$A = \sum_{-K \le a,b \le K} w(a,b).I_x^2(i+a, j+b)$$

$$B = \sum_{-K \le a,b \le K} w(a,b).I_x(i+a, j+b).I_y(i+a, j+b)$$

$$C = \sum_{-K \le a,b \le K} w(a,b).I_y(i+a, j+b).I_x(i+a, j+b)$$

$$D = \sum_{-K \le a,b \le K} w(a,b).I_y^2(i+a, j+b)$$

where $w(a,b)$ is the weight given to the neighborhood, $I_x(i+a, j+b)$ and $I_y(i+a, j+b)$ are the partial derivatives sampled within the $(2K+1) \times (2K+1)$ window centered at each selected pixel.

Proposed System - Matching (Lukas Kanade Tracking) [2]

Feature at location (x, y) at time instant t with intensity $I(x, y, t)$ and has moved to the location $(x + \delta x, y + \delta y)$ at time instant $t + \delta t$.

- **Brightness Consistency**: Features do not change much for small δt

$$I(x, y, t) \approx I(x + \delta x, y + \delta y, t + \delta t) \tag{6}$$

- **Temporal Persistence**: Features moves only within a small neighborhood for small δt. Using the Taylor series and neglecting the high order terms, one can estimate $I(x + \delta x, y + \delta y, t + \delta t)$ as

$$\frac{\delta I}{\delta x}\delta x + \frac{\delta I}{\delta y}\delta y + \frac{\delta I}{\delta t}\delta t = 0 \tag{7}$$

Dividing both sides of Eq 7 by δt one gets

$$I_x V_x + I_y V_y = -I_t \tag{8}$$

where V_x, V_y are the respective components of the optical flow velocity for pixel $I(x, y, t)$ and I_x, I_y and I_t are the derivatives in the corresponding directions.

Proposed System - Matching (Lukas Kanade Tracking) [2]

Spatial Coherency: Estimating unique V_x and V_y for every feature point is an ill-posed problem.

- Spatial coherency assumes that a local mask of pixels moves coherently. Hence one can estimate the motion of central pixel by assuming the local constant flow.
- LK gives a non-iterative method by considering flow vector (V_x, V_y) as constant within 5×5 neighborhood (*i.e* 25 neighboring pixels, $P_1, P_2 \ldots P_{25}$) around the current feature point (center pixel) to estimate its optical flow.
- The above assumption is reasonable and fair as all pixels on a mask of 5×5 can have coherent movement.

Proposed System - Matching (Lukas Kanade Tracking)

- we have obtained an overdetermined linear system of 25 equations which can be solved using least square method as

$$\underbrace{\begin{pmatrix} I_x(P_1) & I_y(P_1) \\ \vdots & \vdots \\ I_x(P_{25}) & I_y(P_{25}) \end{pmatrix}}_{\text{C}} \times \underbrace{\begin{pmatrix} V_x \\ V_y \end{pmatrix}}_{\text{V}} = - \underbrace{\begin{pmatrix} I_t(P_1) \\ \vdots \\ I_t(P_{25}) \end{pmatrix}}_{\text{D}} \tag{9}$$

where rows of the matrix C represent the derivatives of image I in x, y directions and those of D are the temporal derivative at 25 neighboring pixels. The 2×1 matrix $\widehat{\mathbf{V}}$ is the estimated flow of the current feature point determined as

$$\widehat{\mathbf{V}} = (C^T C)^{-1} C^T (-D) \tag{10}$$

The final location $\widehat{\mathbf{F}}$ of any feature point can be estimated using its initial position vector $\widehat{\mathbf{I}}$ and estimated flow vector $\widehat{\mathbf{V}}$ as

$$\widehat{\mathbf{F}} = \widehat{\mathbf{I}} + \widehat{\mathbf{V}} \tag{11}$$

Proposed System - Matching (FTS: Features Tracked Successfully)

