Identification of time-invariant unique features of Objects

A. The following research in biometrics revolves around temporally influenced features and algorithms.
   1. Facial verification across age.
   2. Facial verification across age using discriminative methods.
   3. Latent Fingerprint matching using decriptor based hough transform
   4. Fingerprint Spoof Detection: Temporal Analysis of Image Sequence
   5. Iris recognition performance in children: a longitudinal study

1. Facial verification across age

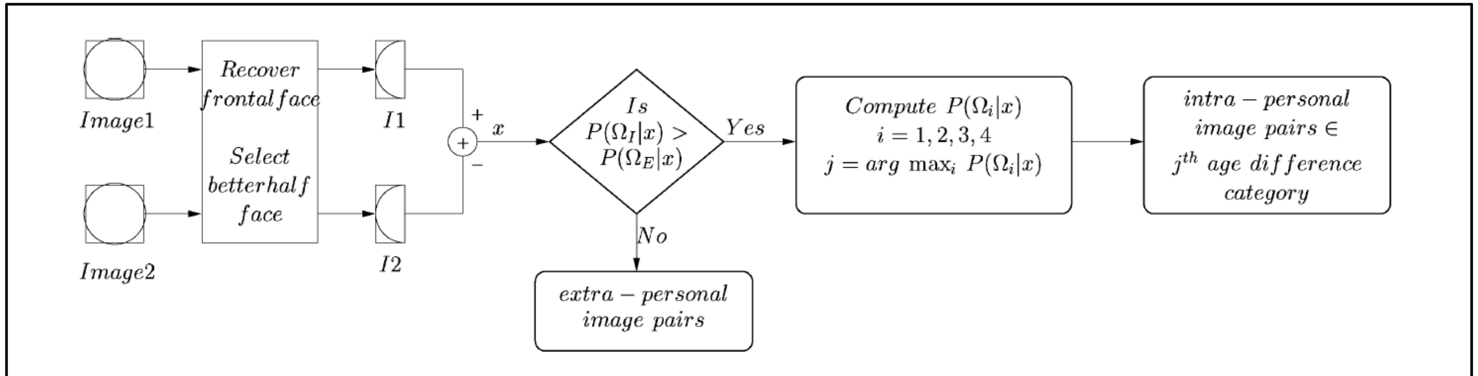
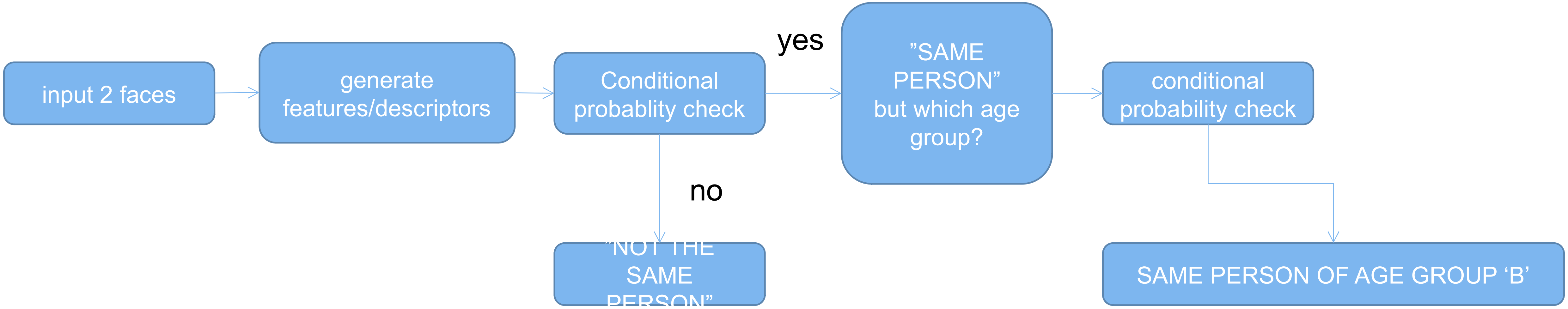


Fig. 7. Overview of the Bayesian age-difference classifier.

