Multibiometrics

CSE 40537/60537 Biometrics

Daniel Moreira

Spring 2020

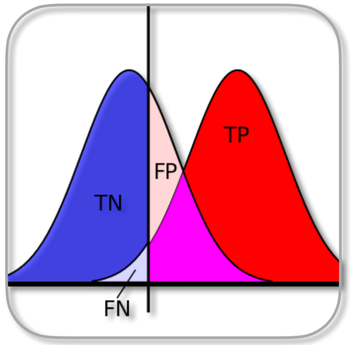
UNIVERSITY OF NOTRE DAME

Today you will…

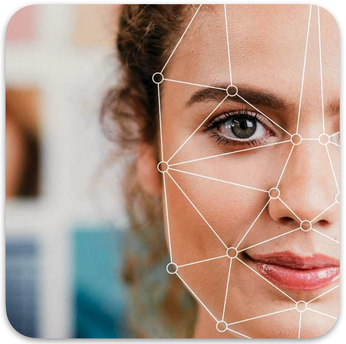
Get to know
Alternative traits.
Importance of Multibiometrics.

Course Overview

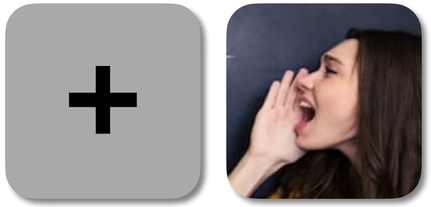
Content



Basics
Concepts
Metrics
Metric implementation



Core Traits (3)
Concepts
Baseline implementation
Evaluation
Assignments



Alternative Traits and Fusion
Concepts

Invited Talks (2)
State of the art
Future work

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Course Overview

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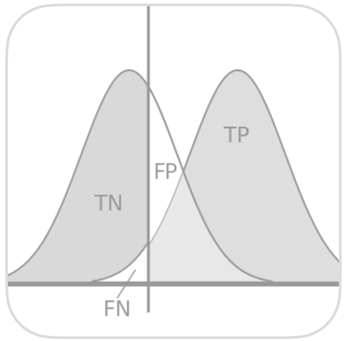

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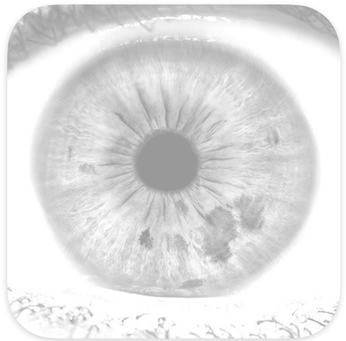

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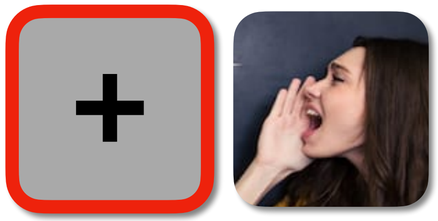

Alternative Traits and Fusion
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Invited Talks (2)
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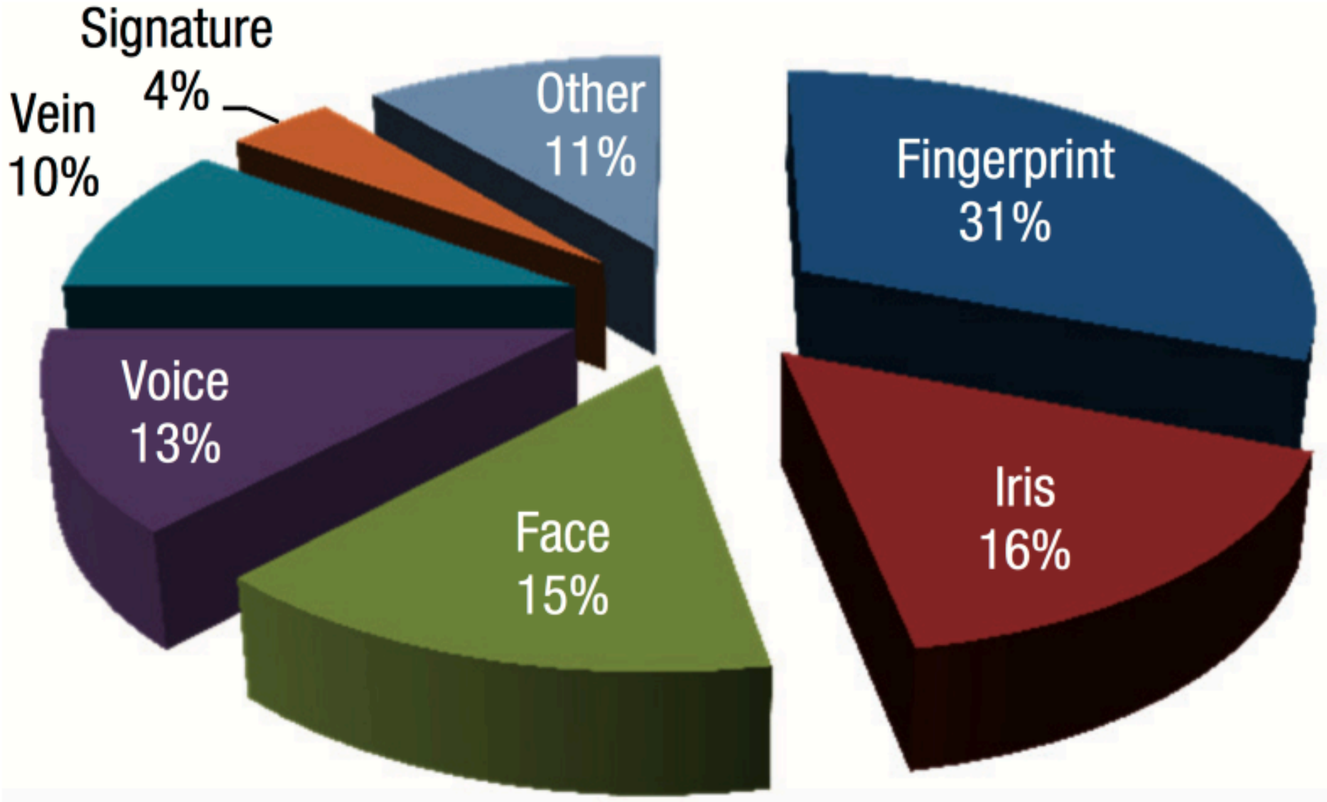
Alternative Traits

Market



Source: Mani and Nadeski, *Processing solutions for biometric systems,* Texas Instruments, 2015

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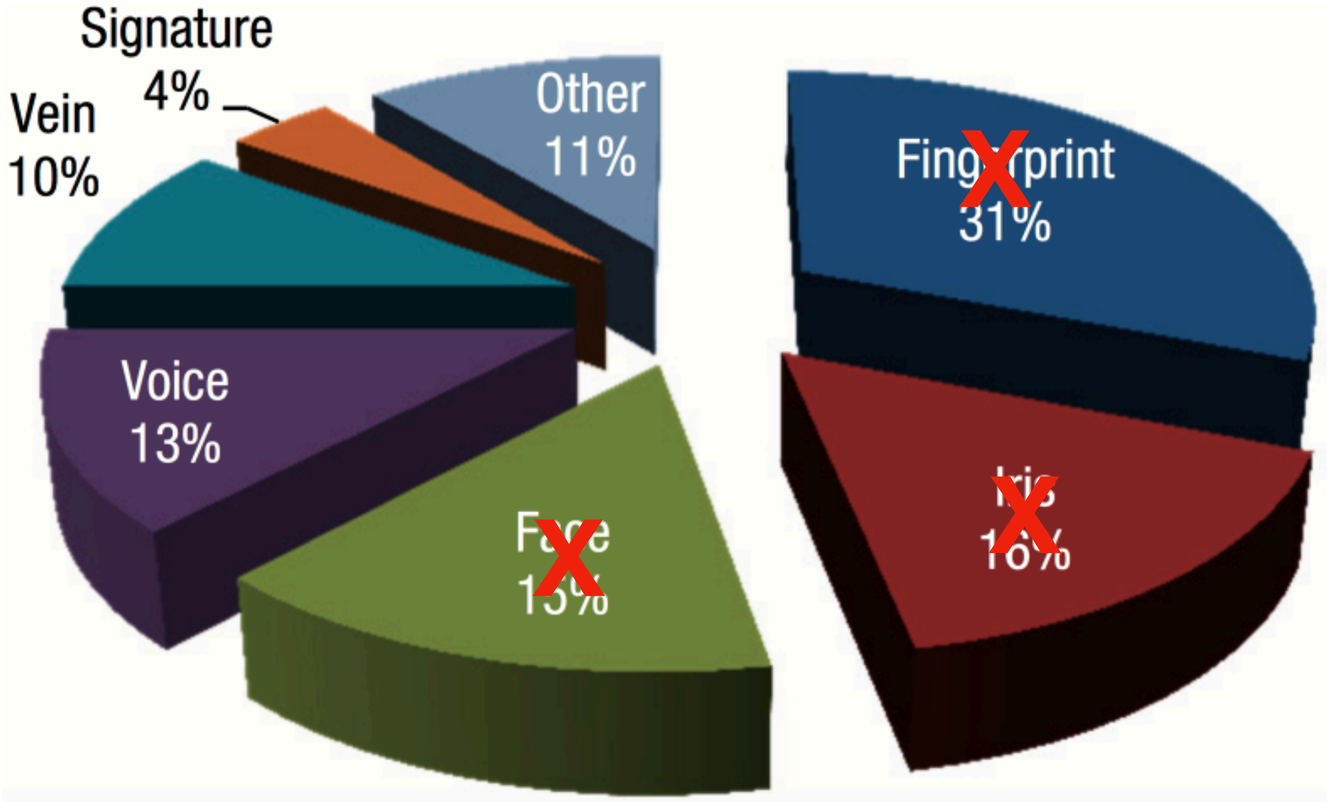
Alternative Traits

Market



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Alternative Traits

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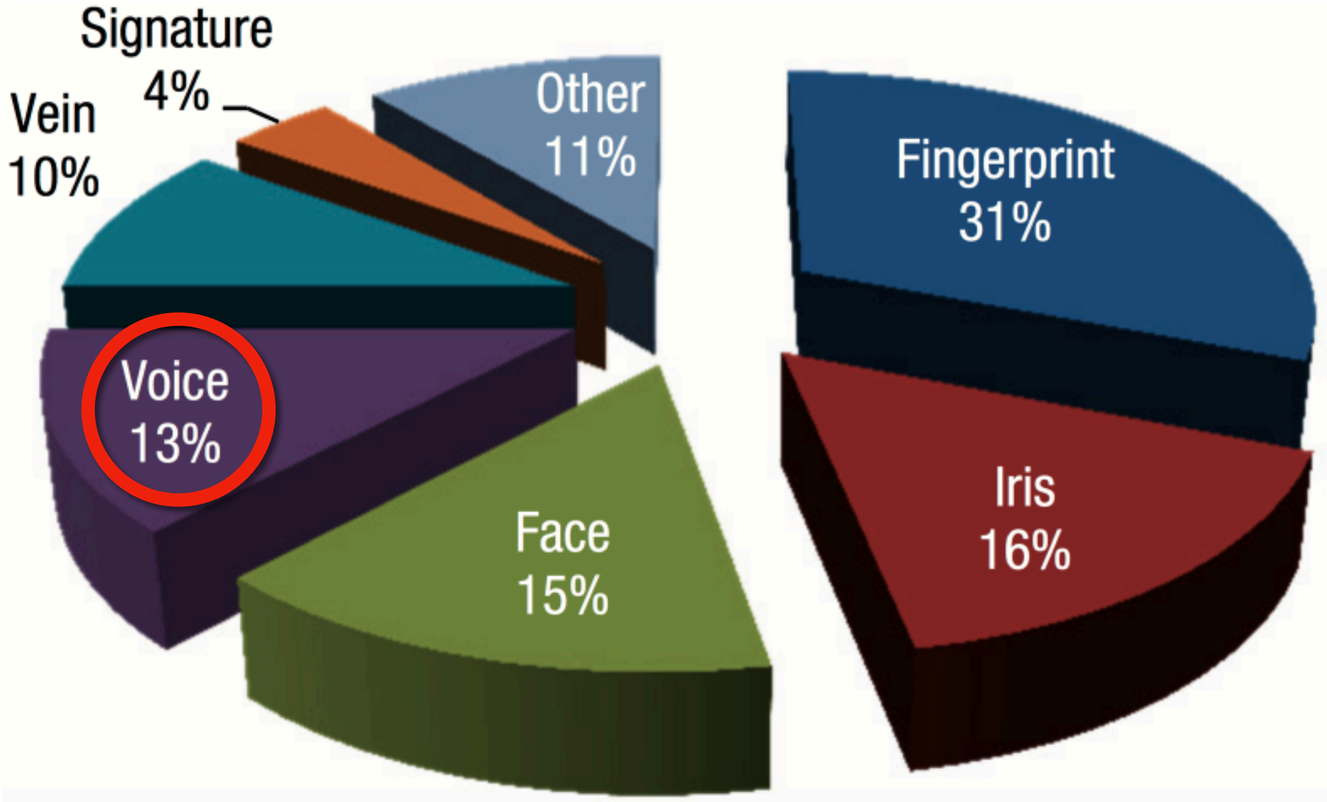

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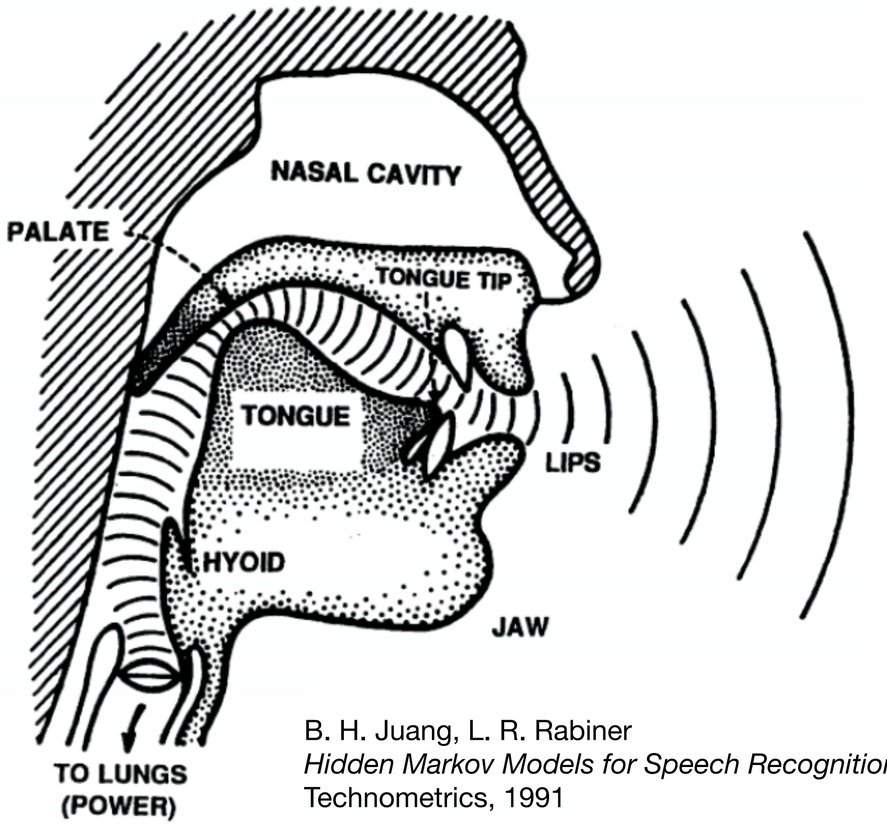
Voice Recognition

Human Vocal System

Complex combination of organs,
rooted on *genetic* factors
but mostly *epigenetic*.

Health, age, mood, stress,
and even mother tongue
will influence somebody's voice.



