Latent Matcher Fusion
-- Lessons Learned

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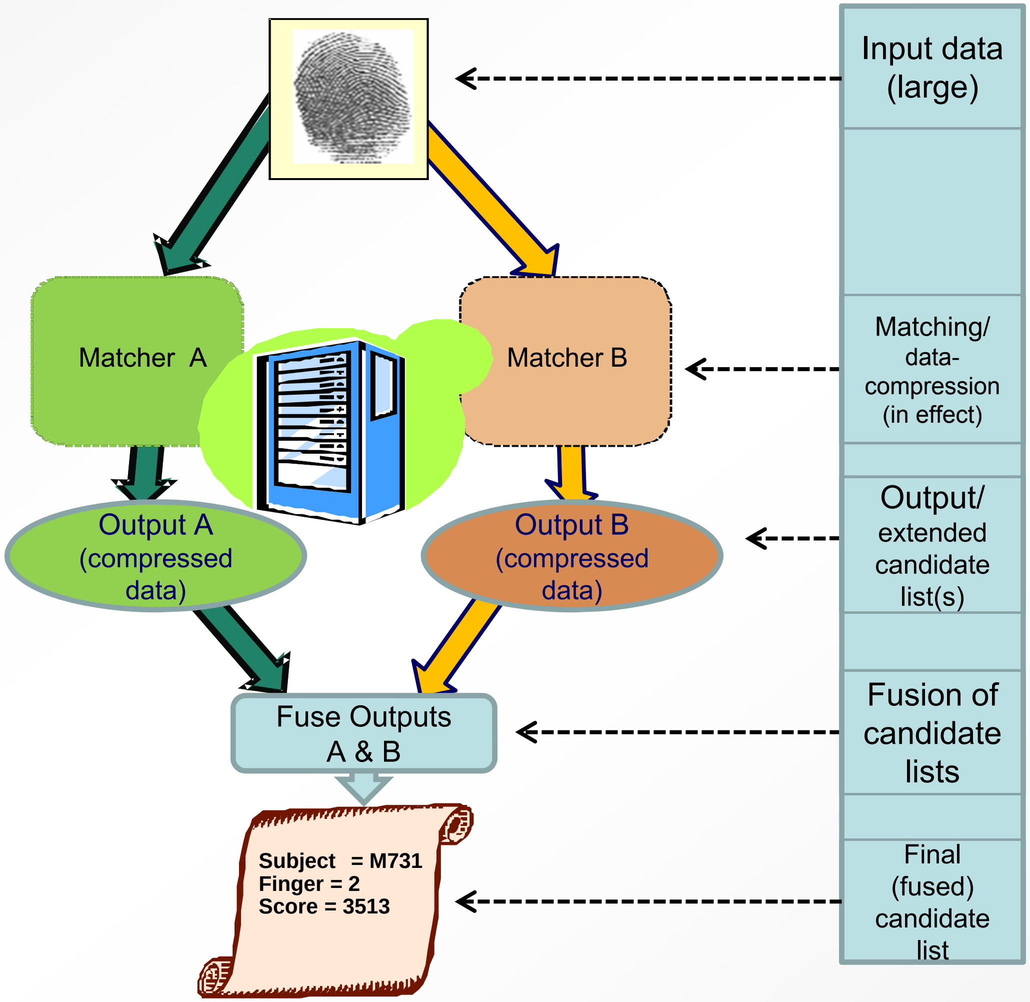
Why Look at Matcher Fusion?

- Matcher fusion provides a simple method for improving matcher performance
- What can be done via matcher fusion can, in principle, be done via a single “monolithic” matcher – but at potentially great increase in code complexity
- Fusion therefore provides us a means of assessing how much performance “headroom”/available-performance-margin exits with current technology
- This “available headroom/margin” is of interest to NIST in connection with its ELFT project

