On automated ear-based authentication

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Outline

1. Problem statement
   - Background and motivation
   - Objectives
2. Data
3. System design
4. Image segmentation
5. Contour detection
6. Feature extraction
7. Feature matching and verification
8. Experiments
   - Protocol
   - Results
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9. Future work

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Background and motivation

A biometric system performs personal authentication based on a specific physiological or behavioural characteristic of the individual.

Biometric systems are increasingly utilised for security purposes, as they are more reliable and secure than most traditional modes of personal authentication.

The human ear is one of the most distinctive human biometric traits that can be employed to establish or verify an individual's identity and may be acquired in a non-intrusive manner.

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- Develop a feature extraction strategy that is based on the discrete Radon transform (DRT) and takes prominent ear contours as input.
- Develop a template matching protocol that quantifies the difference between corresponding feature vectors.
- Set up a rank-based verifier that is able to establish the authenticity of a questioned ear image.

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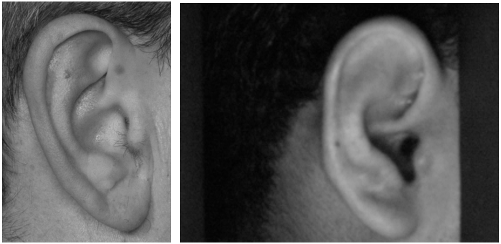
Data

In this study experiments are conducted on two databases, that is

1. the Mathematical Analysis of Images (AMI) ear database (see Figure 1 (a)) and
2. the Indian Institute of Technology (IIT) Delhi ear database (see Figure 1 (b)).



(a) (b)

Figure 1: **(a)** A typical grey-scale image from the AMI ear database. **(b)** A typical grey-scale image from the IIT Delhi ear database.

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System design: enrollment stage

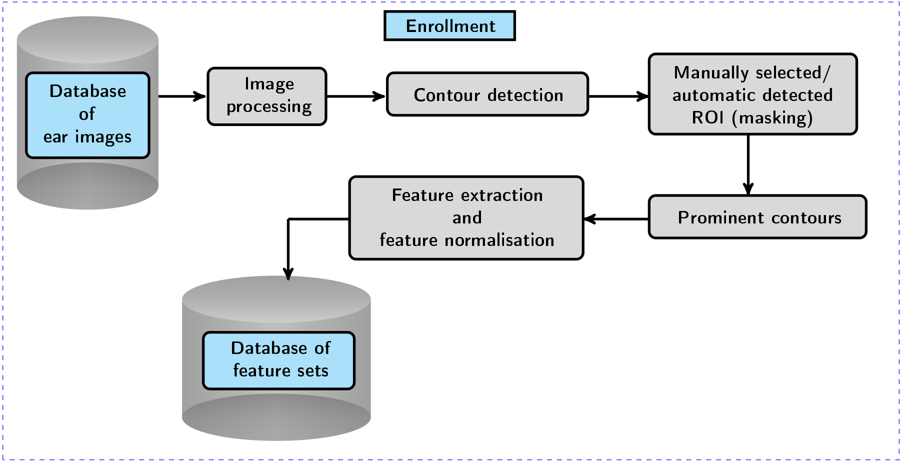

Figure 2: Overview of the proposed **enrollment** stage of the semi-automated and fully automated ear-based biometric authentication systems.

System design: authentication stage

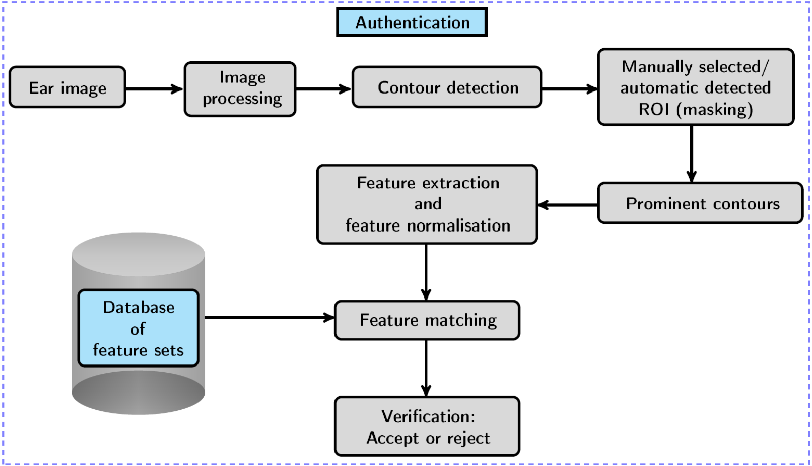

Figure 3: Overview of the proposed **authentication** stage of the semi-automated and fully automated ear-based biometric authentication systems.

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Image segmentation

A CNN-based protocol, combined with appropriate morphological post-processing, is proposed for detecting a suitable ROI that contains the ear shell (see Figure 4).