B. H. Juang, L. R. Rabiner
Hidden Markov Models for Speech Recognition
Technometrics, 1991

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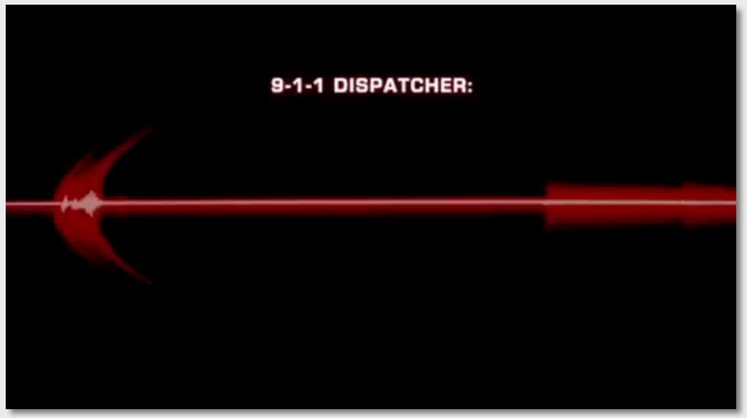
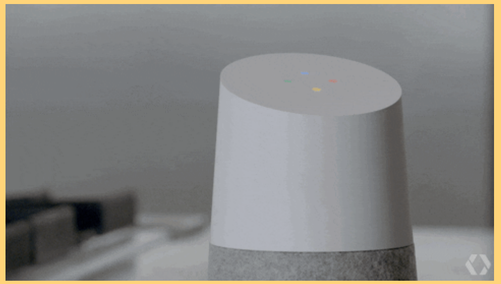
Voice Recognition

Acquisition

Off-line



On-line



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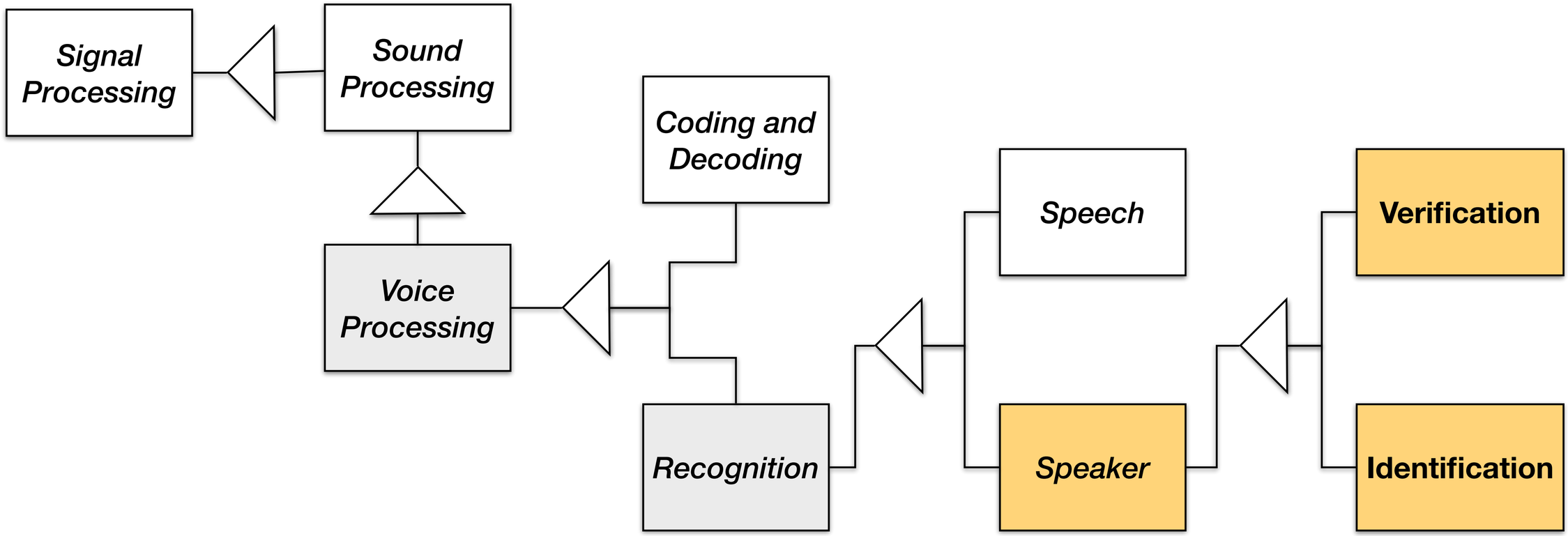
Voice Recognition

Field Development



Voice Recognition

Variants

Fixed-Text
Enrollment and authentication
with the same word.

Text-Dependent
Usage of authentication phrases
(composed from a pre-defined vocabulary).

Text-Independent
Users may say any word/phrase.

Conversational (under development)
Speech and speaker recognition,
with semantic analysis.

Security

increases

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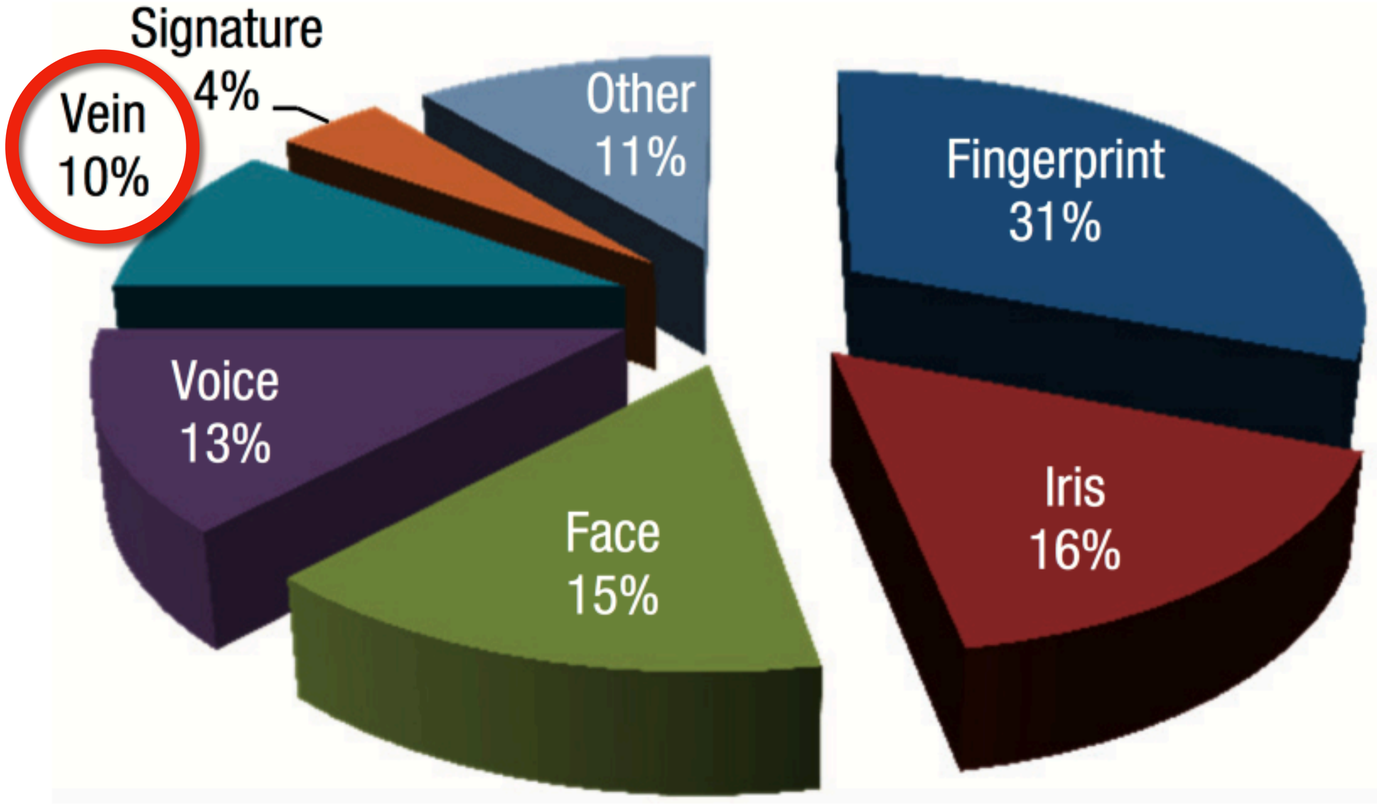
Alternative Traits

Market



Source: Mani and Nadeski, *Processing solutions for biometric systems,* Texas Instruments, 2015

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Vein Recognition

Human Circulatory System

Veins are *epigenetic*.

Commonest modalities:
palm and finger veins.

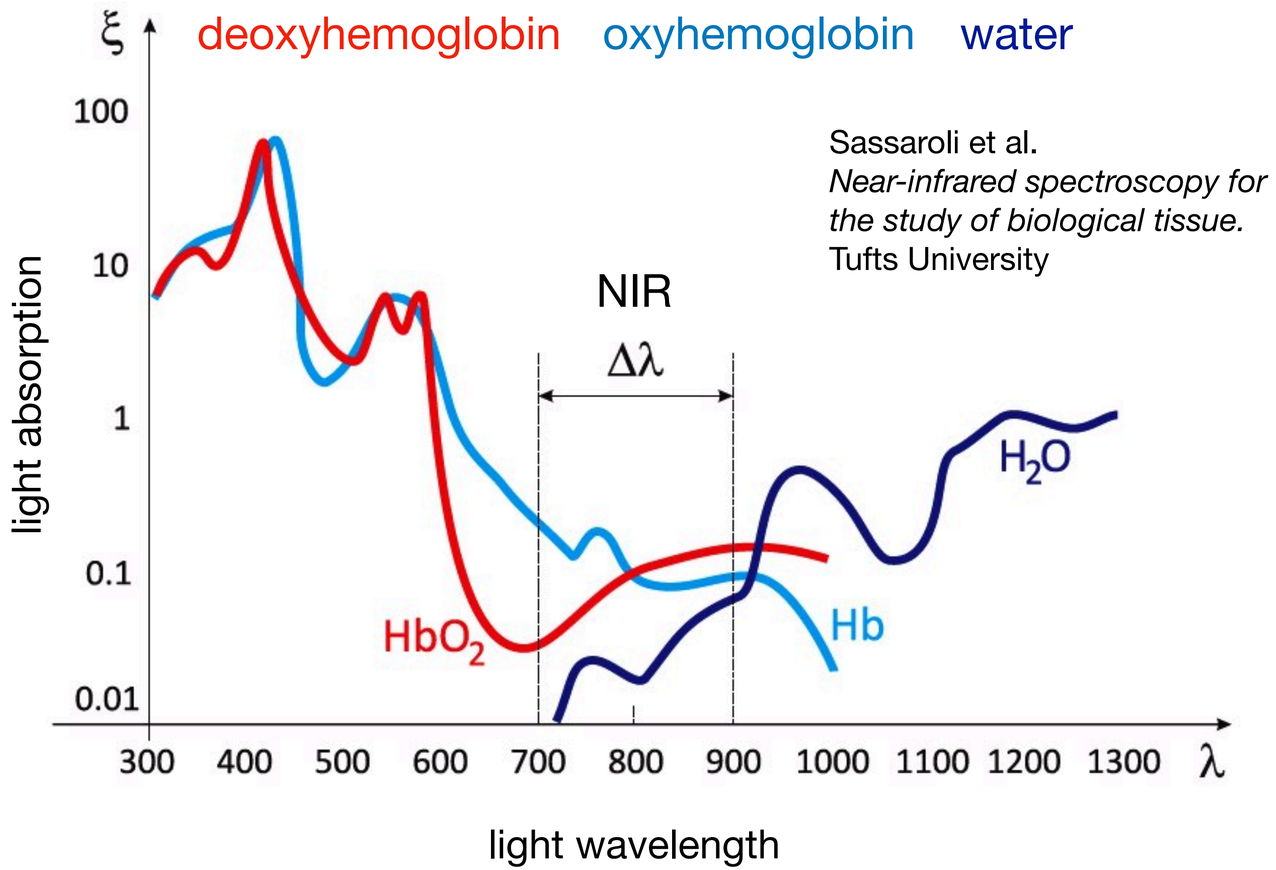
Dr. Adam Czajka

Hitachi
Finger Vein Authentication
White Paper, 2004

Vein Recognition

Acquisition

Dedicated near-infrared (NIR) light sensors
(on-line acquisition).



Sassaroli et al.
Near-infrared spectroscopy for the study of biological tissue.
Tufts University

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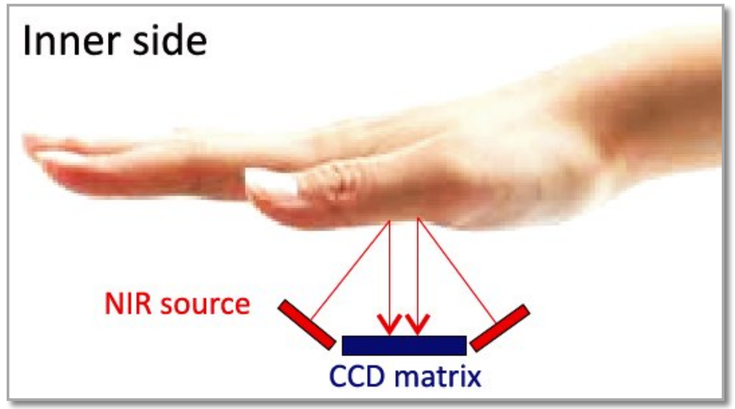
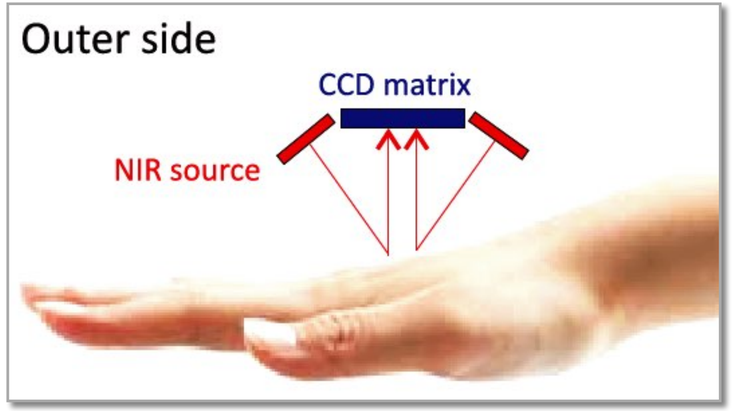
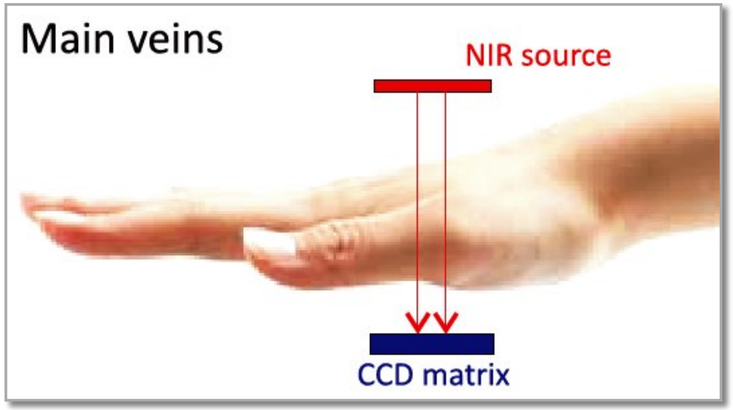
Vein Recognition

Palm Vein Acquisition





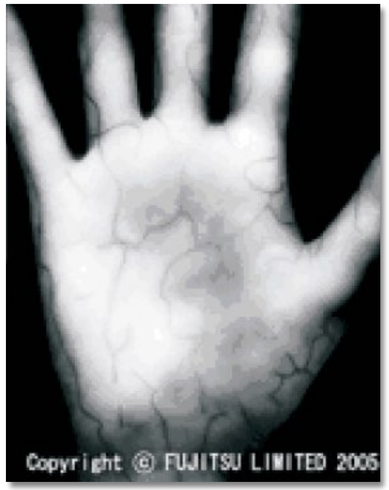


Dr. Adam Czajka

Vein Recognition

Palm Vein Acquisition

MITRE
State of the Art Biometrics Excellence Roadmap
Tech. Report, 2008



Fujitsu PalmSecure reader

Techsphere VP II reader

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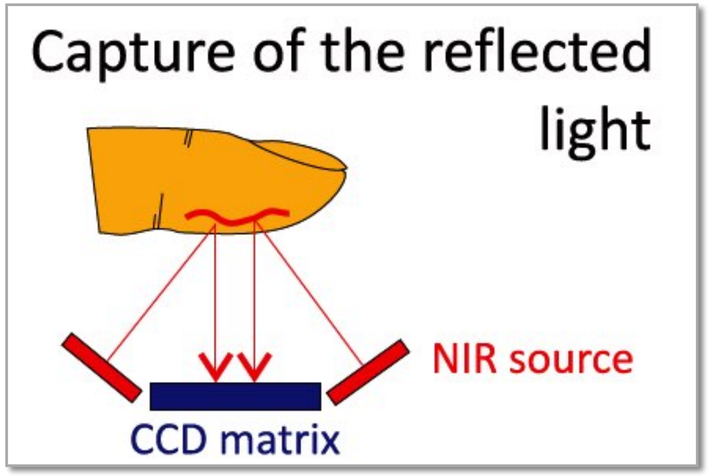
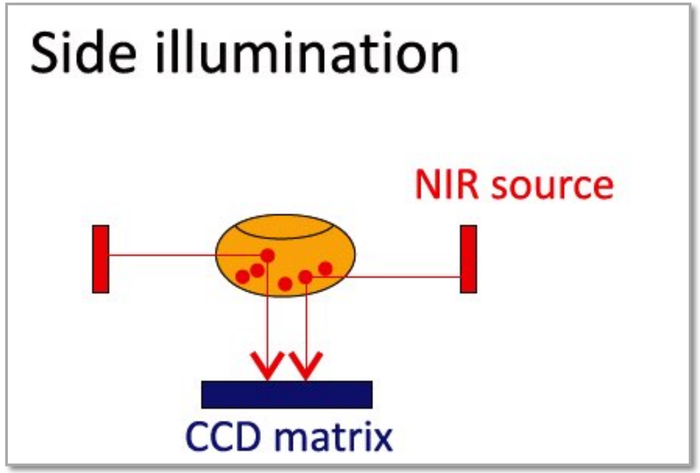
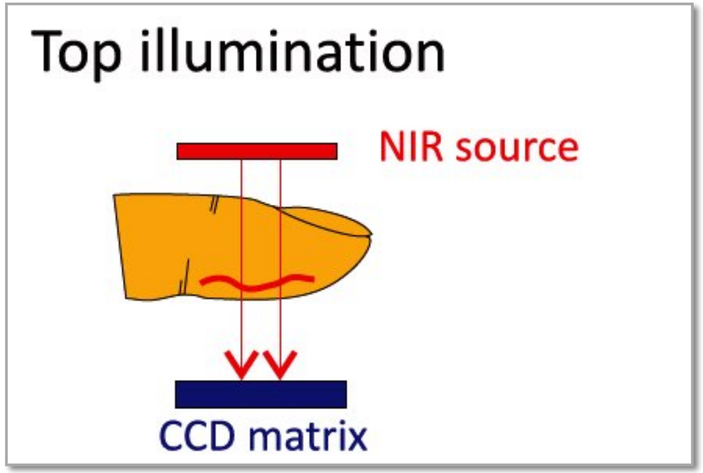
Vein Recognition