Making the features time invariant by removing artifacts that accumulate with time, like illumination, intensity. facial hair etc.,



1. Facial verification across age

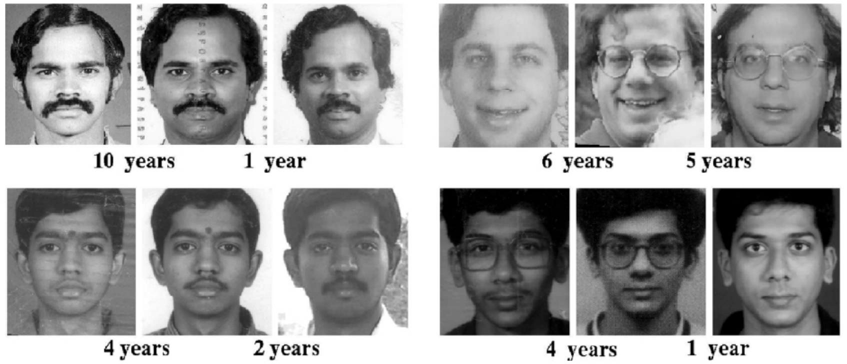
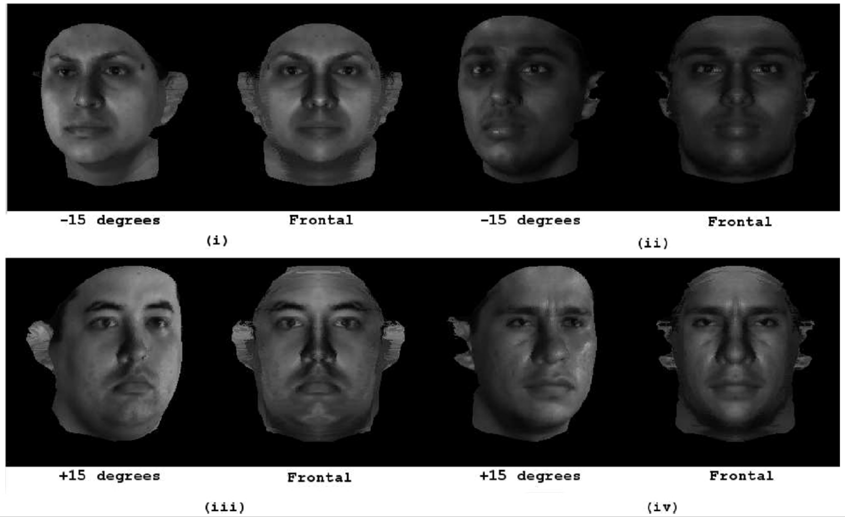


Fig. 1. Some sample age-separated images of individuals retrieved from their passports.

The time separated image samples



Face posture normalisation by unwrapping algorithms. Removing time induced artifacts as much as possible.

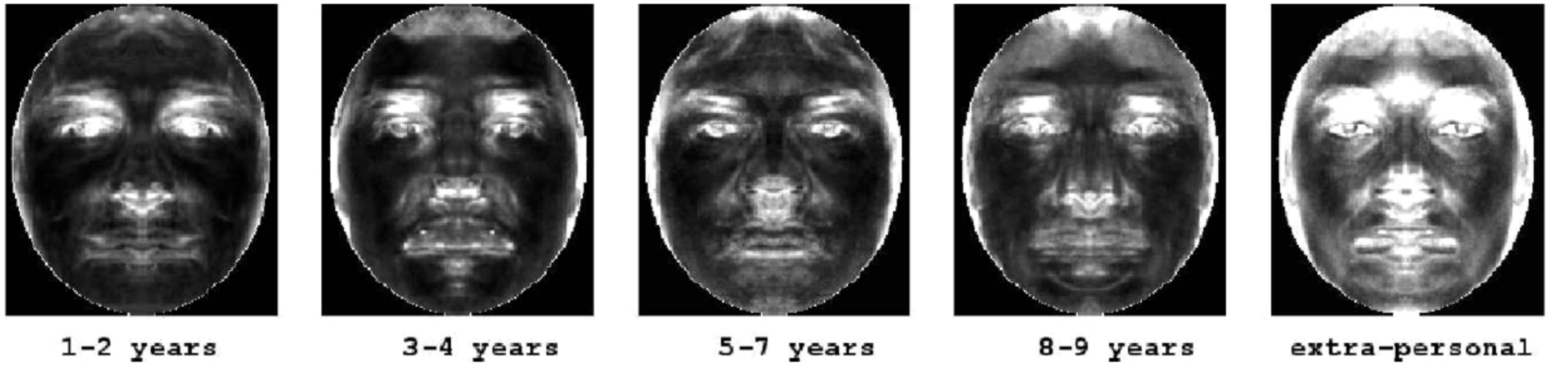


Fig. 6. Average difference images from the intrapersonal (under each of the four age-difference categories) and extrapersonal classes.