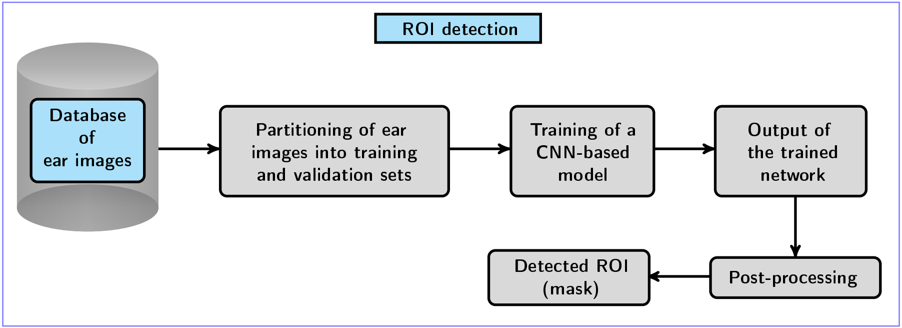

Figure 4: The proposed automatic ROI detection protocol.

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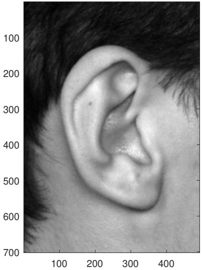
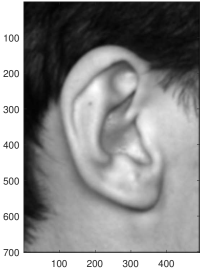
Contour detection

An input ear image is smoothed by applying a Gaussian kernel (see Figure 5).



(a)

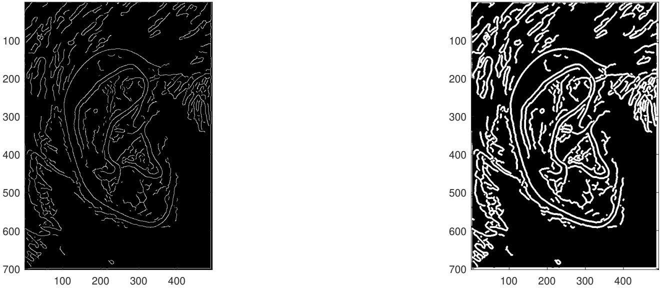


(b)

Figure 5: (**a**) Input image from the AMI ear database. (**b**) Smoothed version of the image on the left after the application of the Gaussian filter.

Contour detection

The Canny edge detector is employed to find contours in the preprocessed ear images (see Figure 6 (a)). Morphological **dilation** is applied in order to connect disconnected contours and remove noise (see Figure 6 (b)).



(a) (b)

Figure 6: (**a**) Original edge map within the context of the AMI ear database. (**b**) Dilated edge image corresponding to the map on the left.

ROI-masking

The manually selected or automatically detected ROI is employed as a mask to remove all of the edges **not** associated with ear contours. This is followed by the removal of the remaining small connected components (see Figure 7).

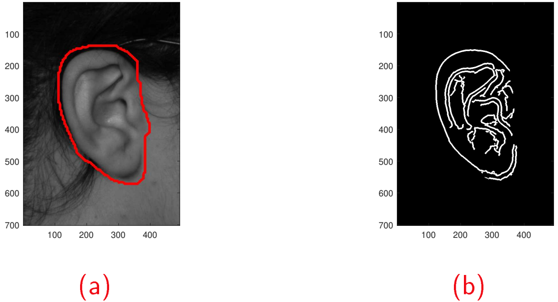
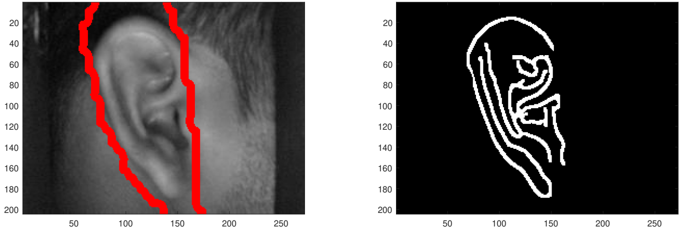


Figure 7: **AMI ear database**. (**a**) The boundary of the automatically detected ROI is indicated in red. (**b**) Prominent contours after ROI-masking and the removal of small connected components.

ROI-masking (IIT Delhi ear database)

In the case of the IIT Delhi ear database, the same protocol (as the one for the AMI ear database) has been followed, except for the fact that the image borders are also cleared (see Figure 8).



(a) (b)

Figure 8: **IIT Delhi ear database**. (**a**) The boundary of the automatically detected ROI is indicated in red. (**b**) Prominent contours after ROI-masking and the removal of small connected components.

