How Quality Influences Human-Computer Face Recognition

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Overview

- Rationale
- Background on the FRGC
- Testing humans
- Results
- Conclusions and implications

Problem

- Are face recognition algorithms ready for applications?
 - enormous improvements over last decade
 - accuracy of algorithms tested intensively
- How accurate do they have to be to be useful?
 - meet or exceed human performance

Why?

- Humans are the competition!
 - Human-machine comparisons virtually never done
- Putting algorithms in the field
 - Impact on security?
- Relative level of performance
 - "Easy" images
 - "Hard" images

Face Recognition Grand Challenge

Independent Evaluation



Technology Development



May 2004 -

Mar 2006

Independent Evaluation



Jan 2006 –

Dec 2006

FRGC Objective



The primary objective of the FRGC is to:

Develop still and 3D algorithms to improve performance an order of magnitude over FRVT 2002

FRGC

Select Point to Measure

- Verification rate at :
 - False accept rate = 0.1%
- Current:
 - 20% error rate (80% verification rate)
- · Goal:
 - 2% error rate (98% verification rate)



FRGC Modes Examined



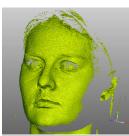


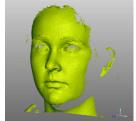
Single Still





Outdoor/ Uncontrolled





3D Single view



3D Full Face



Multiple Stills

FRGC Experiments



Exp 1: Controlled indoor still versus indoor still



Exp 2: Multiple still versus multiple still



Exp 3: 3d versus 3D **3t - Texture only** 3s - Shape only





Exp 4: Uncontrolled still versus indoor still



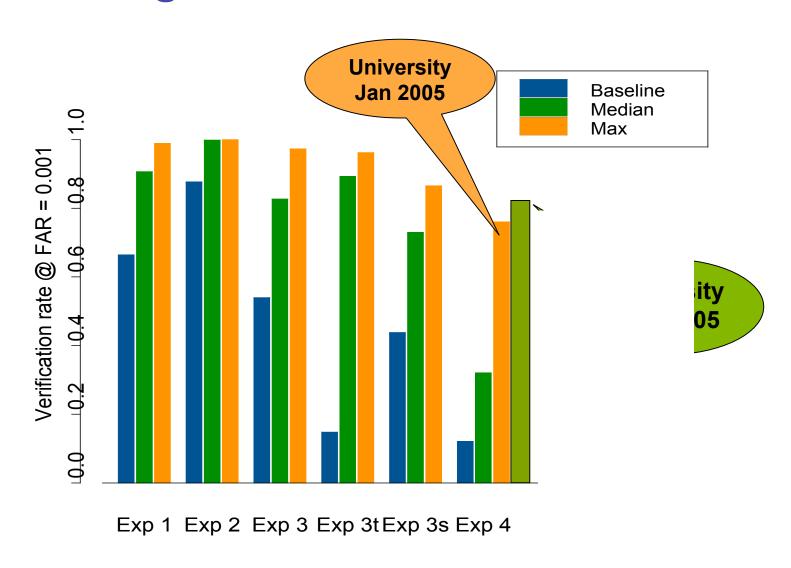


Size of Experiments

Exp.	Target set size	Query set size	No. Sim Scores (million)
1	16,028	16,028	257
2	4,007	4,007	16
3	4,007	4,007	16
4	16,028	8,014	128



FRGC Progress



Human-Computer Comparison

Human-Machine Comparisons

- Same image pairs from Exp. 4
- Seven state-of-the-art algorithms
 - 4 from industry
 - 3 from academic institutions
- Comparisons
 - 120 difficult face pairs
 - 120 easy face pairs

Sampling

- homogeneous
 - caucasian males/females 20-30 yrs
 - comparisons made on identity not
 - age, race, sex

Comparing Humans and Algorithms

- problem
 - 128 million face pairs?
- sample face pairs
 - most difficult
 - easiest

Easy and Difficult

- PCA Baseline Algorithm
 - scaled and aligned images (SAIC)
 - available and widely used since the 90's
 - but not state-of-the-art