first 4 images:
Intra personal difference image

last image:
Extra personal difference image

1. Facial verification across age

- Useful ideas from this paper:
  - Identifying and Removing time induced artifacts can make the features time-invariant.
  - Using Bayesian framework as a classifier can yield good results **only when the features change predictably with time.**
  - for example: we know that “facial wrinkles” are features in older images only.
  - Also the error rate increases with increase in Age gap.

2. Facial verification across age using discriminative methods

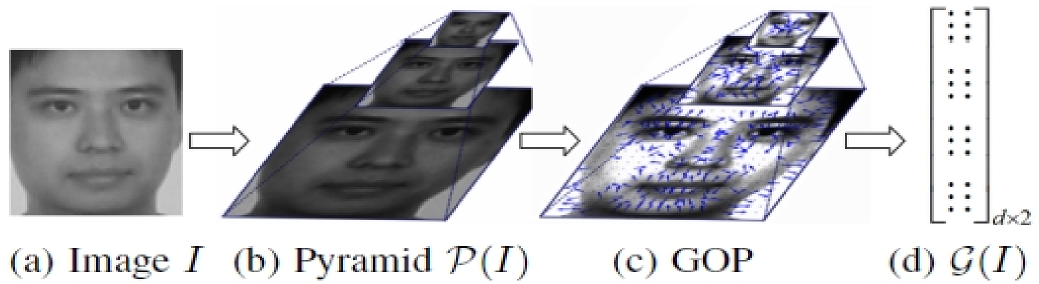
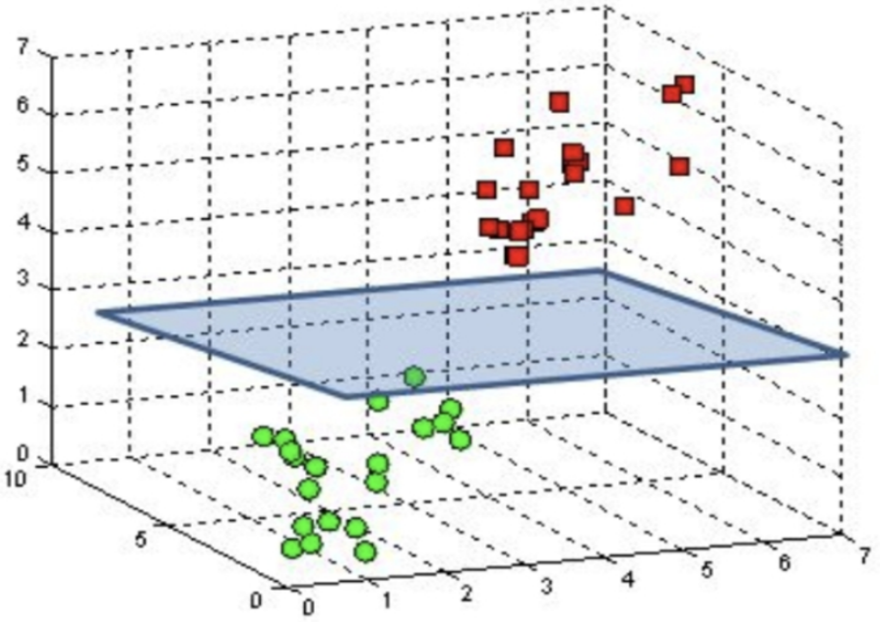