Finger Vein Acquisition







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Vein Recognition

Finger Vein Acquisition

Hitachi H1 reader
(with top illumination)

MITRE
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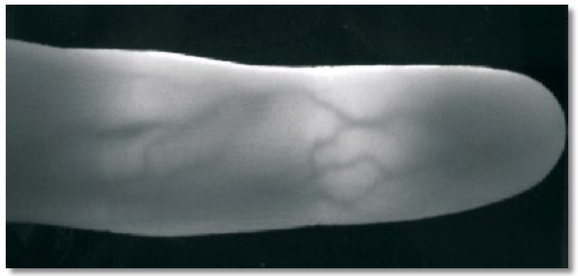
Tech. Report, 2008



Vein Recognition

Vein Description Strategies

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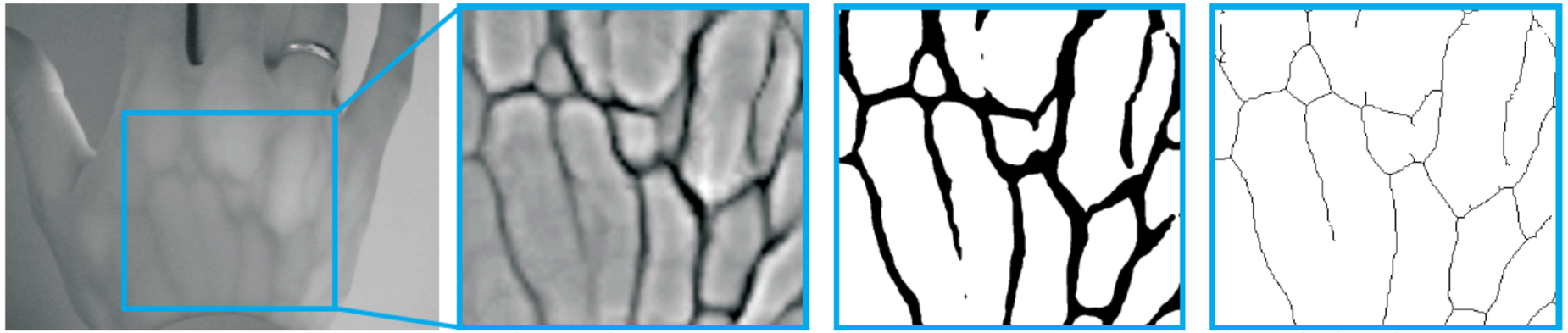


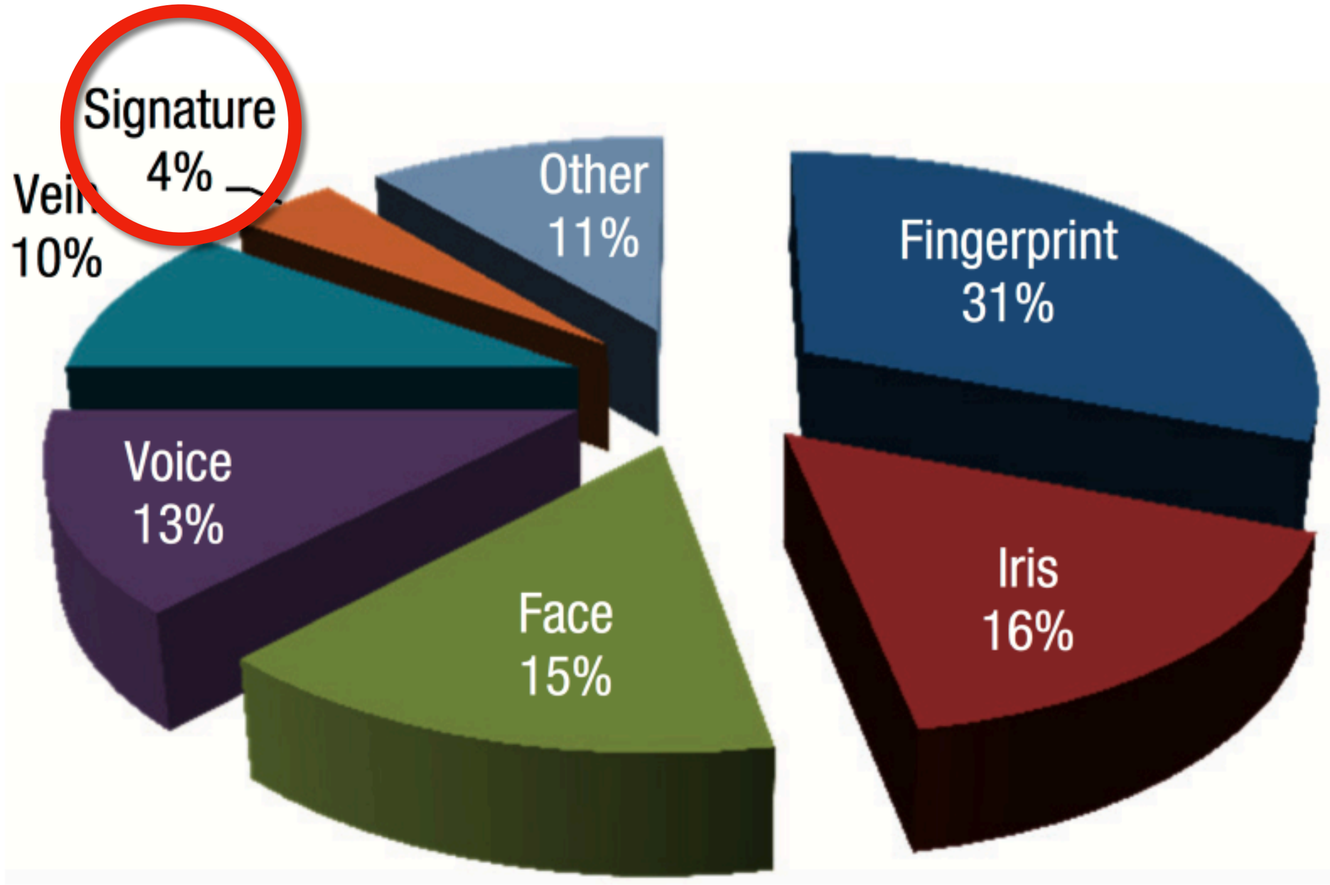
Vein Recognition

Vein Description Strategies

Miura et al.
Extraction of Ginger-Vein Patterns Using Maximum Curvature Points in Image Profiles
IAPR 2005

Alternative Traits

Market



Source: Mani and Nadeski, *Processing solutions for biometric systems,* Texas Instruments, 2015

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Signature Recognition

Behavioral Trait

Signature Recognition

Acquisition

Off-line

On-line

https://www.youtube.com/watch?v=Y1449tOo7Xw

Signature Recognition

Off-line Acquisition

Based on visual content only.

General-purpose sensor
(e.g., scanner, camera).

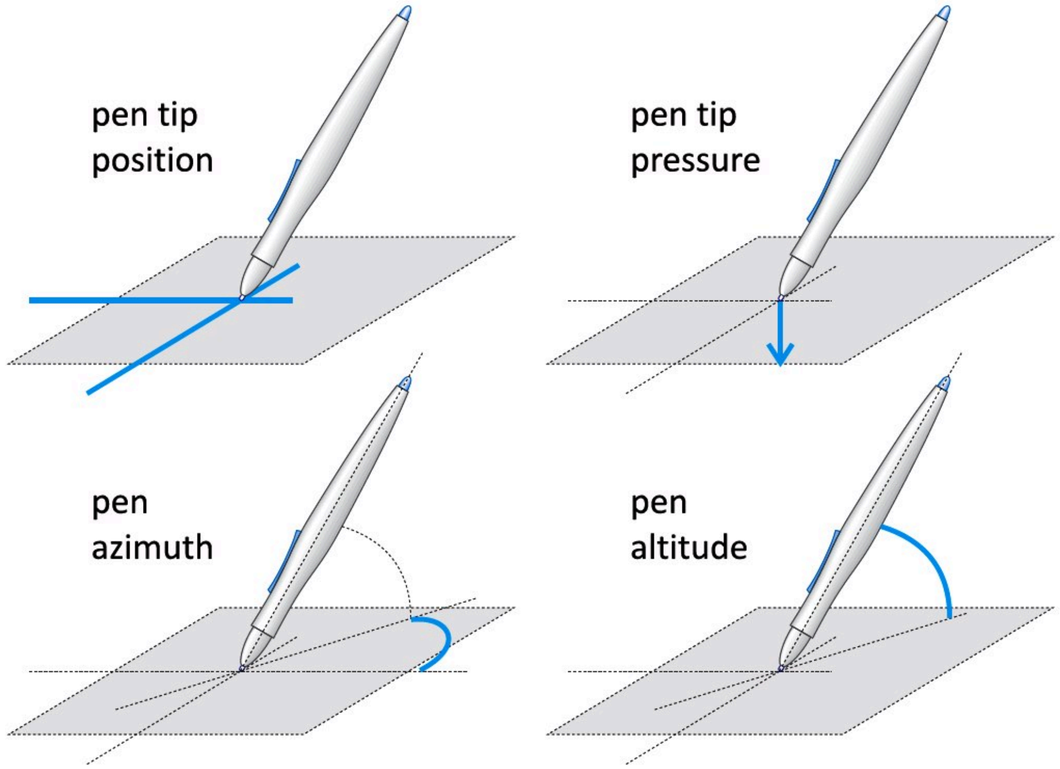
Not necessarily aided by a computer.

https://www.youtube.com/watch?v=NPf2otAxB8U

Signature Recognition

On-line Acquisition

Various components are captured from the signing behavior.



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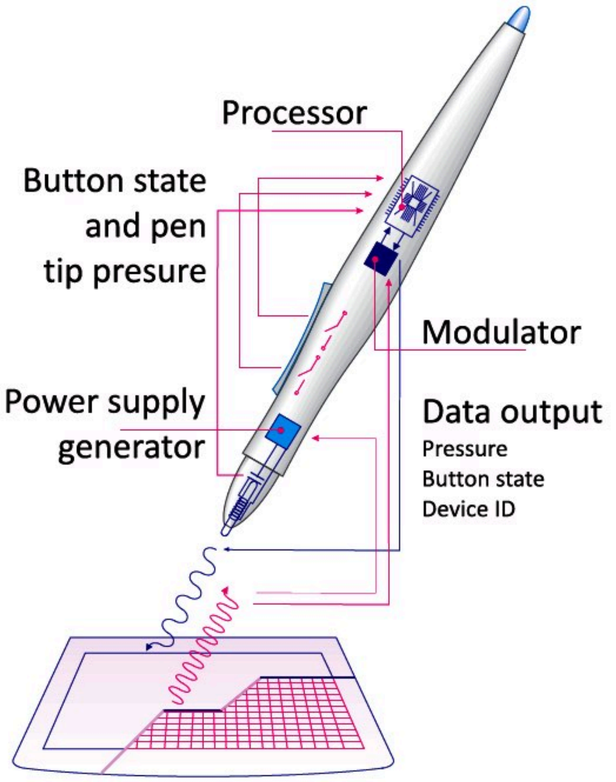
Signature Recognition

On-line Acquisition

Various components are captured from the signing behavior.

Special sensors
(such as digitizing tablets).



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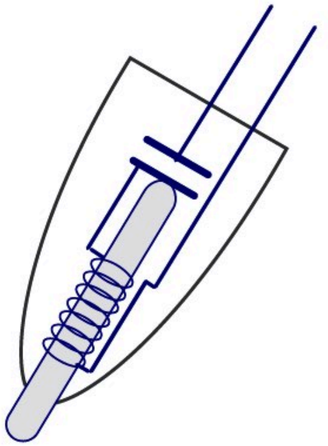

Inductor-capacitor
circuit (LC circuit)

Signature Recognition

On-line Acquisition

Various components are captured
from the signing behavior.

Special sensors
(such as digitizing tablets).

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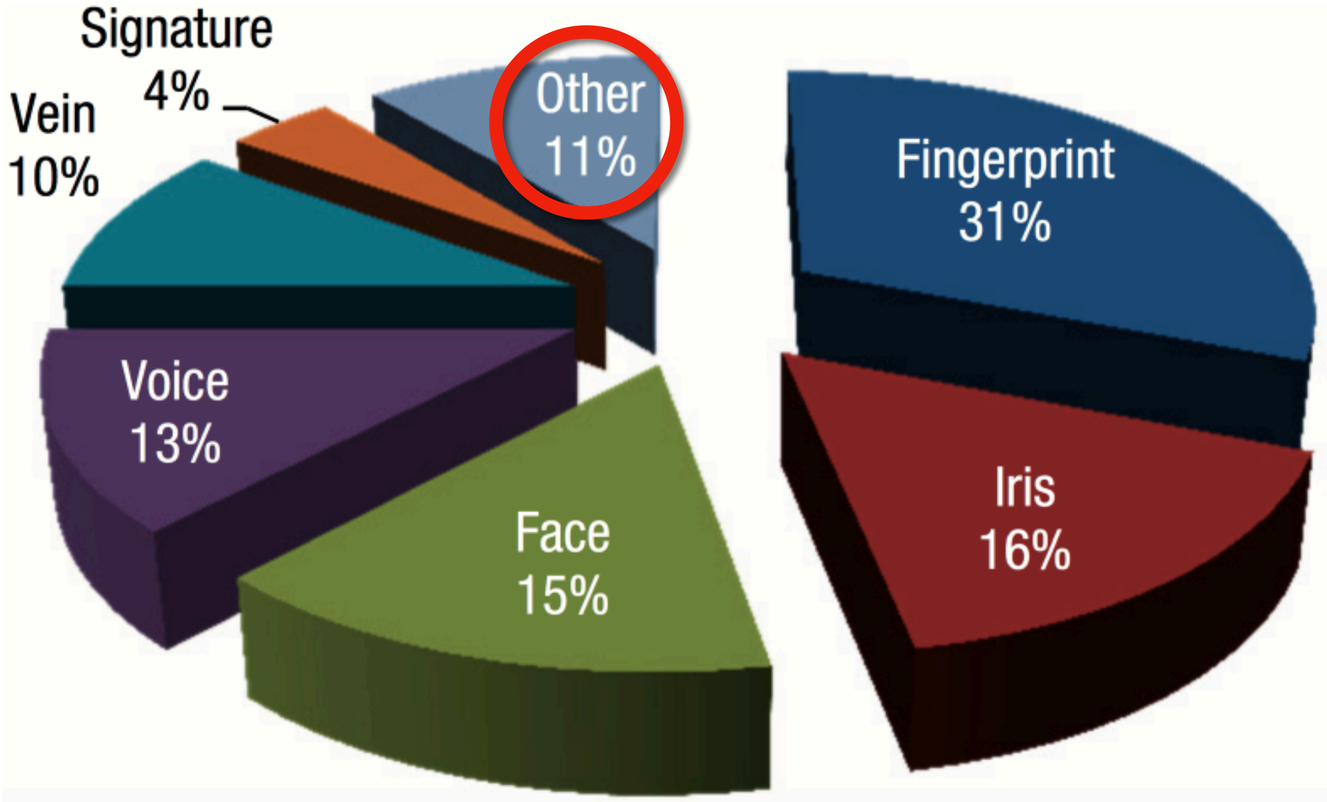
Aided by computer
(*acquisition*, *enhancement*, *feature extraction*, *matching*, *decision*).