Selecting Easy/Difficult Pairs

- "easy" match pairs
 - 2 "similar" images of same person
 - similarity scores > 2 sd above mean similarity of match pairs
- "difficult" match pairs
 - 2 "dissimilar" images of same person
 - similarity scores < 2 sd below mean similarity of match pairs
- "easy" no-match pairs
 - 2 "dissimilar" images of different people
 - similarity scores < 2 sd below mean similarity of no-match pairs
- "difficult" no-match pairs
 - 2 "similar" images of different person
 - similarity scores < 2 sd *above* mean similarity of no-match pairs



Methods

- Stimuli
 - 240 pairs of faces
 - 120 male pairs
 - 60 easy
 - 60 difficult
 - 120 female pairs
 - 60 easy
 - 60 difficult

Procedure

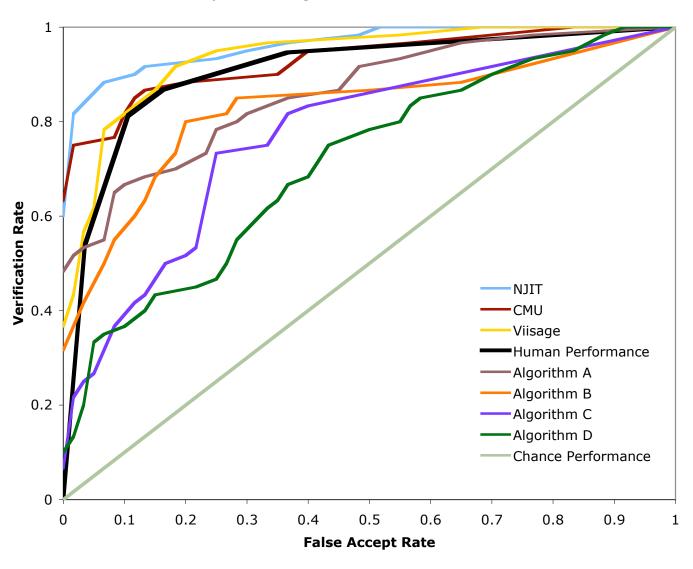




Human subject raters respond...

- 1. sure they are the same person
- 2. think they are the same person
- 3. not sure
- 4. think they are not the same person
- 5. sure they are not the same person

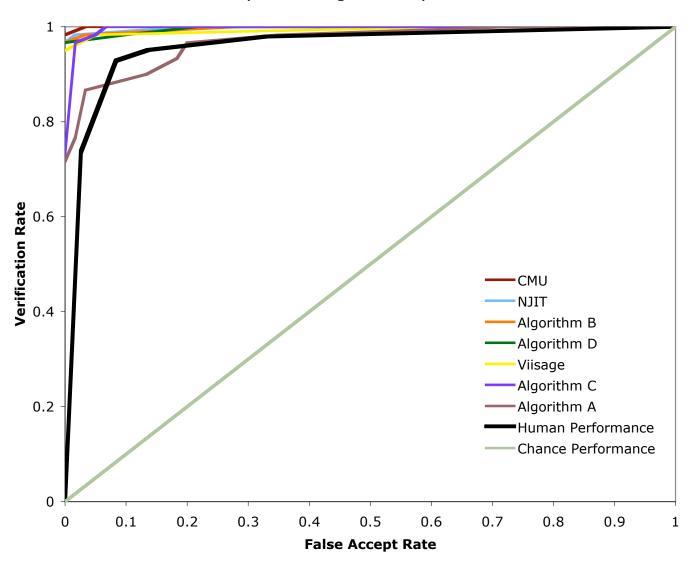
Identity Matching for Difficult Face Pairs



Results Summary

- 3 algorithms surpass humans!
 - NJIT (Liu, IEEE: PAMI, in press)
 - CMU (Xie et al., 2005) (In three talks)
 - Viisage (Husken et al., 2005)
- 4 less accurate than humans

Identity Matching for Easy Face Pairs



Conclusions

- Algorithms compete favorably with humans on the difficult task of matching faces across changes in illumination
 - some algorithms are better than humans on "difficult" face pairs
 - nearly all are better than humans on "easy" face pairs

We Have Quality