- Let a be an array of corner features in an *edgecode* of knuckleprint image A.
- Then $a(i,j)$ is some corner feature in *edgecode* of knuckleprint image A. Let LK Tracking estimates its location in *edgecode* of B at $b(k,l)$.
- Then $a(i,j)$ is tracked successfully/unsuccessfully is decided as:

$$Tracked(a(i,j), edgecode_B) = \begin{cases} 1 & \textbf{if } ||a(i,j), b(k,l)|| \leq TH_d \\ & \textbf{and } \; T_{Error} \leq TH_e \\ \\ 0 & \textbf{otherwise} \end{cases} \tag{12}$$

where T_{Error} is the tracking error.

Proposed System - Matching (FTS: Features Tracked Successfully)

- Features Tracked Successfully (fts) for a to $edgecode_B$ can be defined by

$$fts(a, edgecode_B) = \sum_{\forall a(i,j) \in a} Tracked(a(i,j), edgecode_B)) \qquad (13)$$

- Finally, the average number of features tracked successfully (FTS) for a to $edgecode_B$ and b to $edgecode_A$ is defined by

$$FTS(A, B) = \frac{1}{2} \times [fts(a, edgecode_B) + fts(b, edgecode_A)] \qquad (14)$$

Results

- Experiments done on each finger individually.
- First 6 images are taken as gallery and rest are taken as probe images.
- Correct Recognition Rate is defined as:

$$CRR = \frac{N_1}{N_2} \tag{15}$$

where N_1 denotes the number of correct (Non-False) top best match of FKP images and N_2 is the total number of FKP images in the query set.

- Equal error rate (EER) is the value of FAR for which FAR and FRR are equal.

$$EER = \{FAR|FAR = FRR\} \tag{16}$$

Table: Identification Performance

	CRR % Left Index	CRR % Left Middle	CRR % Right Index	CRR % Right Middle
Proposed	**0.9910**	**0.9926**	**0.9936**	**0.9922**

Results

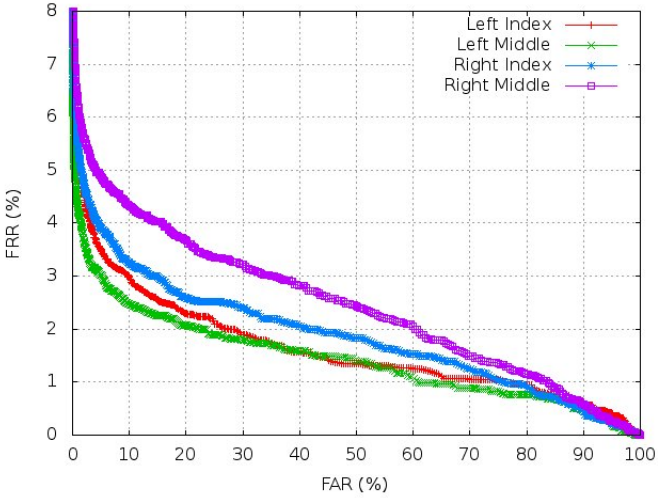


Figure: Verification Performance

Conclusion and Future work

- Bigger database should have to be developed and tested.
- Its performance along can be compared with fingerprints (workers and cultivator subjects).
- New features can be explored.

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Competitive coding scheme for palmprint verification.
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In *International Joint Conference on Artificial Intelligence*, IJCAI, pages 674–679, 1981.

Lin Zhang, Lei Zhang, and David Zhang.
Finger-knuckle-print verification based on band-limited phase-only correlation.
In Xiaoyi Jiang and Nicolai Petkov, editors, *Computer Analysis of Images and Patterns*, volume 5702 of *Lecture Notes in Computer Science*, pages 141–148. Springer Berlin / Heidelberg, 2009. 10.1007/978-3-642-03767-2_17.

Lin Zhang, Lei Zhang, David Zhang, and Hailong Zhu.
Online finger-knuckle-print verification for personal authentication.

Pattern Recogn., 43:2560–2571, July 2010.