Alternative Traits

Market



Source: Mani and Nadeski, *Processing solutions for biometric systems,* Texas Instruments, 2015

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Other Traits

DNA

Gate

Ears

Tongue Print

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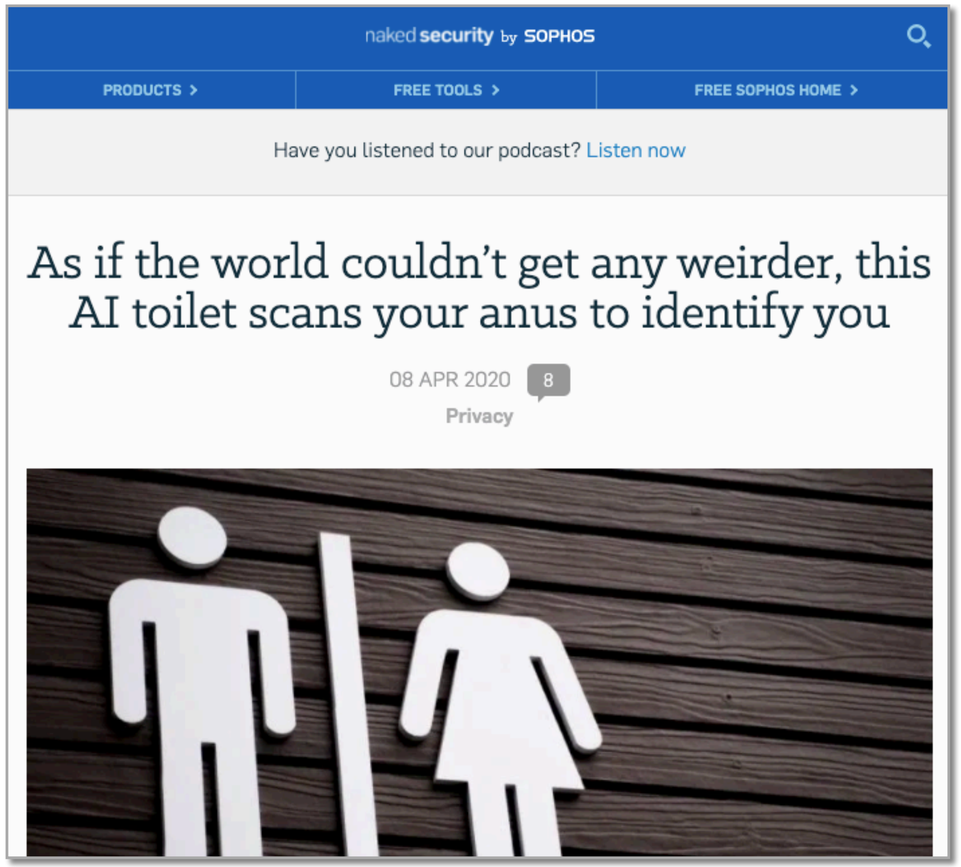
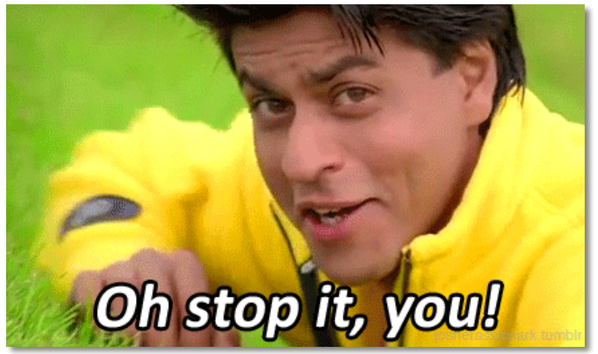
Other Traits

Ahem…



https://nakedsecurity.sophos.com/2020/04/08/as-if-the-world-couldnt-get-any-weirder-this-ai-toilet-scans-your-anus-to-identify-you/



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Multibiometrics

Pick a Trait

Universality (1/8)
Does everybody have the trait?

Uniqueness (2/8)
How likely two or more individuals will present the same trait?

Permanence (3/8)
How easily does the trait change?

Measurability (4/8)
How easy is it to acquire and digitize the trait?

Multibiometrics

Pick a Trait

Acceptability (5/8)
Will individuals collaborate during data collection?

Circumvention (6/8)
How hard can the trait be forged or imitated?

Performance (7/8)
How good is the trait quantitatively
according to objective metrics?

Accountability (8/8)
How easy is it for the everyman to understand the trait comparison?

Multibiometrics

Pick a Trait

There is no silver bullet.
No trait satisfies all *concepts*.

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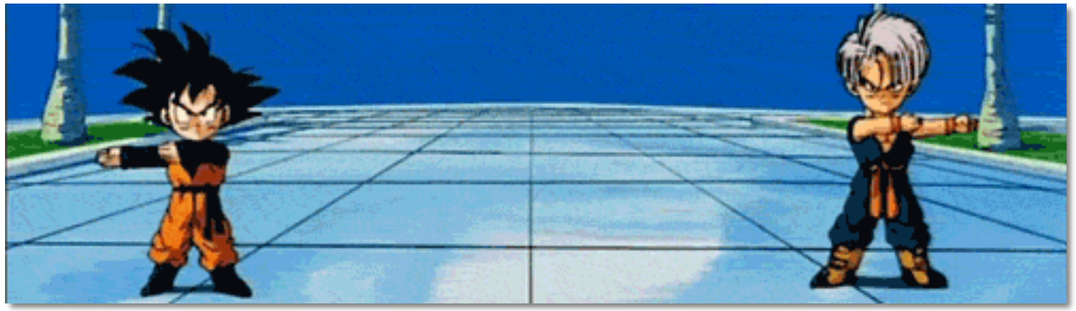
Multibiometrics

Solution
Rely on multiple traits.
Allow various presentations.
Combine results (data fusion).

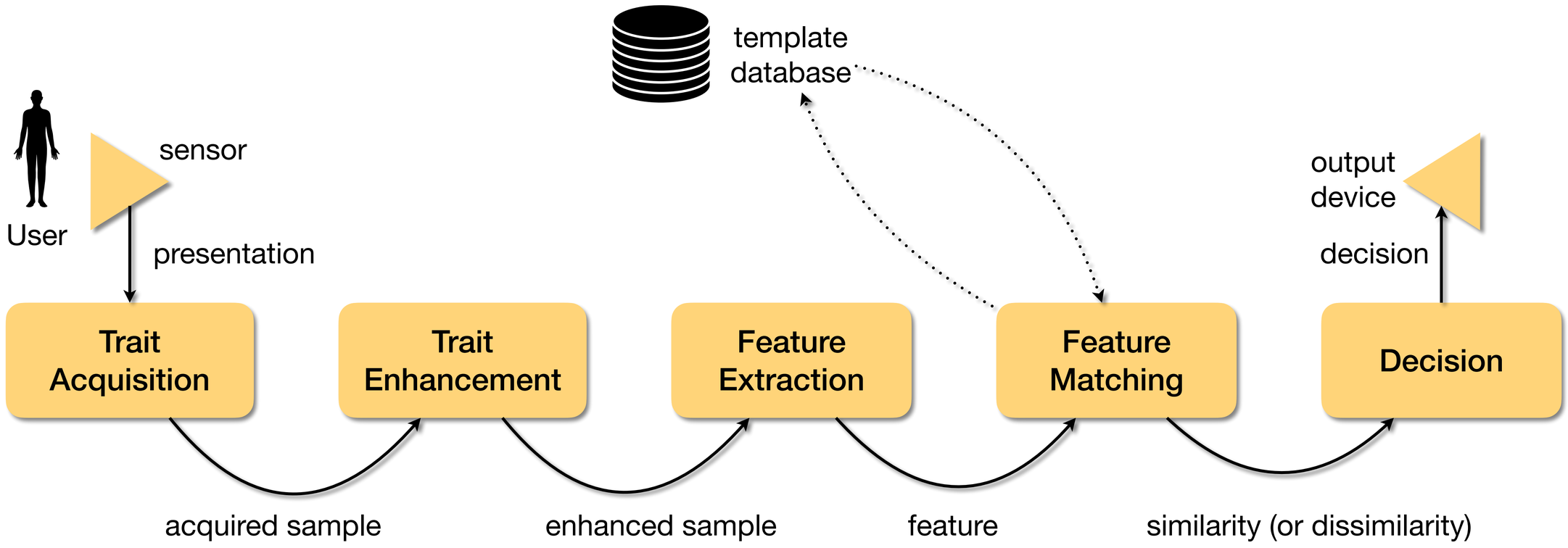


Pros
More concepts can be satisfied.
System is more robust to attacks.
It becomes more expensive
to attack the system.

Cons
System becomes more expensive
(more sensors, more software).
More runtime.
More complexity.

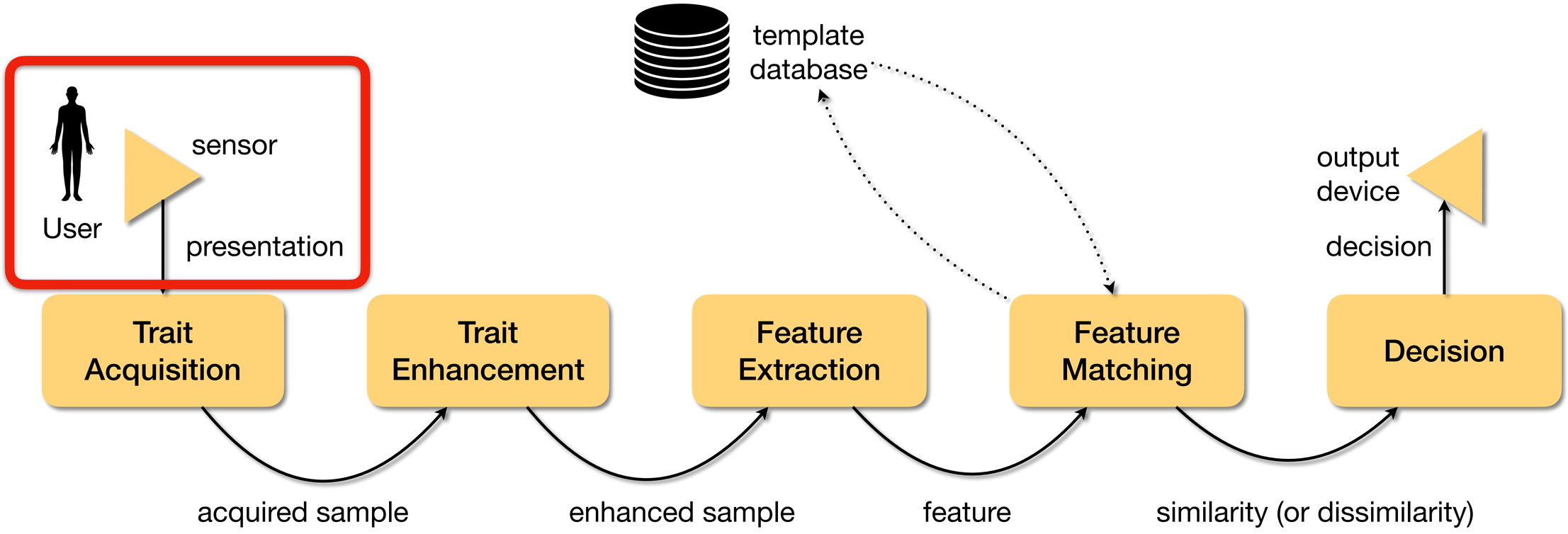
Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems



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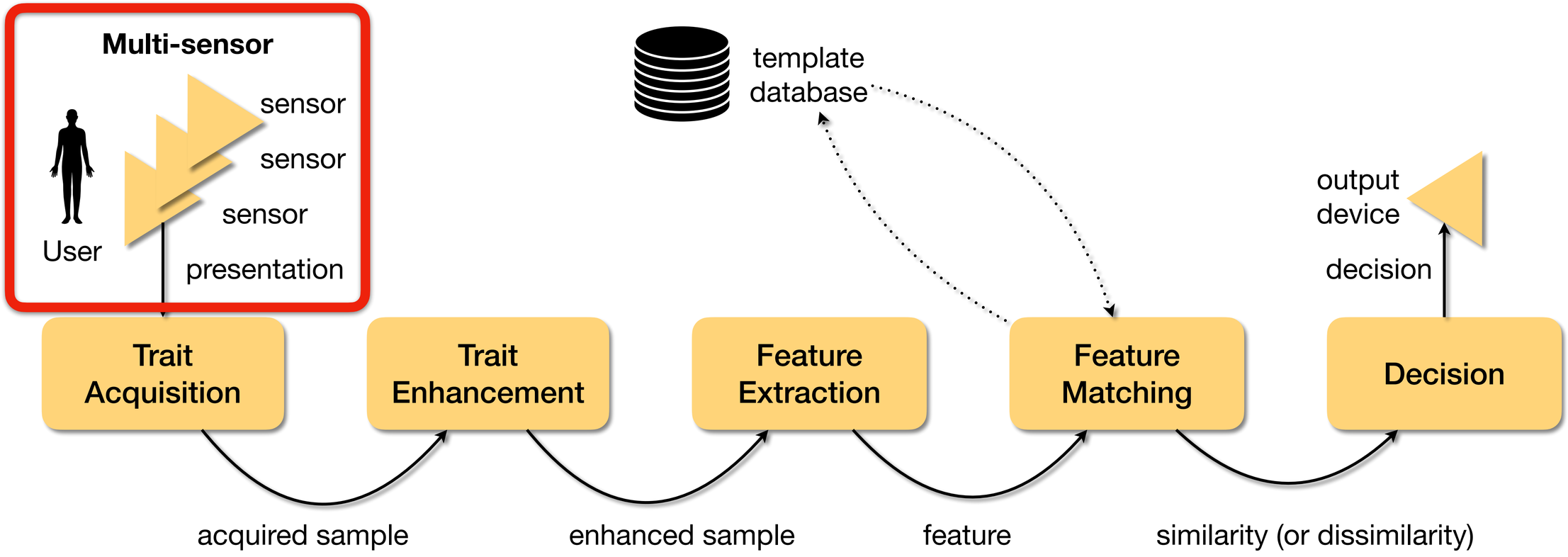
Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems

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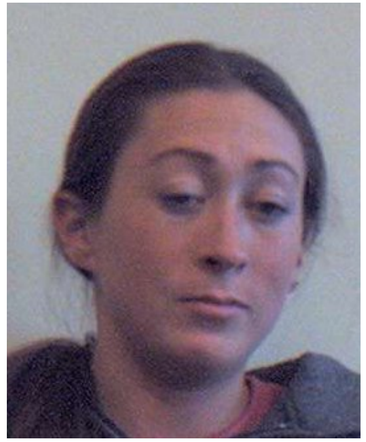
Multi-sensor Systems (1/5)
Single trait, multiple sensors.

If one sensor fails, other sensors might overcome the failure.