Principles of Matcher Fusion

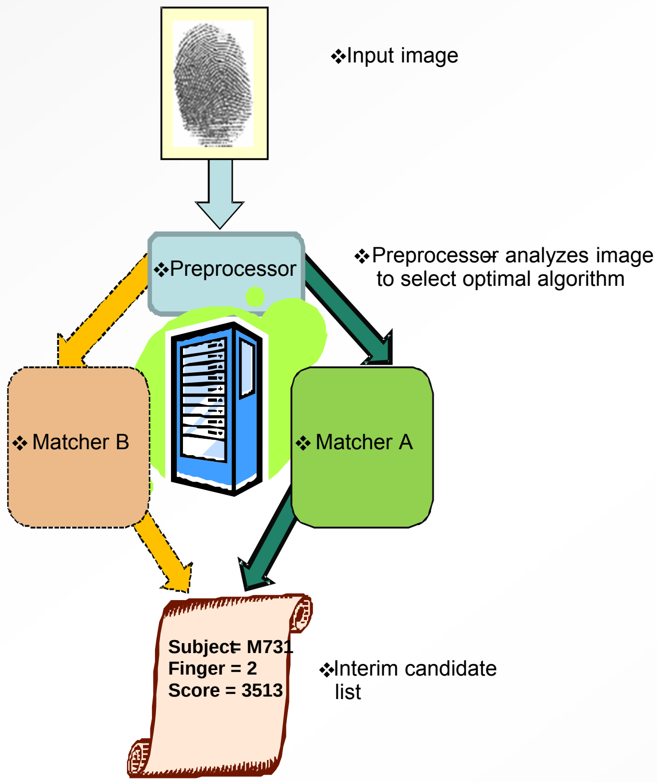
- From an information theoretic viewpoint, matcher fusion consists of two steps:
  - a) data compression – done by the original matchers
  - b) followed by data combining/fusion – performed by a separate algorithm
- The result of fusion is a “virtual matcher” – which for all purposes is indistinguishable from an “actual matcher”
- Because in the “data compression step” some information is theoretically lost, and the resulting matcher might not have the highest possible performance
- In practice, because of the complexity involved, the fused matcher might outperform the “monolithic” (integrated) matcher

Simplified Diagram of Fusion Process



Note: Inputs to the Matchers (A and B) need not be the same; for example: Matcher A could use latent image, while Matcher B uses human-extracted features.

A number of architectures are available for implementing fusion – first architecture



This architecture uses a preprocessor to select the more/most appropriate matcher/algorithm.

In the form shown in diagram, either A or B would be selected, based on the analysis of the input image.
In a slight generalization, both A and B are used, then their outputs are fused using optimal weights, which were computed by the preprocessor.

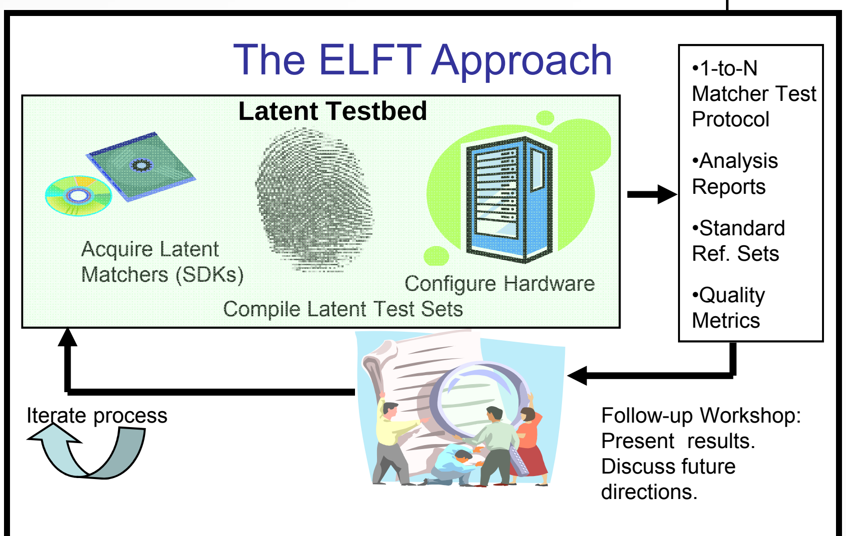
Architecture Employed in this Study

- The third architecture (previous slide) was the one actually used in this study
- This choice was largely dictated by the nature of the available input data

Matchers

- The candidate lists of five different matchers were used in this study
- These are identified as Matchers A through E (The companies supplying these are identified on the NIST website.)
- These matchers were supplied to NIST for feature/matcher performance evaluation
- Generally speaking, Matcher A was strongest, and D weakest