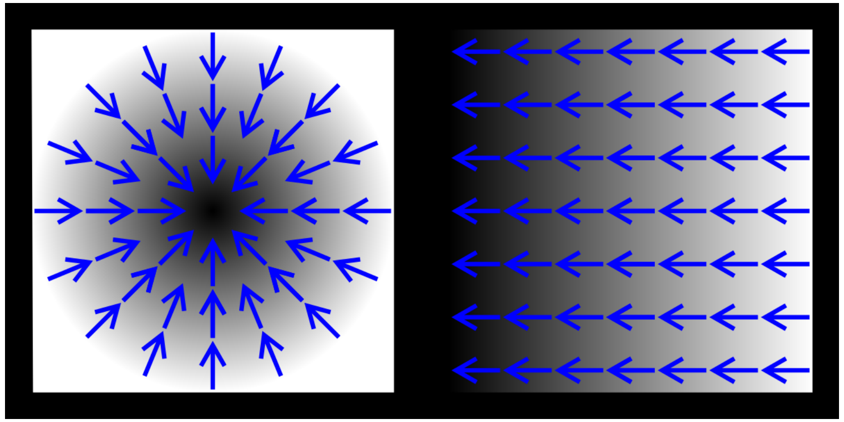
Fig. 2. Computation of a GOP from an input image I. Note: In (c), the figure is made brighter for better illustration.

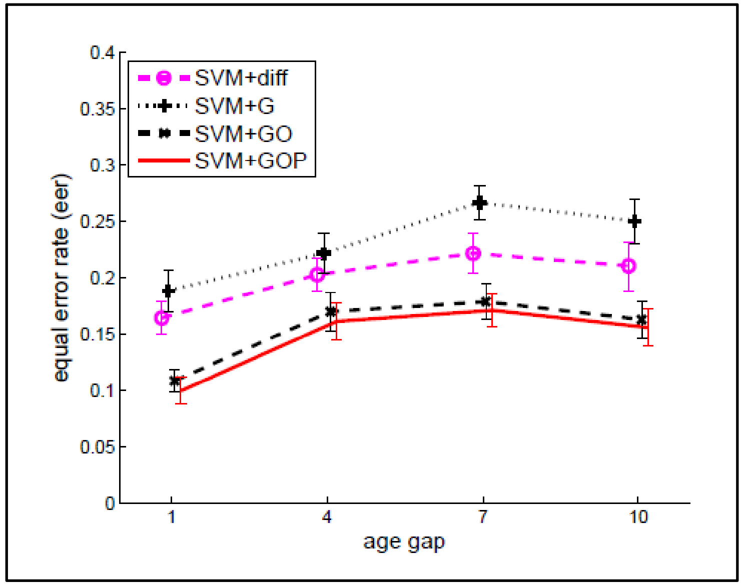


- The paper proposes GOPs(Gradient Orientation Pyramid) as features for classifying OLD vs NEW images.
- The GOP features of input image is classified as “same person” or “different person” by using the classifier called SVM (Support Vector Machine).

2. Facial verification across age using discriminative methods

- Useful ideas from this paper
  - Gradient orientation, in general represents the ‘rate of change’ and ‘direction of change’ at any point.
  - Such a feature in this example proves to be invariant to time induced artifacts like illumination and intensity.
  - ‘Increase in Error rate’ slows downs with ‘increase in age gap’





3. Latent Fingerprint matching using decriptor based hough transform

- Latent fingerprints are fingerprints that are formed by sweat and oil on the skin.
- Such prints are not visible with naked eye and are collected carefully.
- The idea is to extract Miniteaue descriptors and use Hough transforms for alignment.