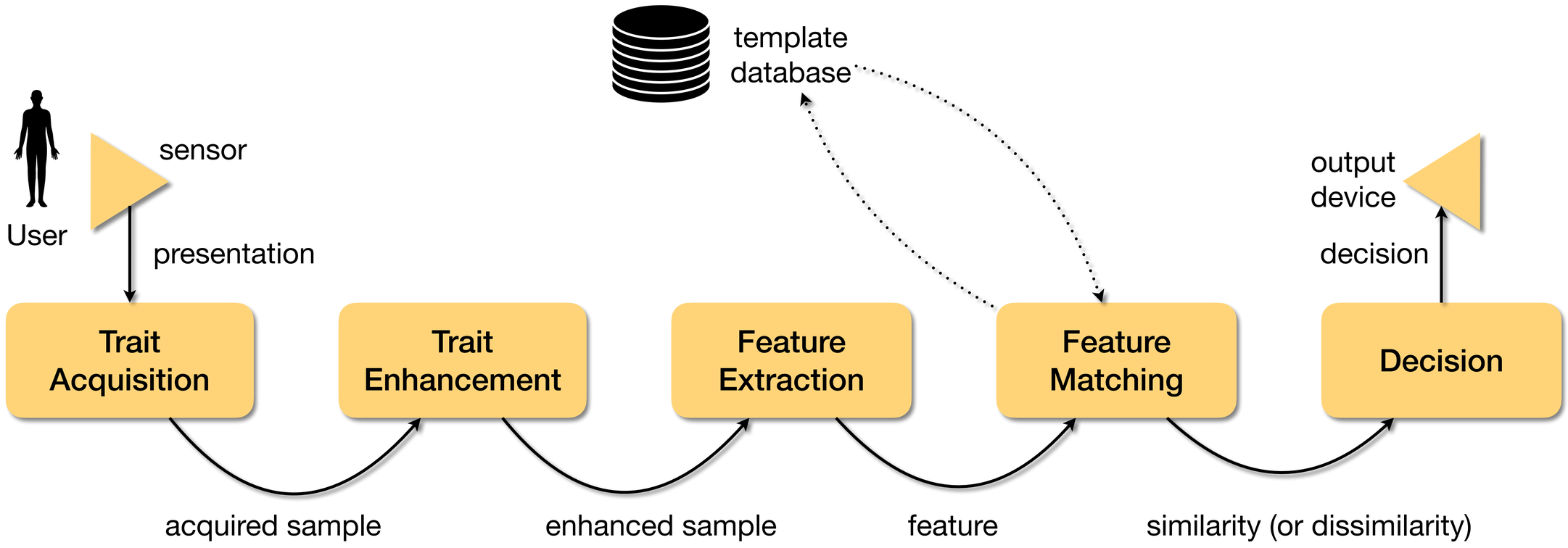
visible light

NIR

thermal

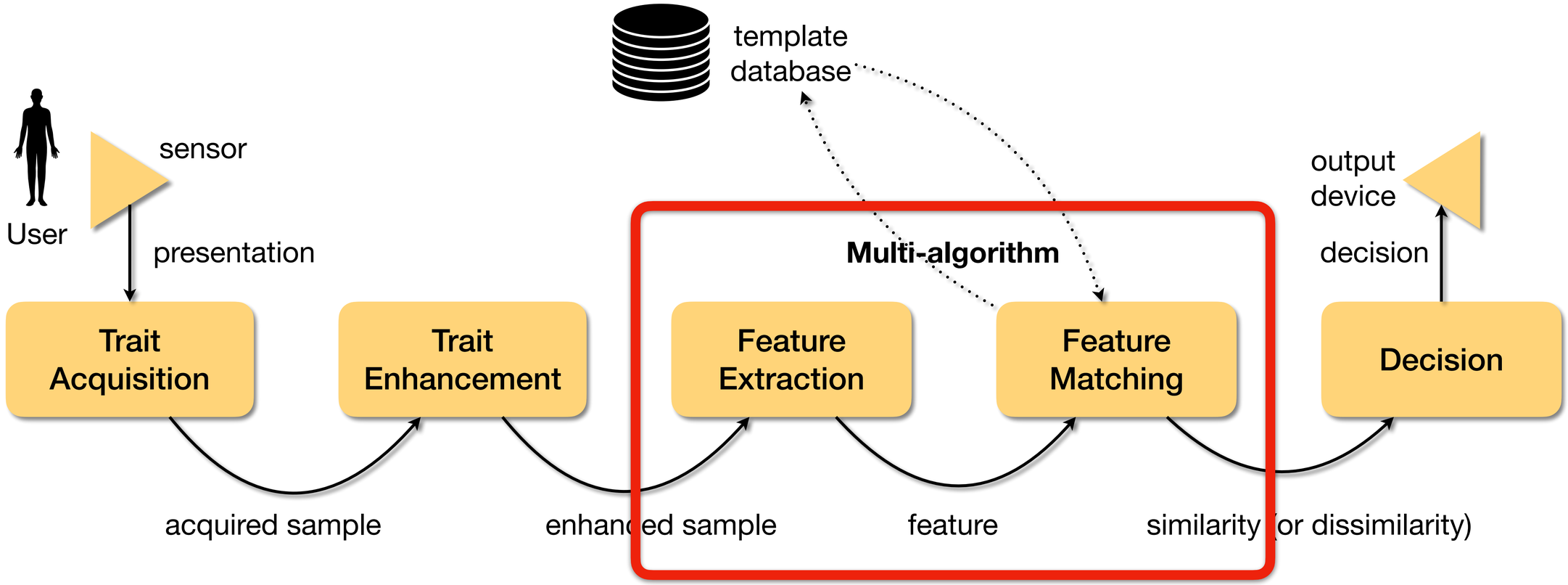
Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems



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Multibiometrics

Types of Multibiometric Systems

Multi-algorithm Systems (2/5)
Single trait, single sensor, multiple feature extractors and matching solutions.

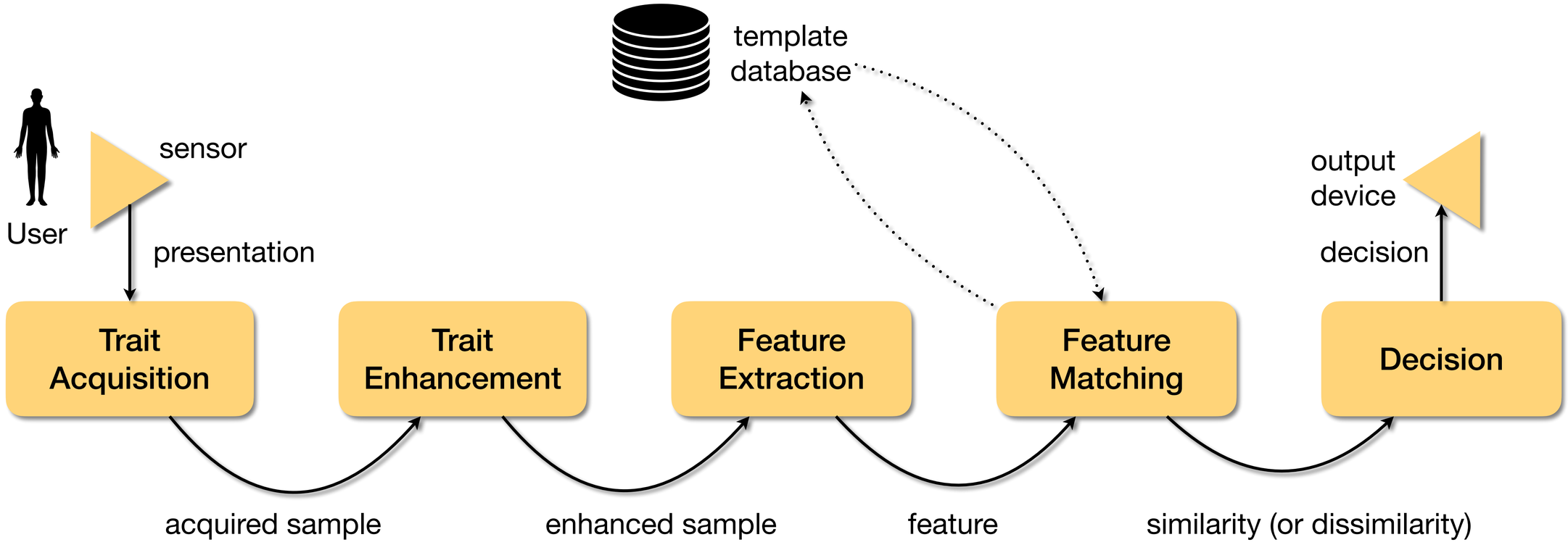
Complementary solutions will lead to higher accuracy in the end.

Daugman's iris code from 2D Gabor filters

Binary code from BSIF filters.

Multibiometrics

Types of Multibiometric Systems



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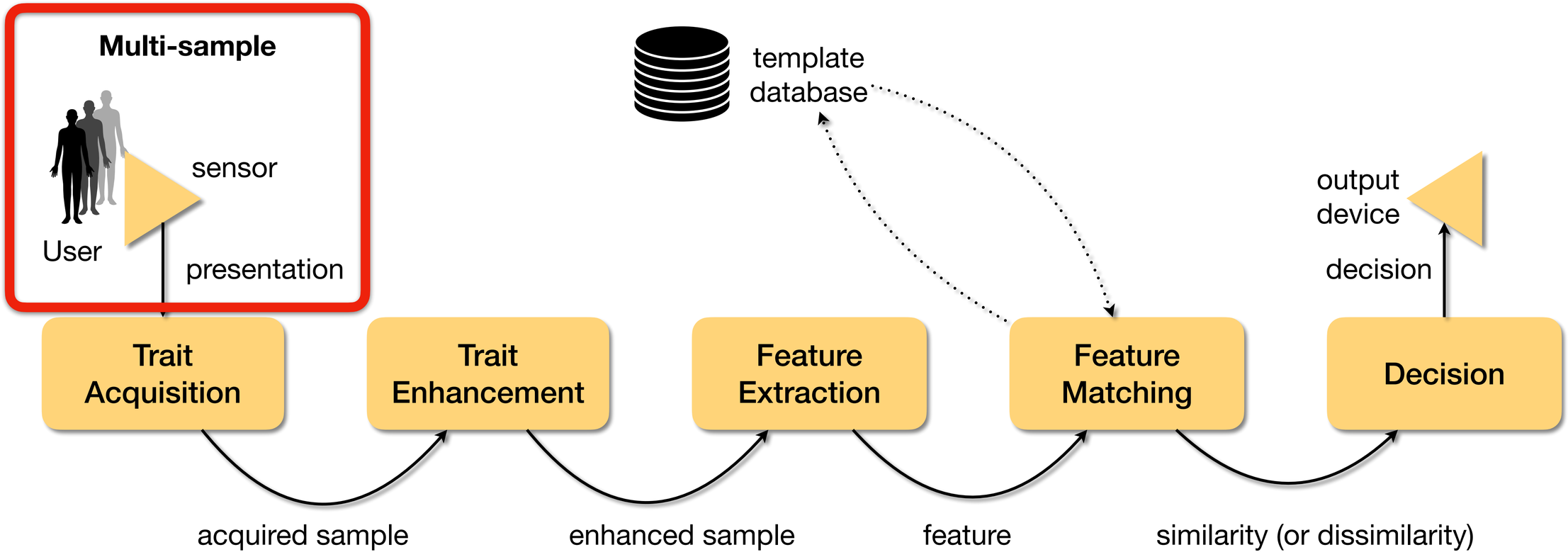
Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems

Multi-sample Systems (3/5)
Single trait, single sensor,
multiple presentations.

More complete representation
of the trait (account for variations).

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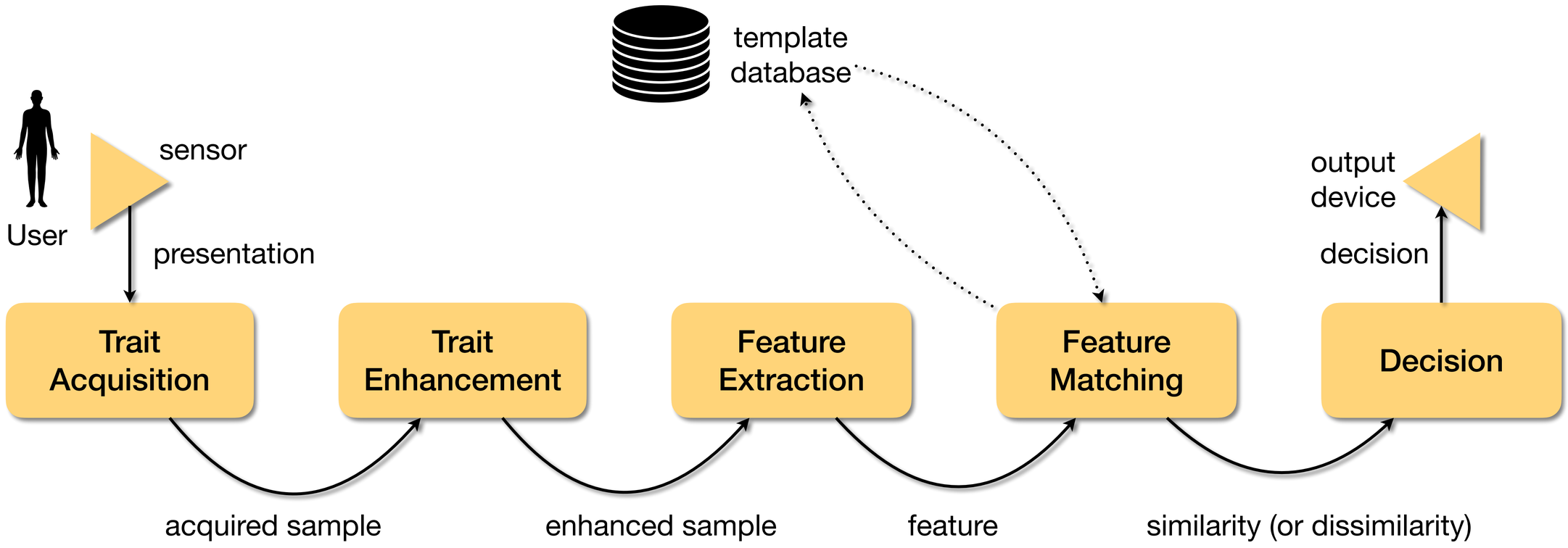
Multibiometrics

Types of Multibiometric Systems



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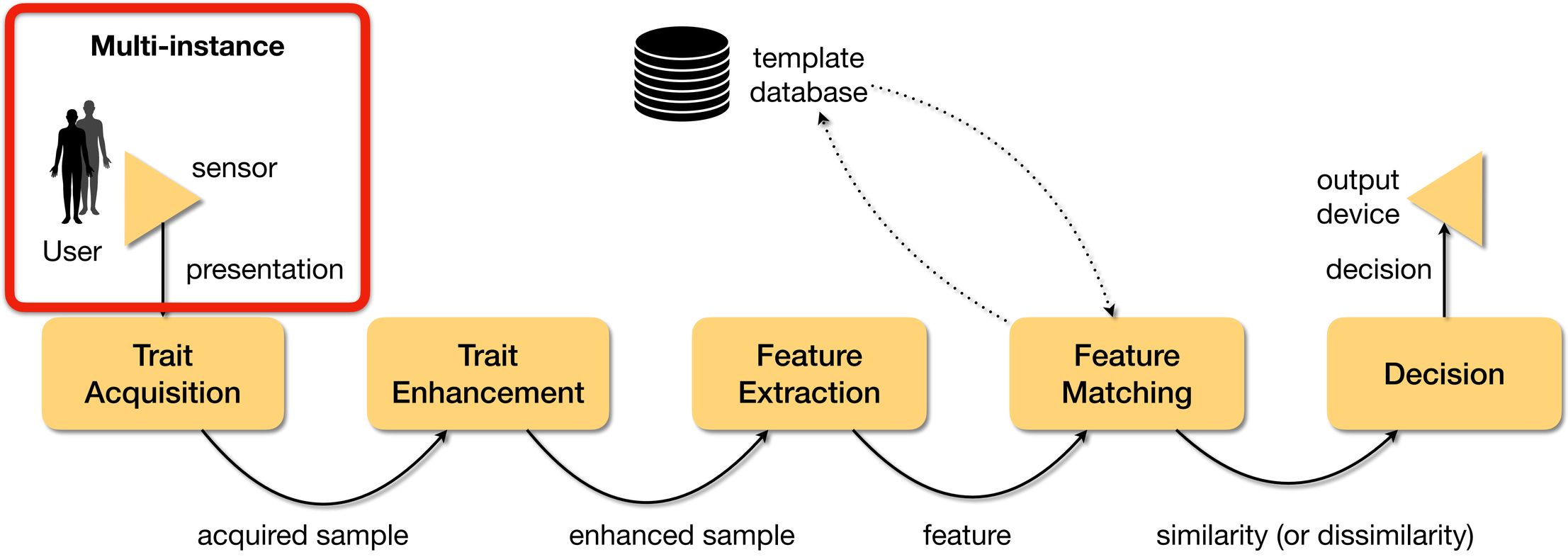
Multibiometrics

Types of Multibiometric Systems



Multibiometrics

Types of Multibiometric Systems

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Multi-instance Systems (4/5)
Single trait, single sensor,
multiple instances
(e.g., right and left irises,
or each one of the 10 hand fingerprints, etc.).

No need for extra sensors or extra software.
Successful presentations might overcome
the failed ones.