Evaluation of Latent Fingerprint Technology (ELFT)



Scope Statement:

•**The overall purpose of NIST's ELFT project is to advance the state-of-the-art in latent fingerprint searches via:** a) decreased dependence on human experts thru greater automation ; b) standardization of feature sets to facilitate data interchange; and c) standardized scores and performance measures

•To accomplish this, NIST has planned a series of tests for evaluating the state of the art in automated latent fingerprint matching. These tests will quantify the core algorithmic capability of contemporary matchers, and assist contractors/private-industry in improving their products. Some test have been completed; some are in progress; and some are future plans

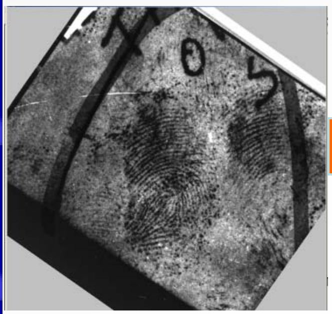
•Testing Phases I and II, and EFS Eval. #1 and #2 have been completed, and the results can be found on the NIST website

• Latent Website Mainpage ➔ http://fingerprint.nist.gov/latent/

How are Candidate Lists Generated?

AFEM = *Automated Feature Extraction and Matching*

Latent Fingerprint Image



Input

Fingerprint Matching System

Automatic Feature Extractor

features

Latent Fingerprint Matcher

Output

Candidate List

Rank	Subject	Finger #	Score	"Probability"
1	0731	2	2903	85
2	1303	7	1805	13
3	3950	1	1754	11
…	…	…	…	…
20	0121	4	350	0

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Input to Matchers

- The inputs to the matchers came in a number of "flavors":
  - ***Image only*** means the matcher is given only the image of the latent print – and no other information; the matcher must extract its own (native) search features
  - ***Features only*** means the matcher was given search feature extracted by human experts – and no other information (such as the image); as a minimum, these features would include the traditional features such as a) minutiae; b) core & delta; and c) pattern class; however in some cases these were augmented by extended features
  - ***Image plus Features*** means that both a) the latent fingerprint image, and b) the human-extracted features were supplied
  - ***Dual images*** means that two images from the same subject went to the matchers (one to each matcher); these might or might not have come from the same finger; if from the same finger they are different captures

Number of Searches and Background

- The principal search set consisted of 1357 latent fingerprints; these consisted of representative criminal casework, supplemented by special collections
- A second set consisted of 437 cases of multiple captures from subjects; the multiple capture might, or might not, be from the same finger
- The background consisted of 100K subjects = 1M fingers. (Actually this refers to background + foreground, where foreground are the mates of the searches.)

Input to Fusion Algorithm

- The input to the fusion algorithm nominally consisted of two candidate lists, each 100 candidates long
- In exceptional cases, the candidate list might be truncated or entirely missing; the fusion algorithm needed to handle these cases
- When the same input data is used for both matchers the two matchers need be different for meaningful results
- Otherwise, with different inputs, the two matchers being fused can be the same matcher (but operating on different data)