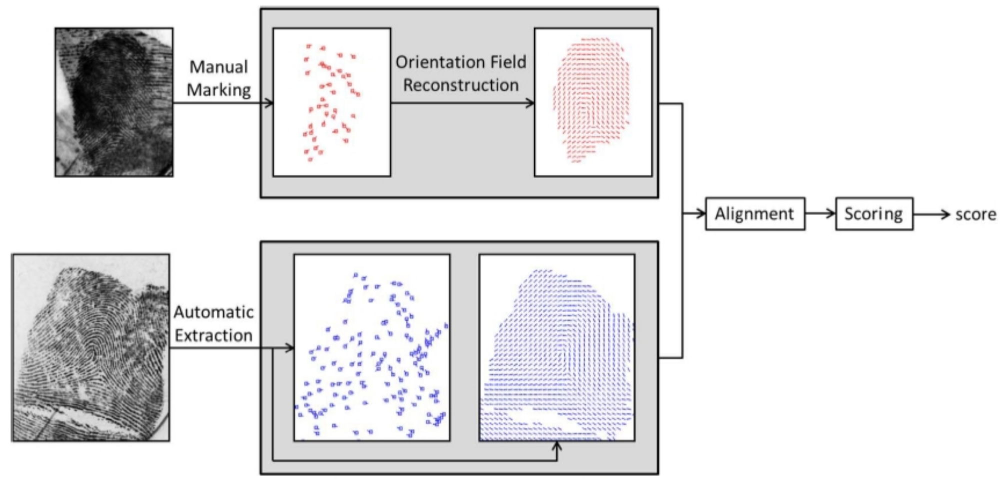


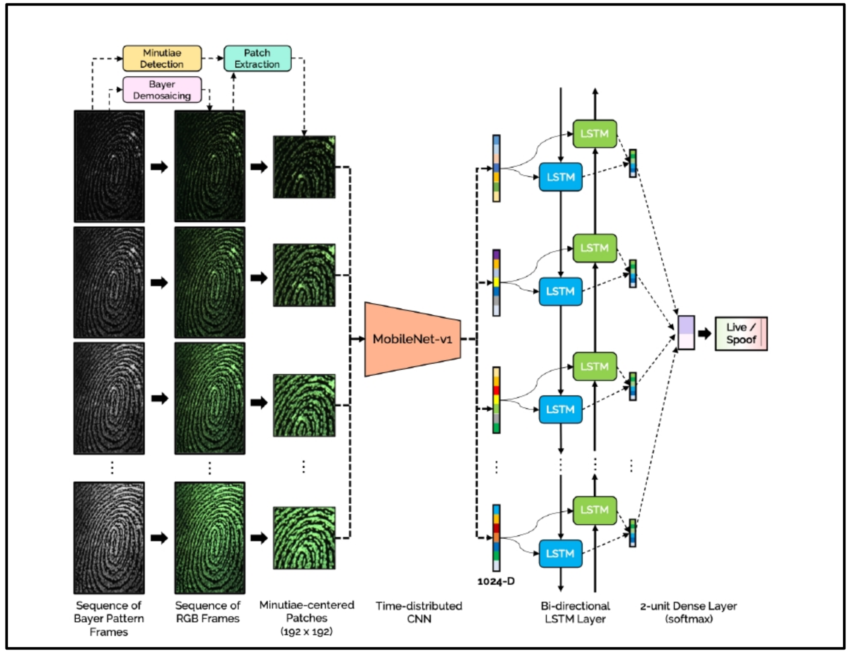
Fig. 3. Overview of the proposed approach.

3. Latent Fingerprint matching using decriptor based hough transform

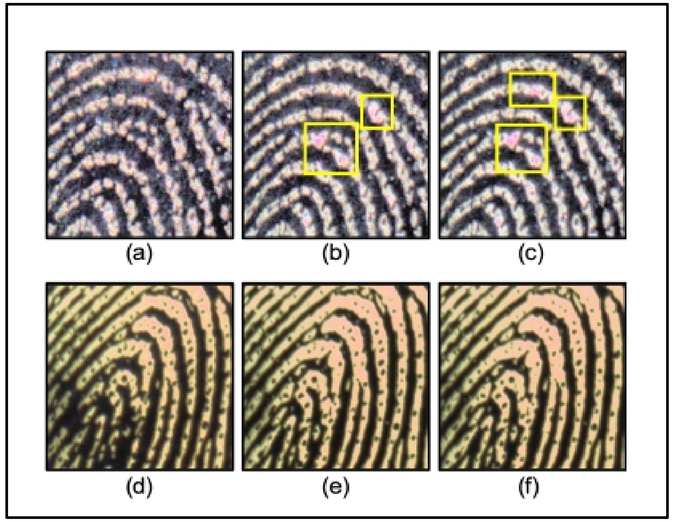
- Useful ideas from this paper
  - Latent fingerprints are usually contaminated by lot of external influence. The randomness in this influence can represent the randomness of the world and time.
  - The identification of features like ‘Orientation field’ at minutiea points, even if only few are identified, it will help in matching with a template.
  - The usage of descriptor based Hough transforms to extract the orientation information of the lines on fingerprint is uniquely effective for fingerprints.
  - 2d representation of the fingerprints is ‘set of lines’.

4. Fingerprint Spoof Detection: Temporal Analysis of Image Sequence

- Fingerprint spoof: Trying to fool the system by scanning fingerprint impressions made from any thing, but not human.



The architecture of CNN-LSTM model used in this paper.



The preprocessing filters highlight the intricate skin imperfections as feature and compare with previous detections (LSTM).