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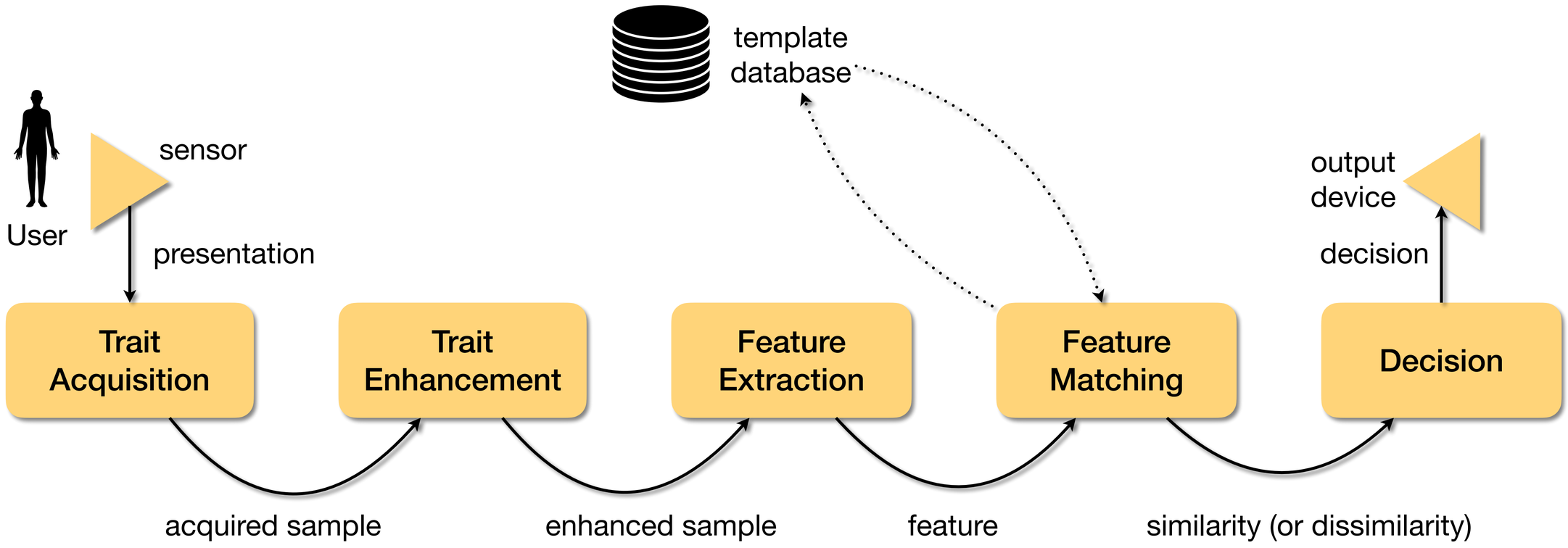
Multibiometrics

Types of Multibiometric Systems



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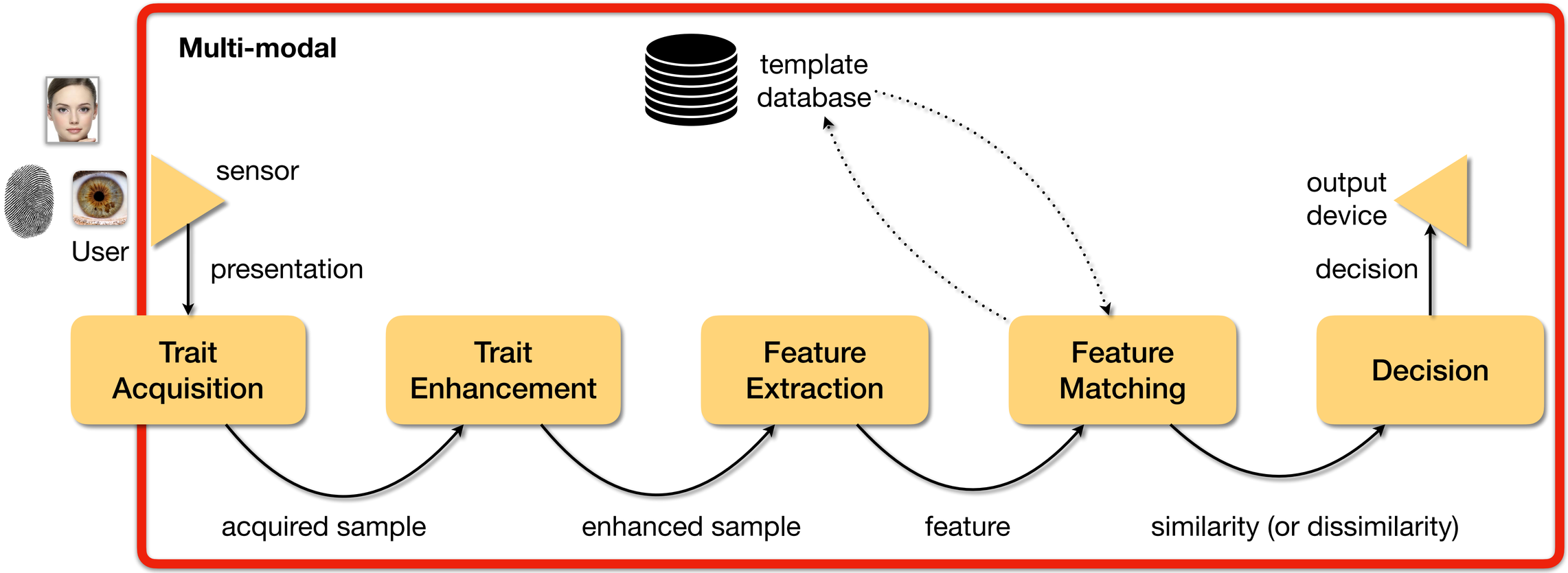


Multibiometrics

Types of Multibiometric Systems

Multi-modal Systems (5/5)
Multiple traits (modalities).

Complementary solutions will lead to higher accuracy in the end.

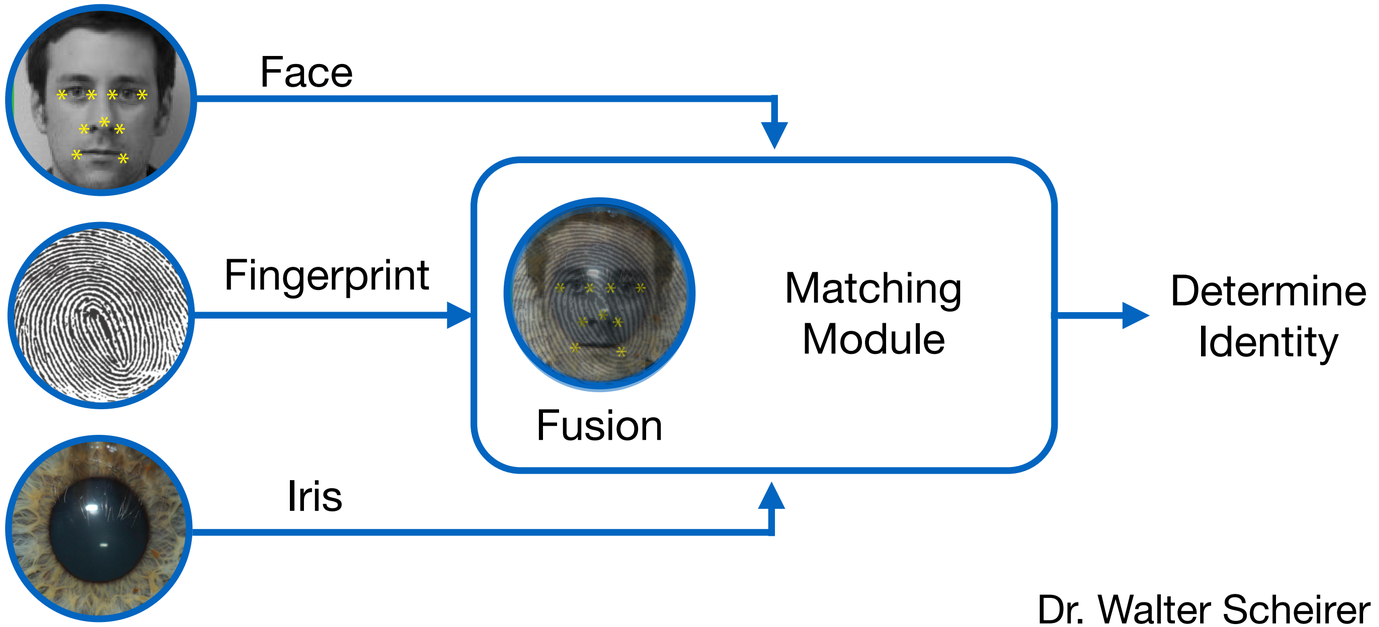
How to combine solutions?

Perform data **fusion!**

Multibiometrics

Architectures

Parallel (1/2)
Evidence acquired from multiple sources is processed simultaneously.



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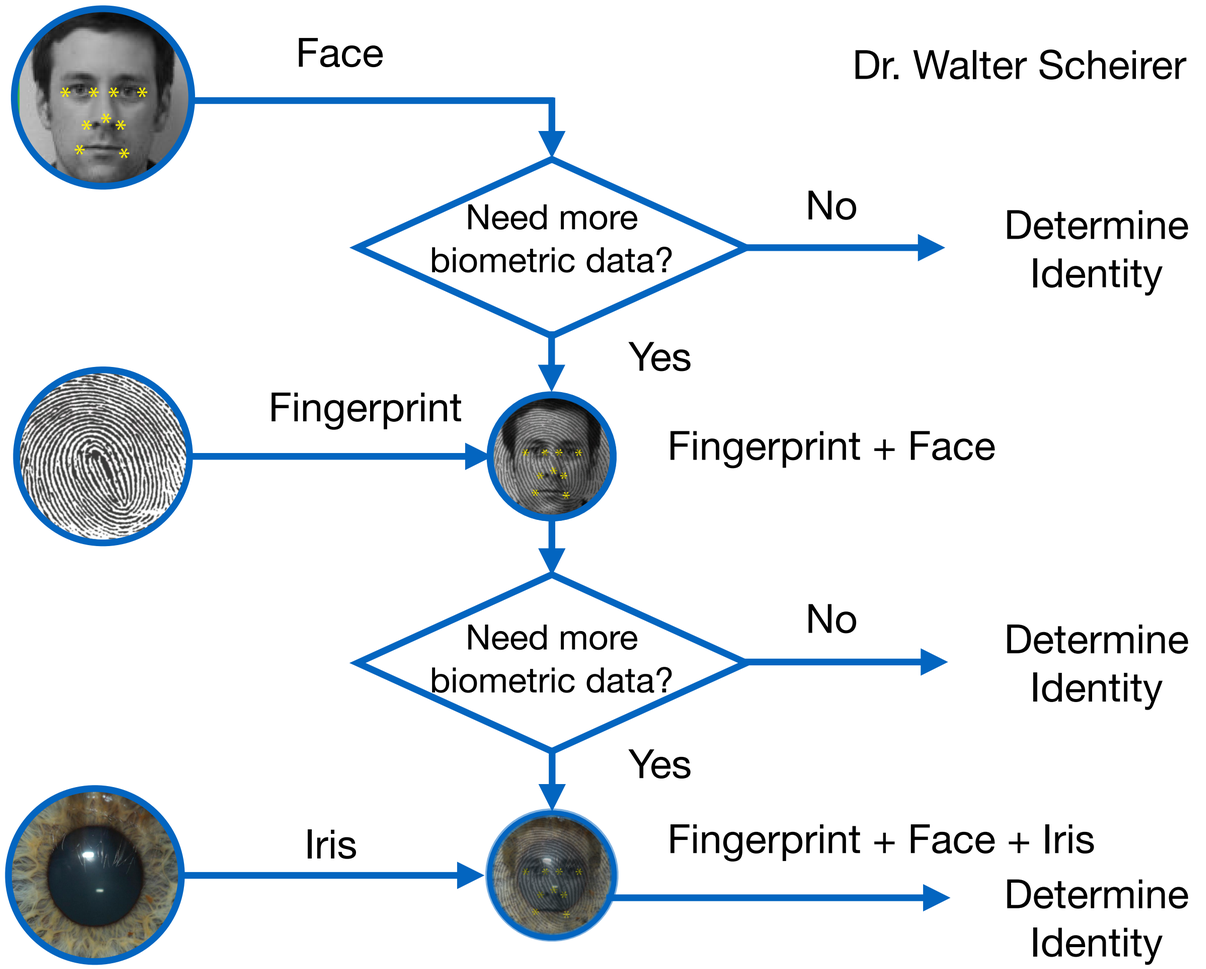
Multibiometrics

Architectures

Cascade (2/2)
Multiple sources are processed on demand (e.g., whenever a decision score is not confident enough).



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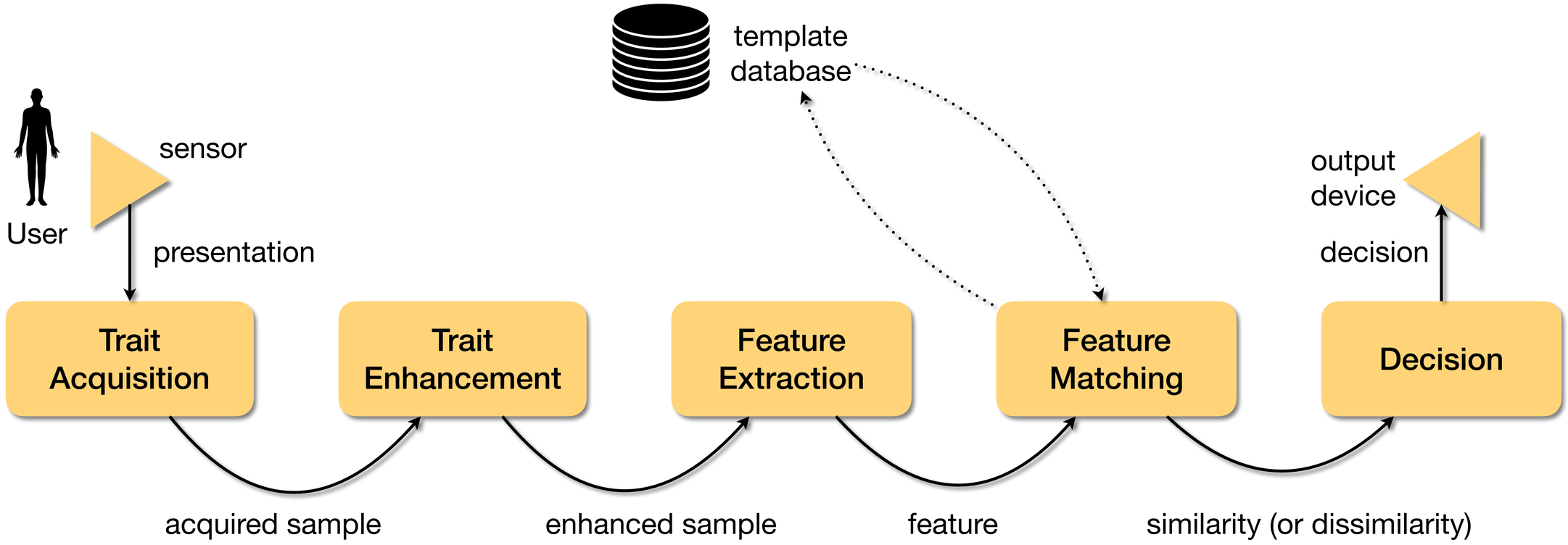
Multibiometrics

Data Fusion Levels



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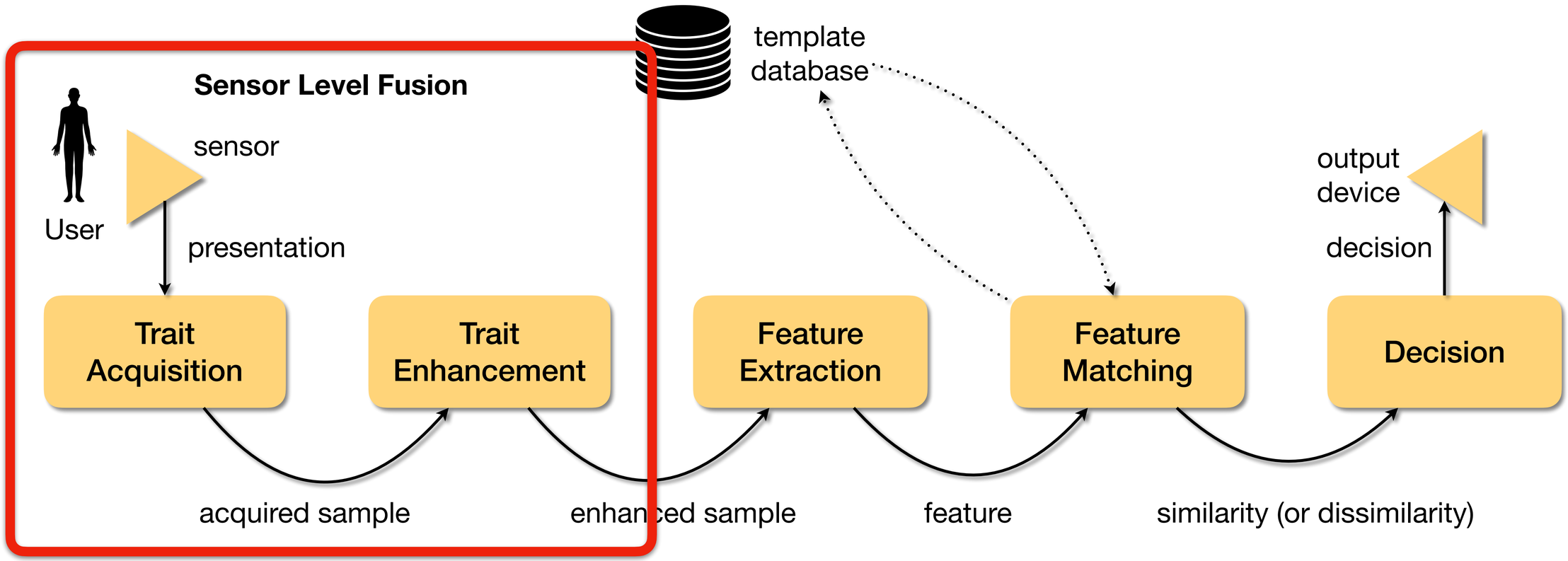
Data Fusion Levels

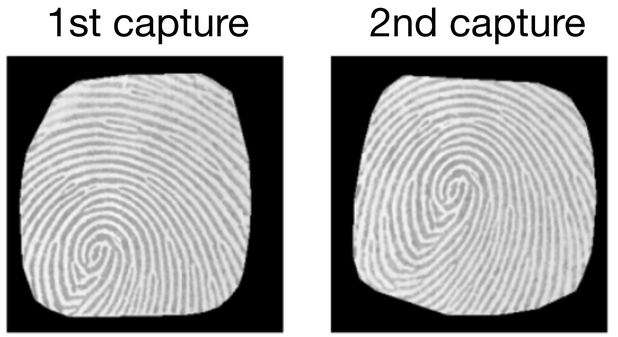


Multibiometrics

Data Fusion Levels

Sensor Level Fusion
Multiple sources of raw data are consolidated before feature extraction.

Example
Different captures of the same fingerprint are combined to generate sample larger than sensor capacity.