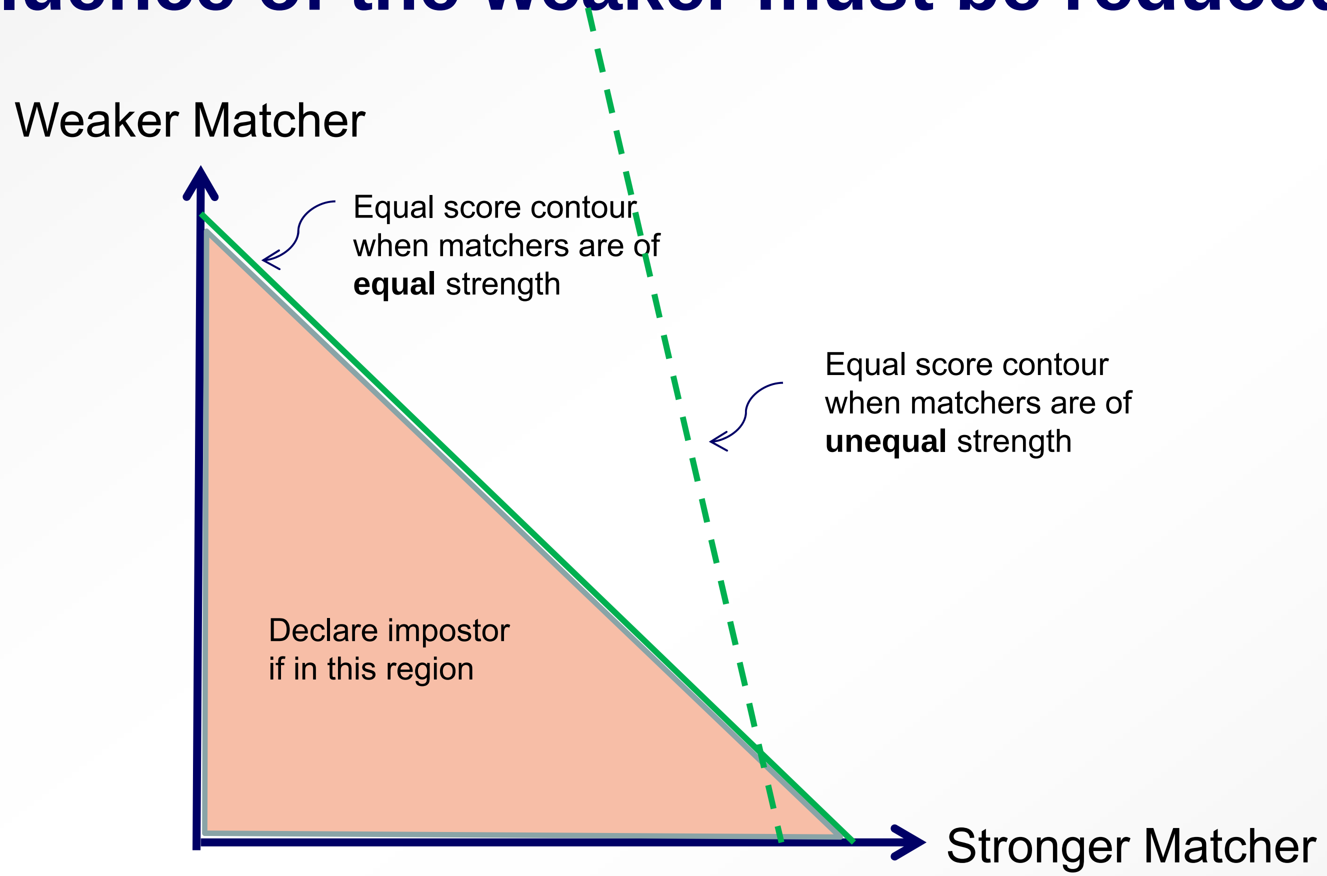
The Fusion was in Two Steps

- Step 1 – a reduced working candidate list was created consisting of:
  - First place candidates from both lists
  - Selectively, second place candidates form both lists
  - Any candidates appearing on both lists (subject and finger number same)
- Candidate list were then checked for duplications; these were eliminated

Step Two of Fusion

- **The second step** consisted of computing a new score; to avoid confusion with the original “native score” we called this fused score a “figure of merit” (FOM)
- Three different types of FOM were used: a) score-based; b)rank-based; and c) “probability”-based
- For subjects appearing on both lists, their FOM was boosted by adding the two FOMs (after suitable scaling)
- “Probability,” in the present context, refers to a special kind of normalized score appearing on candidate lists
- The final step was to reorder the list based on FOM