5. Iris recognition performance in children: a longitudinal study

- The study was performed on Children between ages 4-11 for 3 years every 6 months.
- Pupil data collected is combined with other data like
  - Time difference
  - Enrollment Age
  - Dilation
  - Delta dilation
- The matching score is a function of both dilation data and time difference.

$$\begin{aligned}\mathrm{MS} \sim\ & \beta_0 + \beta_1 \mathrm{TD} + \beta_2 \mathrm{EA} + \beta_3 \mathrm{PD} + \beta_4 \Delta \mathrm{D} \\ & + \beta_5 \mathrm{EA}^2 + \beta_6 \Delta \mathrm{PD}^2 + \beta_7 \Delta \mathrm{D}^2 + \mathrm{b}_{0i} \\ & + \mathrm{b}_{1i} \mathrm{TD} + \mathrm{b}_{3i} \mathrm{PD} + \mathrm{b}_{4i} \Delta \mathrm{D} + \mathrm{b}_{6i} \mathrm{PD}^2\end{aligned}$$

Time difference as a parameter is highlighted

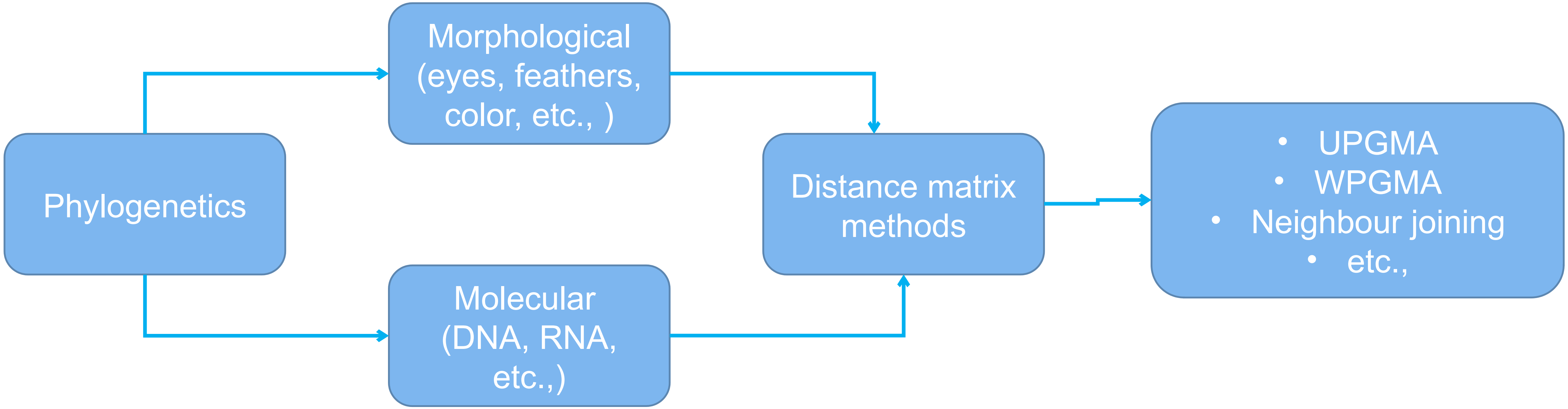
5. Iris recognition performance in children: a longitudinal study

- Useful ideas from this paper:
  - The tiny variations/changes in the pupil dilation measure will contribute 29 to 45 times more than that of due to **Time difference**.
  - The feature that is being studied in this paper varies very little with time. Dilation is computed as ratio of pupil radius and iris radius.

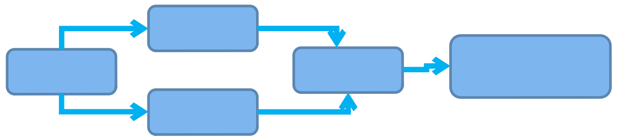
ΔD > Subject > Dilation of the probe image > Time Difference

Interestingly, we can infer from the model that dilation difference between two comparing images (in our case from 2 different TFs) adds in the most variability to the match score than any other significant factor. Aging effect contributes to the least variability in MS.

B. Phylogenetics



B. Phylogenetics



Maximum parsimony

Which tree to choose? Choose the simplest one.

Maximum Likelihood

- Obtain probabilistic distribution for mutations from “Substitution models”.
- Penalises complex mutations

Substitution model: describe changes over evolutionary time

Bayes inference

- Assumes apriori probability odistribution of possible trees. (Naive assumptions)