Multibiometrics

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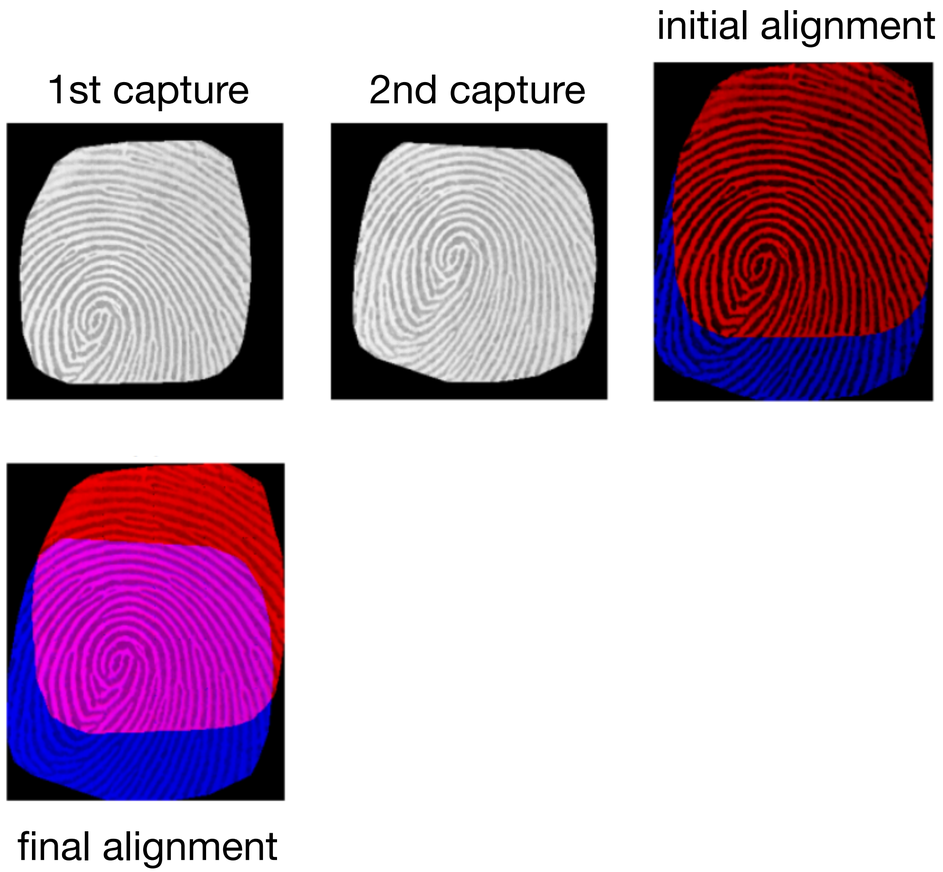

Multibiometrics

Data Fusion Levels

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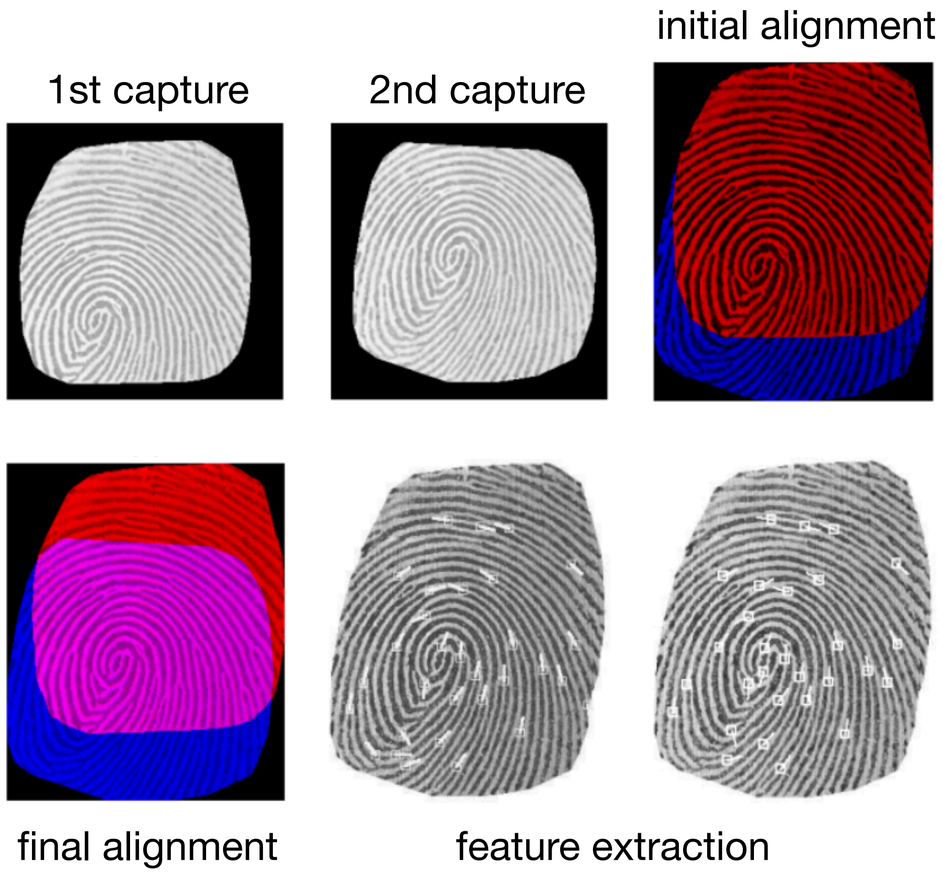
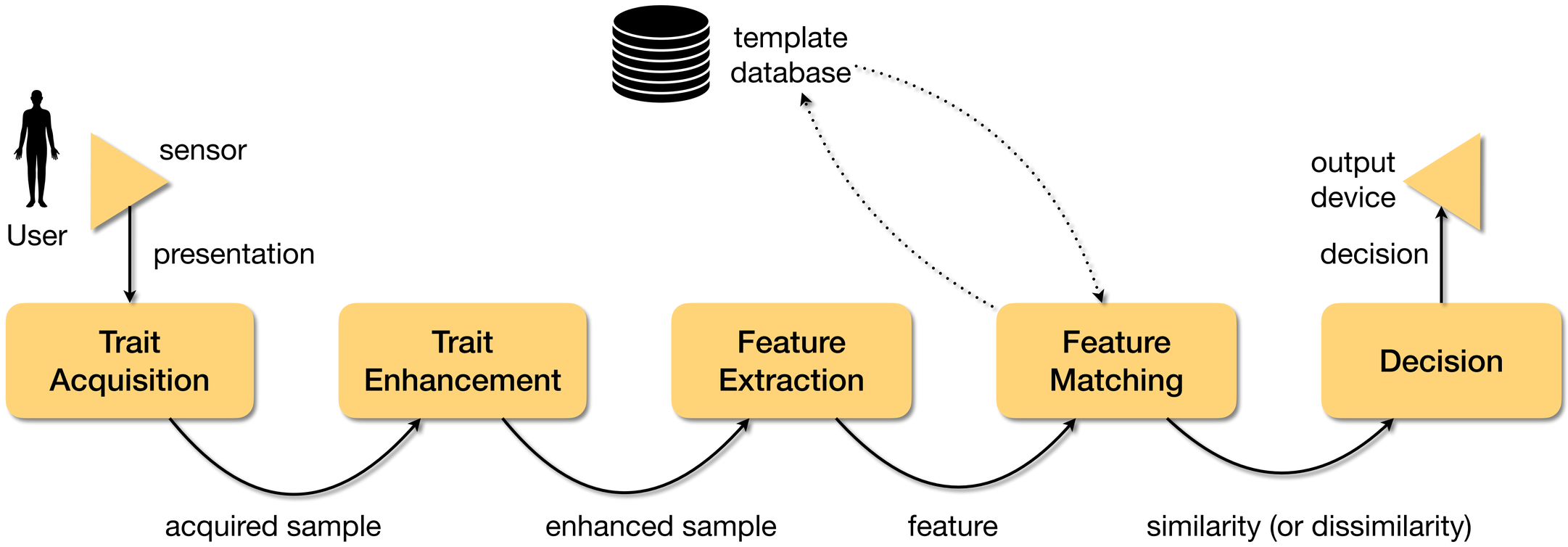


Jain and Ross
Fingerprint Mosaicking
ICASSP 2002

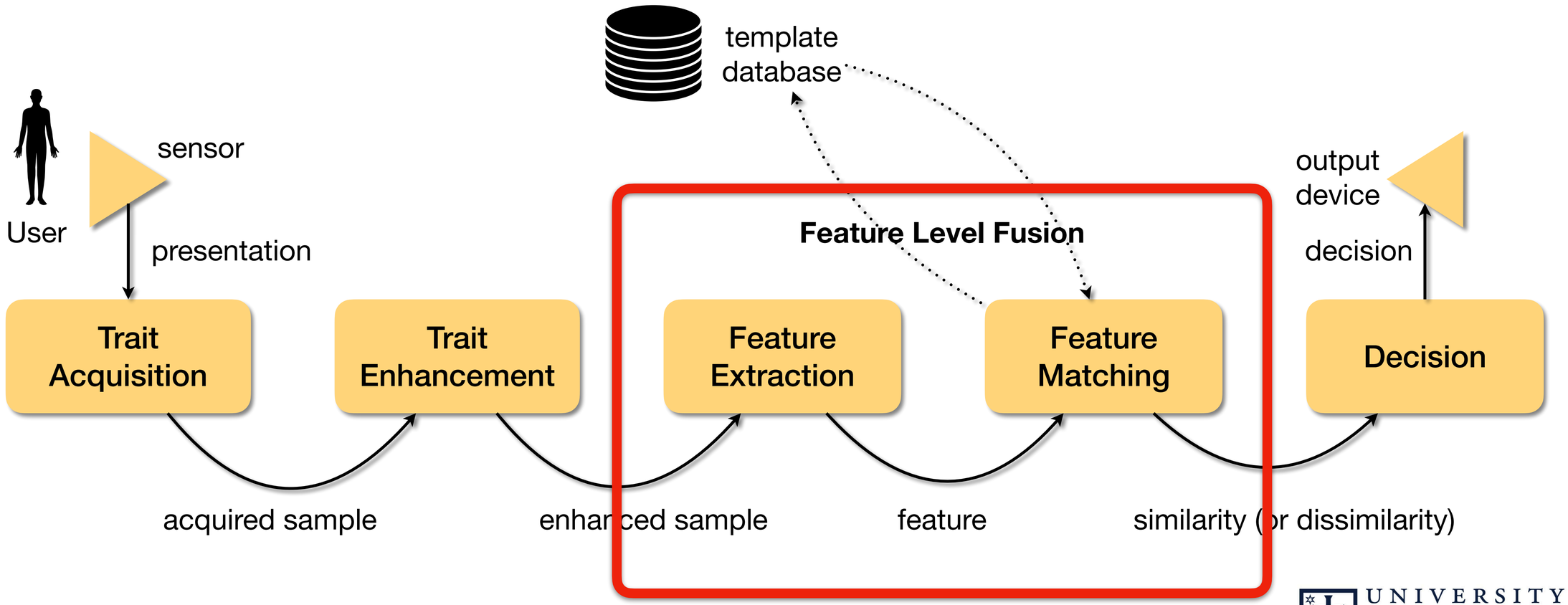
Multibiometrics

Data Fusion Levels



Multibiometrics

Data Fusion Levels

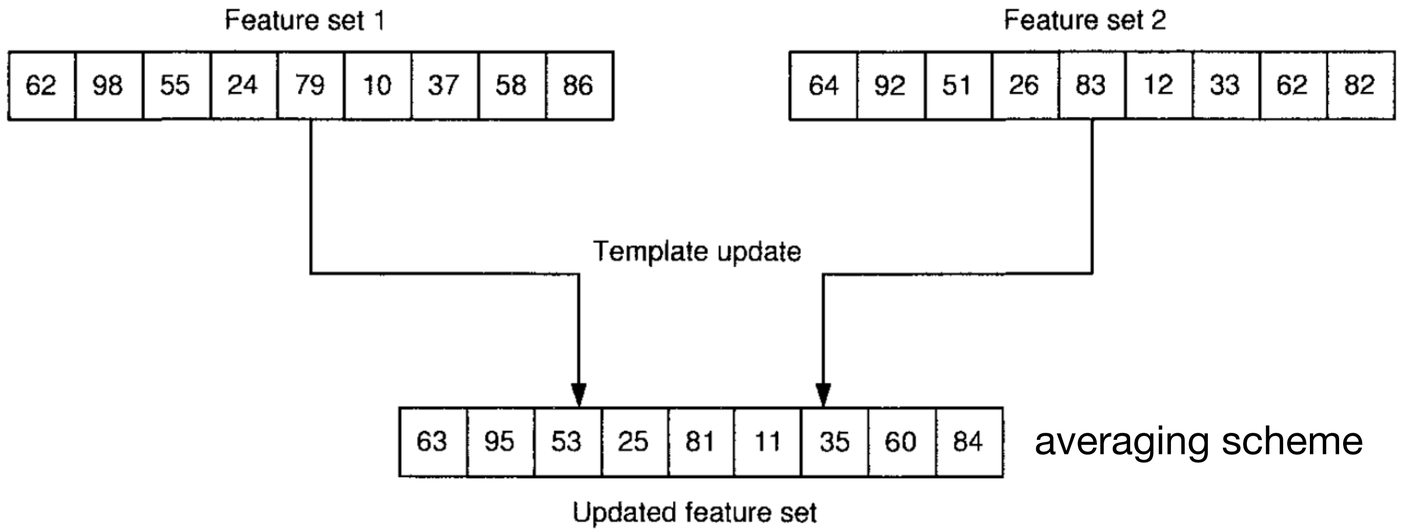


Multibiometrics

Data Fusion Levels

Ross, Nandakumar, and Jain
Handbook of Multibiometrics
Springer Books, 2006

Feature Level Fusion
Multiple feature vectors from the same individual are combined into a single feature vector, prior to matching.



Example Strategies
Linear combination, concatenation, etc.

Multibiometrics

Data Fusion Levels

Feature Level Fusion
Challenges

Multi-sensor Systems	Different-nature feature vectors.
Multi-algorithm Systems	Different-nature feature vectors.
Multi-sample Systems	Same-nature feature vectors.
Multi-instance Systems	Same-nature feature vectors.
Multi-modal Systems	Different-nature feature vectors.

Multibiometrics

Data Fusion Levels

Feature Level Fusion
Challenges

Multi-sensor Systems	**Different-nature feature vectors.**
Multi-algorithm Systems	**Different-nature feature vectors.**
Multi-sample Systems	Same-nature feature vectors.
Multi-instance Systems	Same-nature feature vectors.
Multi-modal Systems	**Different-nature feature vectors.**

Multibiometrics

Data Fusion Levels

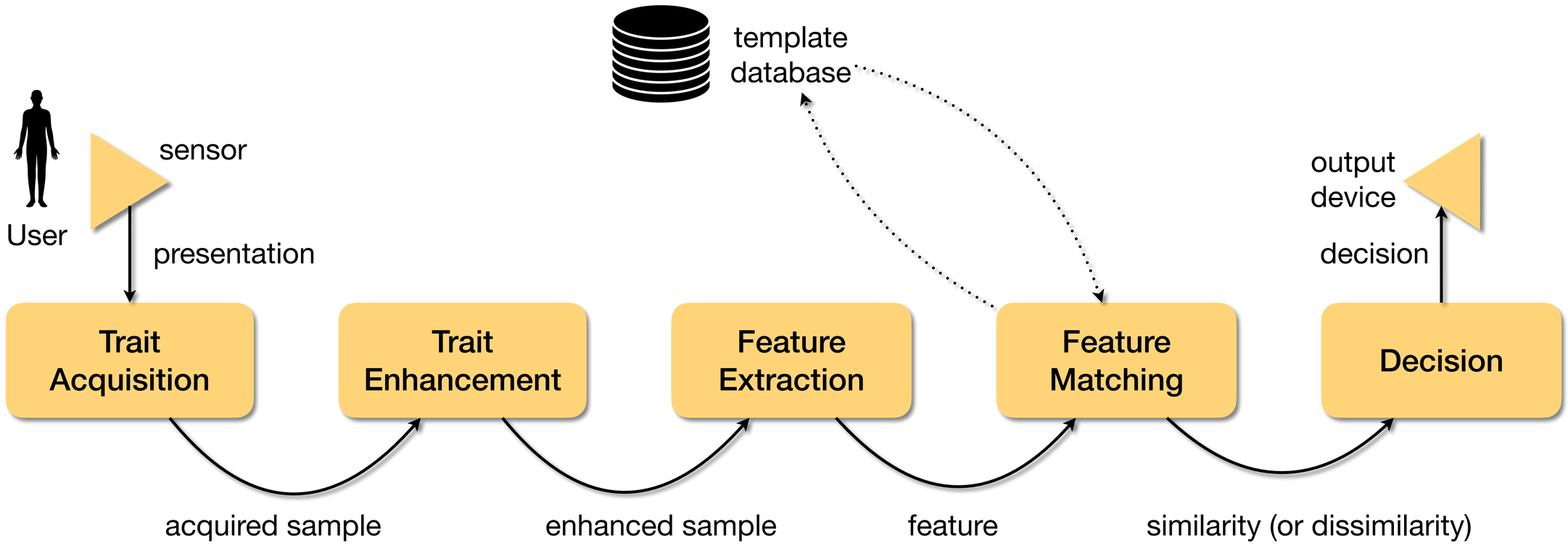
Feature Level Fusion
Challenges

How to combine features of
different nature?
(e.g., different domains, different scales,
different ranges of values, etc.).