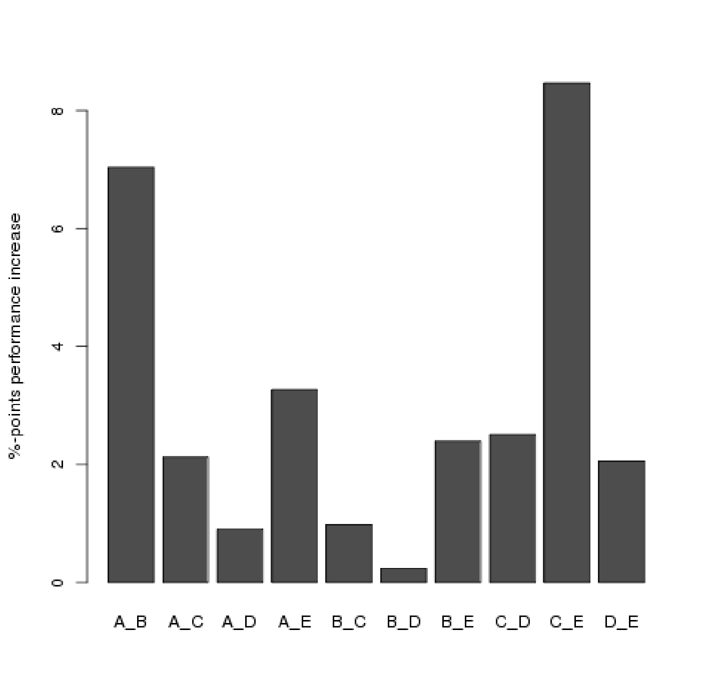
When matchers are of uneven strength, the influence of the weaker must be reduced

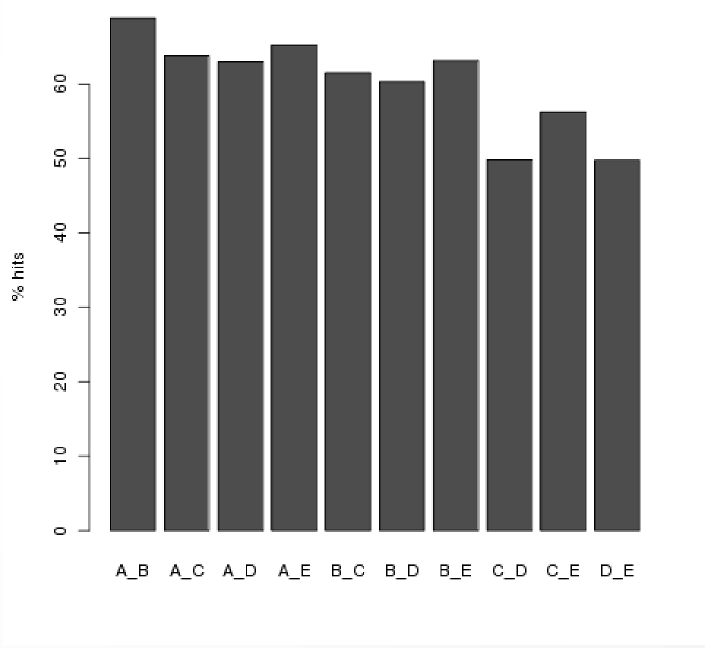


Method of Gauging Performance Gain

- Two different performance gains were computed:
  - a) candidate-list-level gain
  - b) first-position gain
- In each case the gain was based on the performance increase over the better of the two matchers
- For the candidate-list-level gain, we compared the probability that the true mate is on the reduced list with the probability it is on a list of equal length for the better matcher (this might require interpolation)
- A major reason for interest in the reduced candidate list was our “candidate list reduction” goal

Representative Gains from Fusion
-- gains range from over 8%-points to under 1%-point