Typical solutions: **concatenation, normalization**.
Caution: too-large vectors will suffer from the **curse of dimensionality**.

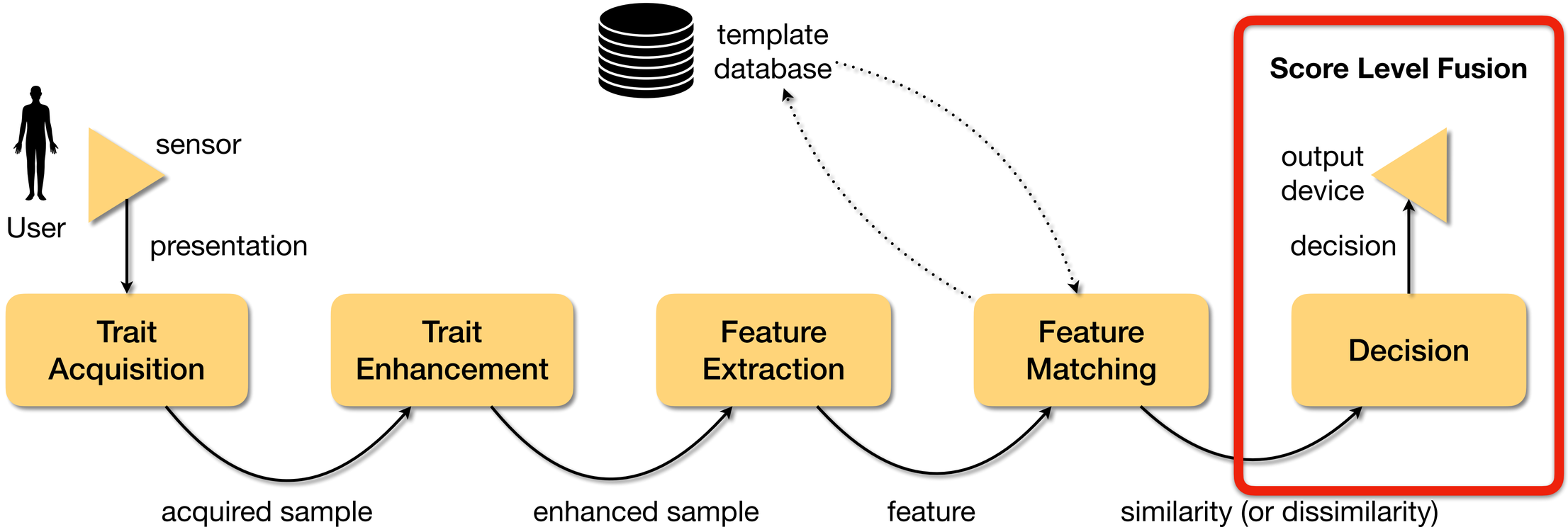
Multibiometrics

Data Fusion Levels



Multibiometrics

Data Fusion Levels



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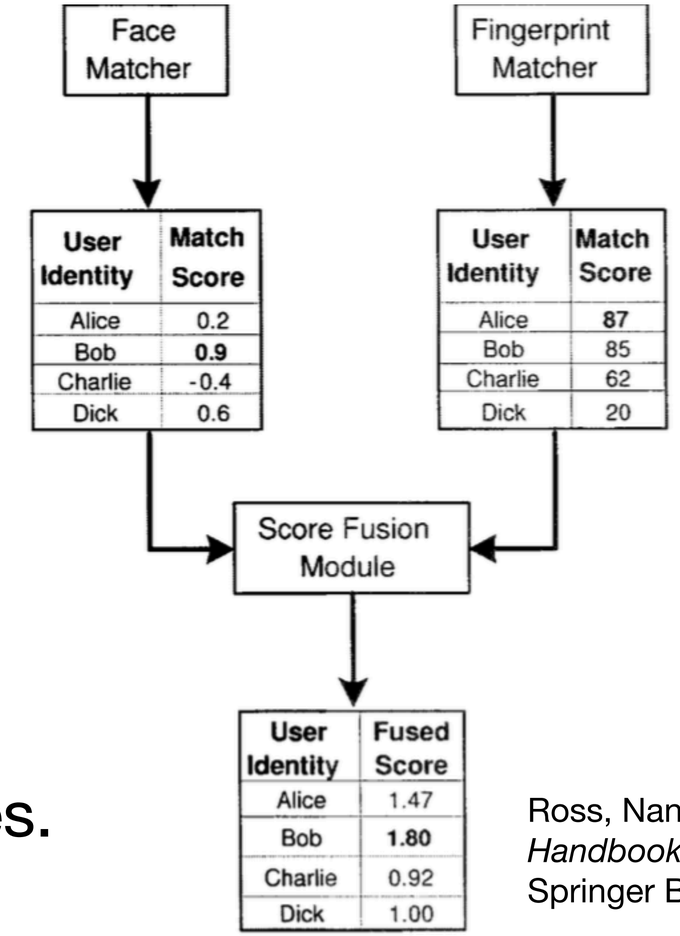
Data Fusion Levels

Score Level Fusion
Scores (similarities or dissimilarities) from different matching algorithms are consolidated before final decision.

Strategies
Discriminative versus *generative* approaches.



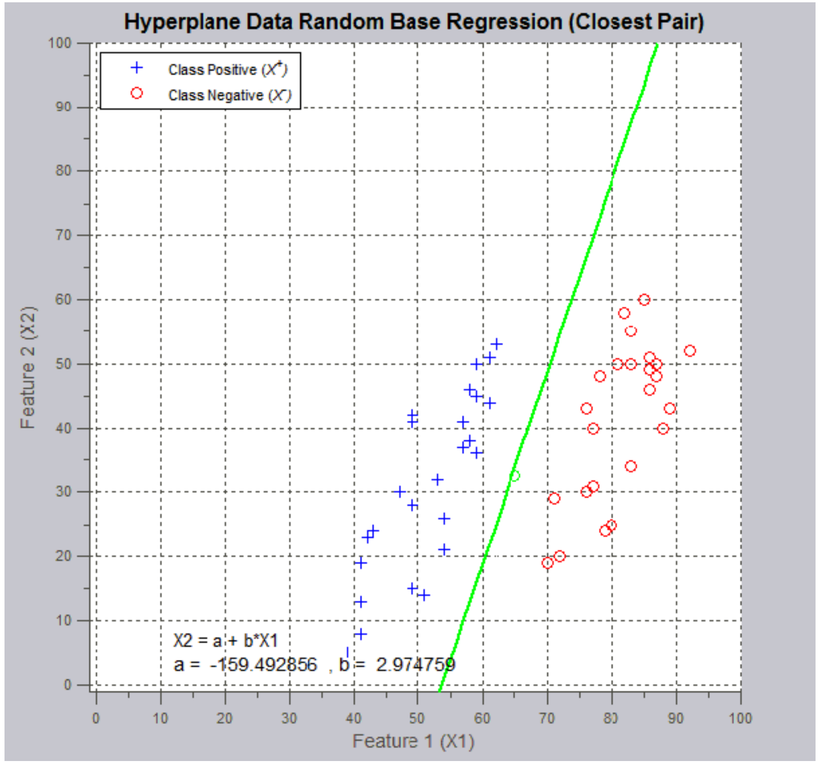
Ross, Nandakumar, and Jain
Handbook of Multibiometrics
Springer Books, 2006

Multibiometrics

Data Fusion Levels

Score Level Fusion
Discriminative Approaches

Thresholds, separation hyperplanes, decision trees, etc. are used to decide the Biometric system outcome (impostor versus genuine).



Example: Support Vector Machine (SVM)

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Data Fusion Levels

Score Level Fusion
Discriminative Approaches

Examples:
AND and OR rules.

	Face	Fingerprint	Iris	Decision
AND	X Non-Match	 “Ursula”	 “Ursula”	Non-Match
AND	 “Ursula”	 “Ursula”	 “Ursula”	Ursula
OR	X Non-Match	 “Ursula”	 “Ursula”	Ursula

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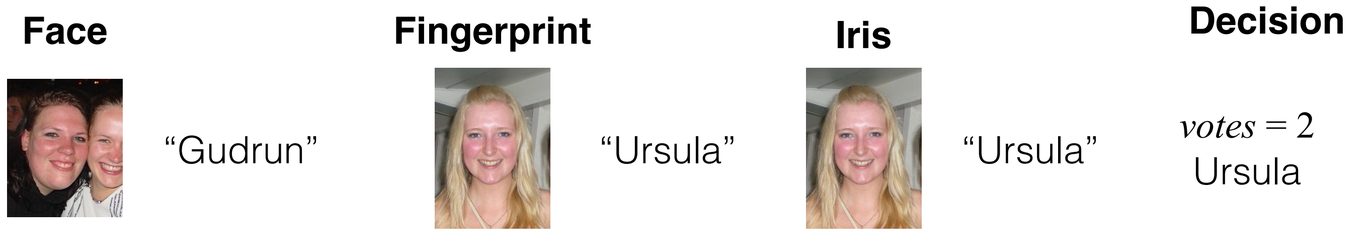
Data Fusion Levels

Score Level Fusion
Discriminative Approaches

Examples:
Majority Voting.



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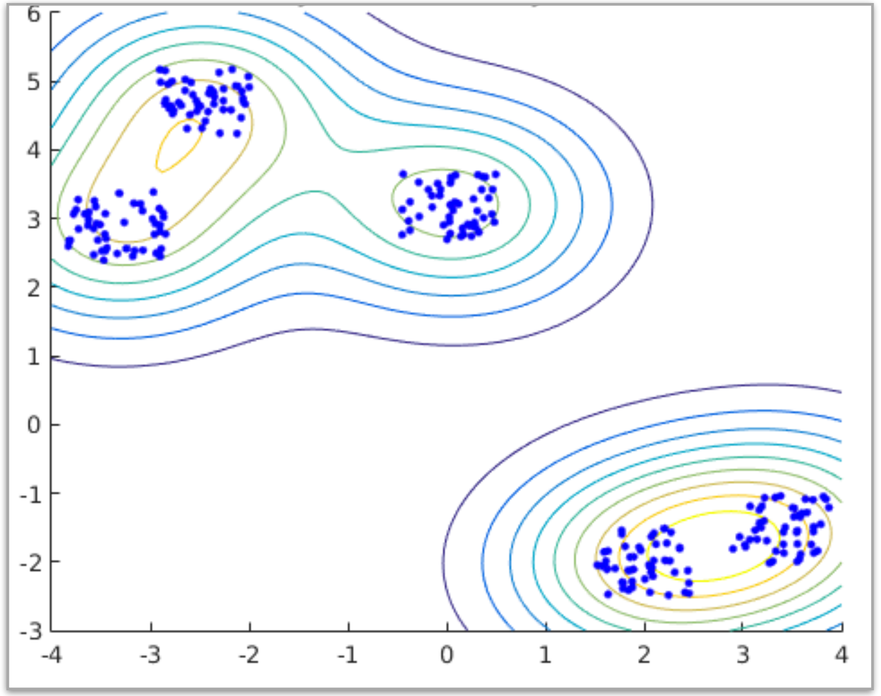
Data Fusion Levels

Score Level Fusion
Generative Approaches

Data distribution models of the
joint probability of observations and
scores are computed in *training* time
and further used in *operation* time
to return the probability of a presentation
be either impostor or genuine.



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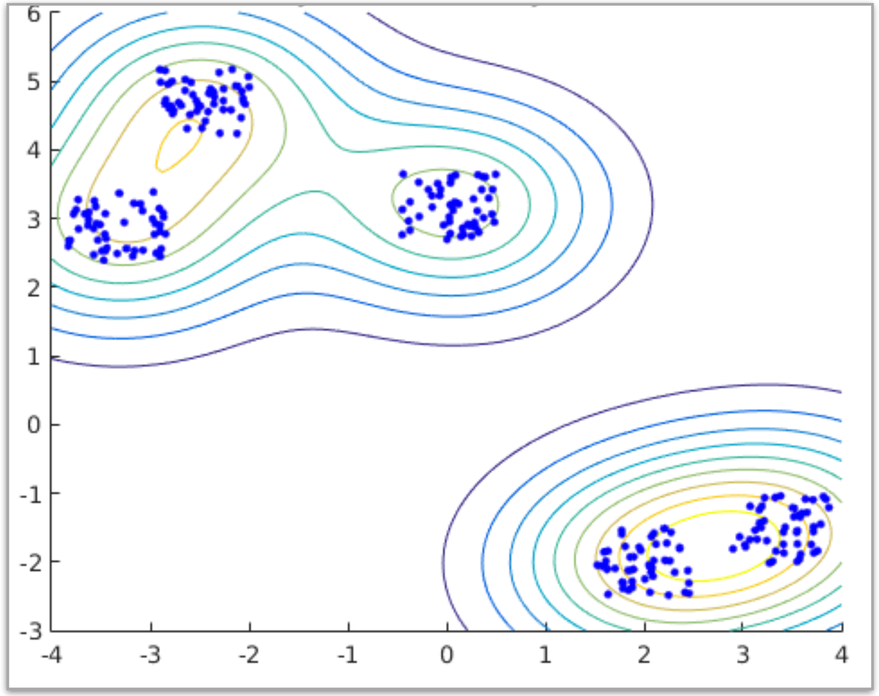
Data Fusion Levels

Score Level Fusion
Generative Approaches

Examples: Naïve Bayes,
Gaussian Mixture Models (GMM),
Extreme-Value Theory, etc.



Multibiometrics

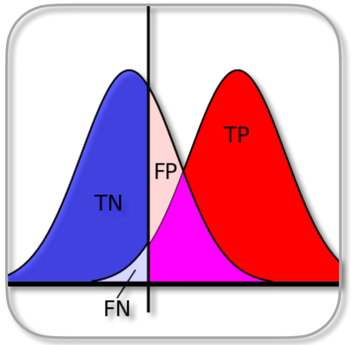
Data Fusion Levels

Score Level Fusion
Pros

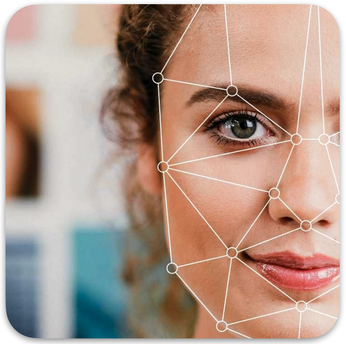
Regardless of being either discriminative or generative, it can be used with commercial off-the-shelf matchers that do not expose their feature vectors but return confidence scores.

Course Overview

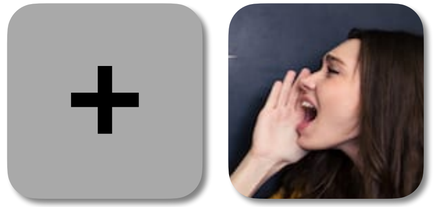
Content



Basics
Concepts
Metrics
Metric implementation



Core Traits (3)
Concepts
Baseline implementation
Evaluation
Assignments

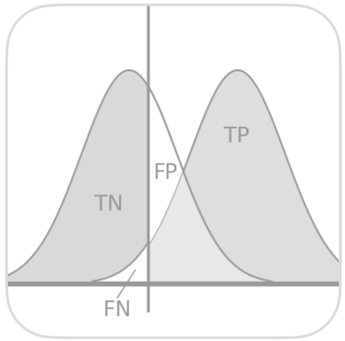


Alternative Traits and Fusion
Concepts

Invited Talks (2)
State of the art
Future work

S’up Next?

Content



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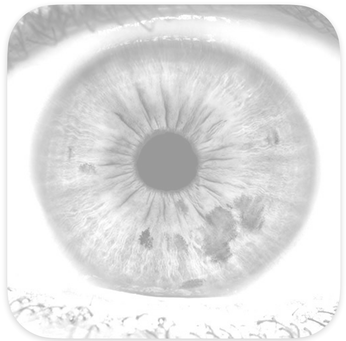

Core Traits (3)
Concepts
Baseline implementation
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Alternative Traits and Fusion
Concepts

Invited Talks (2)
State of the art
Future work

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First Talk

Dr. Andrey Kuehlkamp
https://crc.nd.edu/about/people/andrey-kuehlkamp/

TUE, April 14, 5:05 PM (EST)
https://notredame.zoom.us/my/dmoreira

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Second Talk

Dr. Adam Czajka
https://engineering.nd.edu/profiles/aczajka

THR, April 16, 5:05 PM (EST)
https://notredame.zoom.us/my/dmoreira

Acknowledgments

This material is heavily based on
Dr. Adam Czajka's and Dr. Walter Scheirer's courses.
Thank you, professors, for kindly allowing me to use your material.

https://engineering.nd.edu/profiles/aczajka
https://www.wjscheirer.com/

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