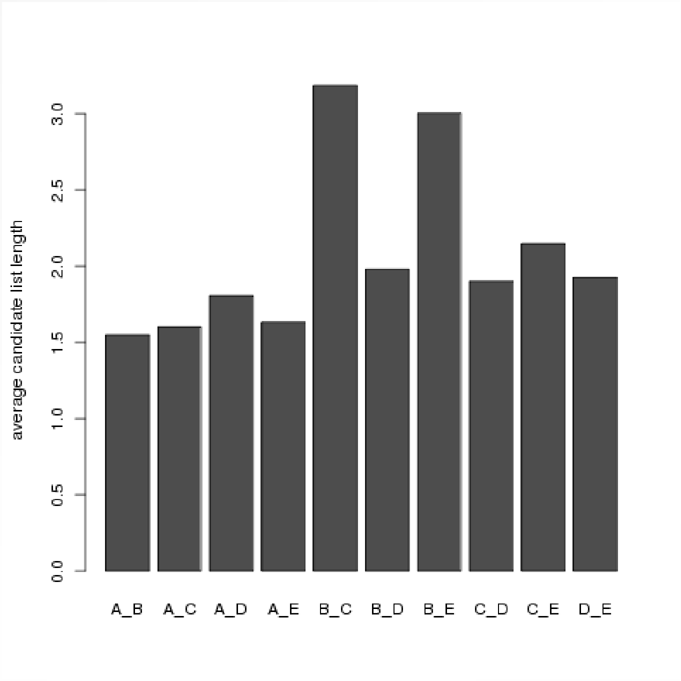


Performance Deltas for pairs of matchers, candidate-list-level, image-only data

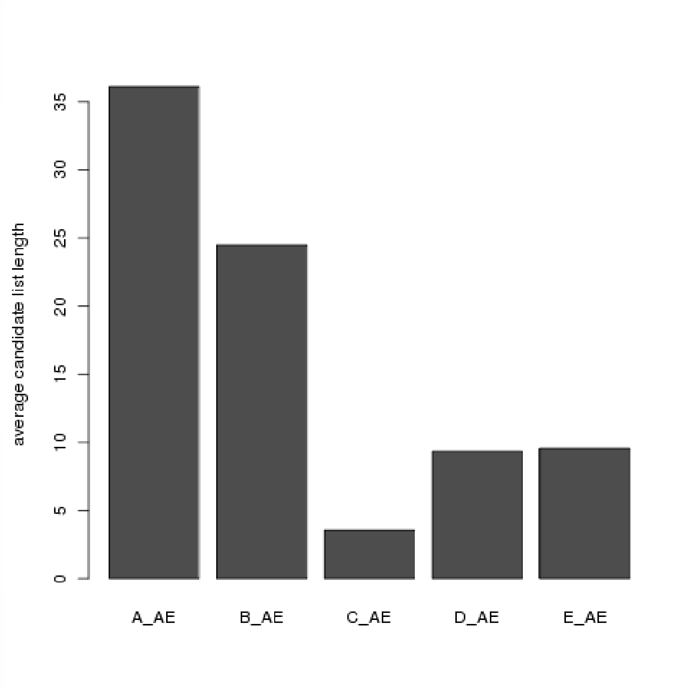
Net performance (fused) for pairs of matchers, candidate-list-level, image-only data
Note that although C-E showed highest gains, it did not have highest performance

Average Candidate List Length

-- In favorable cases the average length can be under three; in unfavorable cases it might be greater than 35



Average Reduced Candidate List Length
-- favorable case



Average Reduced Candidate List Length
-- unfavorable case

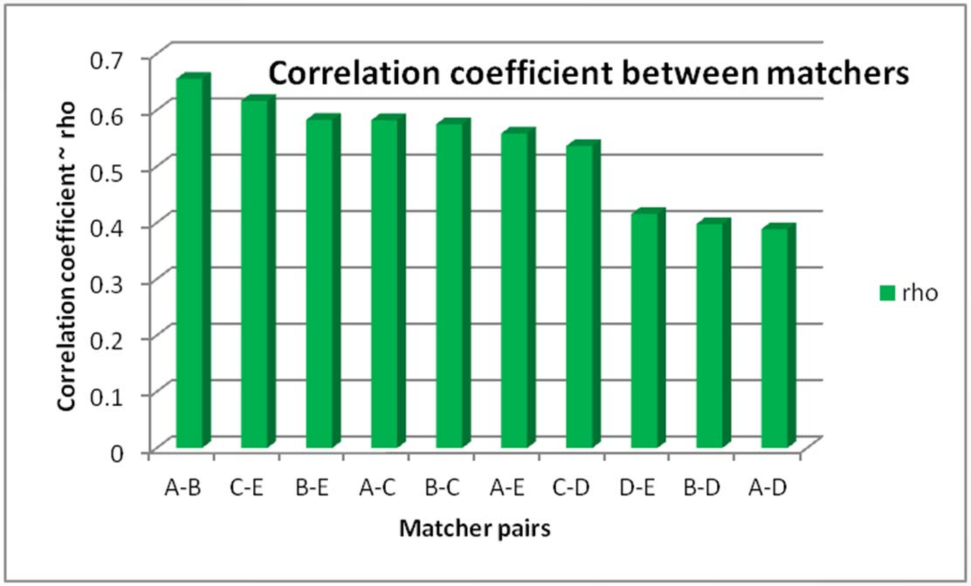
Notes:

1) Left graph shows two different matcher pairs working on image-only data – there a few impostors in common
2) Right graph shows a) matchers A-E working on image-only fused with b) matcher A using LE
– there are many impostors in common for the combination A/LA & A/LE

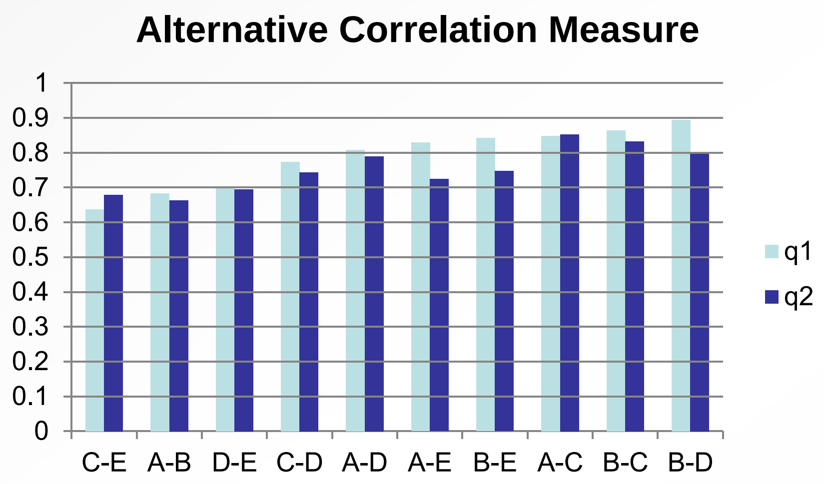
When operating on different input data, the stronger (of the two) matcher should get the better (more information) dataset

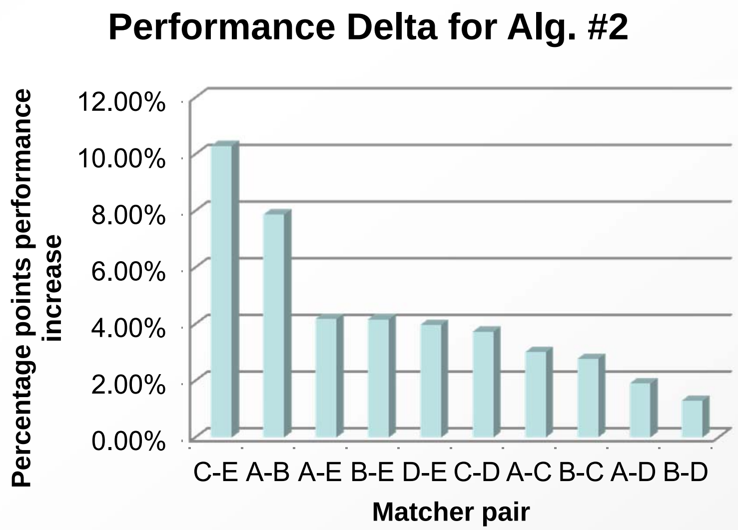
		Operating on Dataset LG				
	Matcher	A	B	C	D	E
Operating on Dataset LE	A	67.9	69	68.8	65.4	66.7
	B	64.8	65	65.1	61.5	63
	C	62.5	64.3	62.6	59.6	61.3
	D	45.5	48.7	48.7	22.3	35.1
	E	59.8	61	60.4	50.6	53.8

Pearson correlation measure was found NOT to be the most useful for predicting fusion gains



An “Alternative” Correlation Measure (q) is Proposed – and it does well!



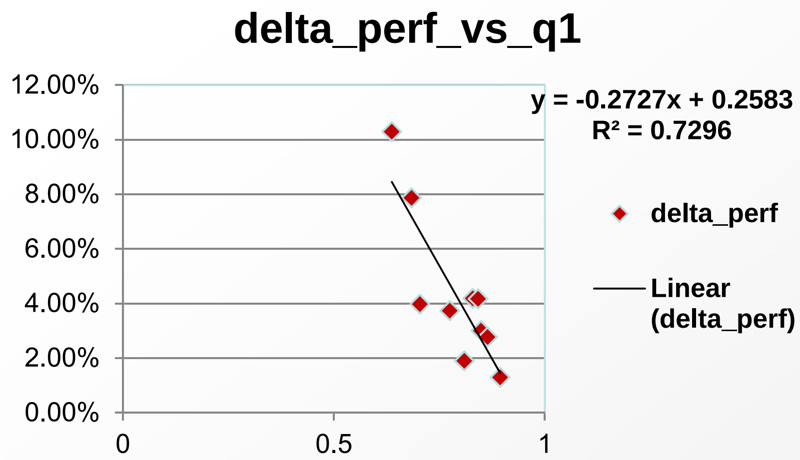


How is this “Alternative” correlation defined?

- Suppose we have two matchers, A & B, and A is the better performing of the two in terms of “hits” in first place
- Consider now creating another (virtual) matcher, call it B*, which is a “dumbed-down” version of A, having the same first-place performance as B
- We create B* by randomly switching between 1) Matcher A, and 2) a “random-guessing” matcher; the frequency of switches is so chosen as to reduce performance to B level.
- Now compute the (Pearson) correlation between A and B* (call it r) -- continued

-- More on “Alternative” Correlation

- Let ρ (rho) denote the Pearson correlation between A & B
- The new -- “alternative” – correlation is defined by ρ/r, and we denote this by q
- “q” does a good job in predicting performance gains, as seen below



Ranking FOMs/algorithms

- Four types of scores – referred to as Figures-of-Merit, or FOM – were looked at
  - 1) Rank based (Borda count)
  - 2) “Probability” based
  - 3) Native score based, global normalization
  - 4) Native score based, local normalization
- Giving both matchers equal weight sometimes produced negative gains; however, for simplicity, we retained this scheme in some cases
- Score-based generally produced largest gains

	Matcher pair -->				
		A-B	A-C	E_B	average
FOM type	rank	-5.31%	-5.23%	3.76%	-2.26%
	prob.	0.59%	1.47%	3.32%	1.79%
	score	0.37%	3.02%	6.48%	3.29%
	rel_score	0.22%	2.58%	4.27%	2.36%

Multi-finger Results

- Up to now we have considered fusion where the input comes from the same latent fingerprint image – whether features are extracted by machine, or by human experts
- We now consider the case where the input consists of two **different images** from the **same subject**; but the images which might be from the same finger or different fingers
- The matrix below shows that performance is more than doubled when two different images are used; this can be attributed to the influx of new information; alternatively, we can say S/N has increased by 41%

	Fusion Method -->					
Performance		A only	A & B, using single finger	A & A, two fingers	A & B, two fingers	A & D, two fingers
	P1	62.90%	69.30%	80.50%	77.60%	68.60%
	Delta	N/A	6.40%	17.60%	14.70%	5.70%

Conclusions:

- Matcher fusion can produce significant performance gains -- but do not expect “eye-popping” gains
- Gains are on the order of 6-8% points when based on data coming from a single input image
- As an independent check, we considered scoring a hit if *any of the five matchers placed the true mate in first position*; this resulted in 11% points improvement over the single best matcher
- For two different images (from same subject) gains are much higher, around 15%-points
- Candidate lists can be greatly reduced, 2-6 candidates, but still have performance exceeding 20 candidates from single matcher.

References/Links

- **Evaluation of Fusion Methods for Latent Fingerprint Matchers,** Dvornychenko, V. N.; 5th IAPR International Conference on Biometrics, March 2012 ➔ http://www.nist.gov/manuscript-publication-search.cfm?pub_id=910369

- Latent Website Mainpage ➔ http://fingerprint.nist.gov/latent/

- Final Report on Phase II Testing ➔ http://fingerprint.nist.gov/latent/NISTIR_7577_ELFT_PhaseII.pdf

- **NIST Latent Fingerprint Testing Workshop 2009, March 19 & 20, 2009 ➔** http://fingerprint.nist.gov/latent/workshop09/index.html

- **ELFT-EFS Homepage, April 2009 ➔** http://fingerprint.nist.gov/latent/ELFT-EFS/

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- FBI/Criminal Justice Information Services (CJIS)

Thank you!

Questions?

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