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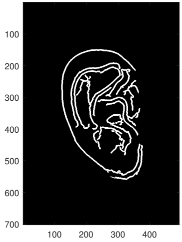
Feature extraction

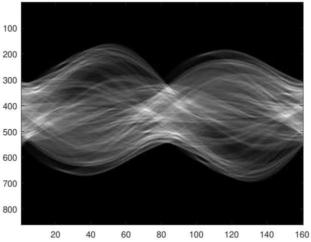
Feature vectors are extracted by applying the DRT to a contour image.

The DRT is obtained when projections of an image are calculated from equally distributed angles within the interval $\theta \in [0^\circ, 180^\circ)$.

An example of a contour image and its DRT (sinogram) within the context of the AMI ear database is depicted in Figure 9.



(a)

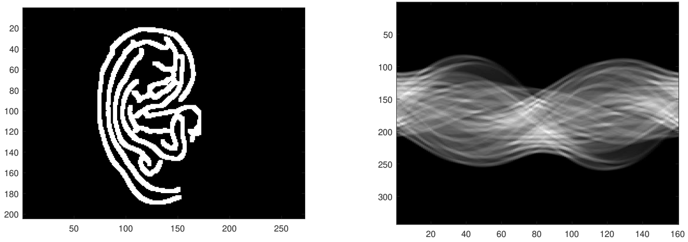


(b)

Figure 9: **AMI ear database**. (**a**) Prominent contours. (**b**) Sinogram corresponding to the contour image on the left.

Feature extraction

An example of a contour image and its DRT (sinogram) within the context of the IIT Delhi ear database is depicted in Figure 10.

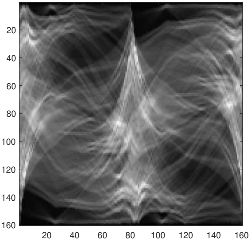


(a) (b)

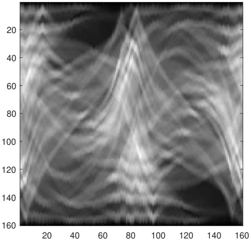
Figure 10: **IIT Delhi ear database**. (**a**) Prominent contours. (**b**) Sinogram corresponding to the contour image on the left.

Feature normalisation

In order to ensure translation and scale normalisation, the zero-valued components are removed from each projection profile, after which the dimension of each projection profile is adjusted to a predefined value through linear interpolation. The DRT image intensities are also normalised in such a way that the standard deviation across all features equals one (see Figure 11).



(a)



(b)

Figure 11: (**a**) Normalised feature set that corresponds to the sinogram in Figure 9 (b). (**b**) Normalised feature set that corresponds to the sinogram in Figure 10 (b).

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Feature matching and verification

- The dissimilarity between two feature sets is quantified by the average Euclidean distance between the corresponding normalised feature vectors.

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- In order to ensure rotational invariance, the normalised feature vectors associated with a questioned sample are iteratively shifted (with wrap-around) with respect to those belonging to a template. The alignment is deemed optimal when the average Euclidean distance is a minimum.

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- A questioned sample is compared to a reference sample (known to belong to the claimed individual), as well as to samples belonging to **other** (ranking) individuals. These dissimilarities are ranked from small to large.

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- A questioned sample is compared to a reference sample (known to belong to the claimed individual), as well as to samples belonging to **other** (ranking) individuals. These dissimilarities are ranked from small to large.
- Verification is based on the relative rank of the dissimilarity associated with the reference ear (known to belong to the claimed individual) when compared to the dissimilarities of the ears belonging to the known negative ranking individuals.

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     a. Experiment 3A: Rank-1 scenario

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     a. Experiment 3A: Rank-1 scenario
     b. Experiment 3B: Optimal ranking scenario
- A *k*-fold cross-validation protocol is employed for each experiment

Experiment 1A: Rank-1 scenario

A questioned ear is accepted as authentic if and only if the reference sample has a ranking of one.

Within this context, both of the ear datasets are partitioned into two sets that is, the evaluation and ranking sets.

For the **AMI ear database**, a 100-fold cross-validation procedure is conducted as conceptualised in Figure 12.

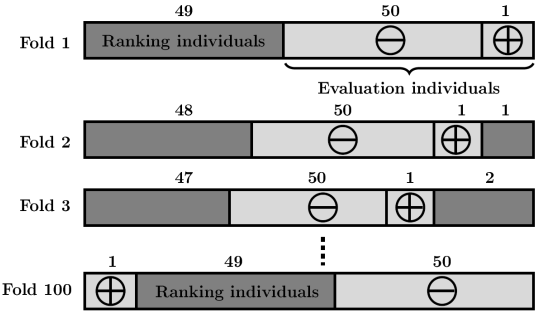

Figure 12

Experiment 1A: Rank-1 scenario

The proposed data partitioning protocol for the **evaluation** individuals, within the context of rank-1 scenario and the **AMI ear database** is conceptualised in Figure 13.

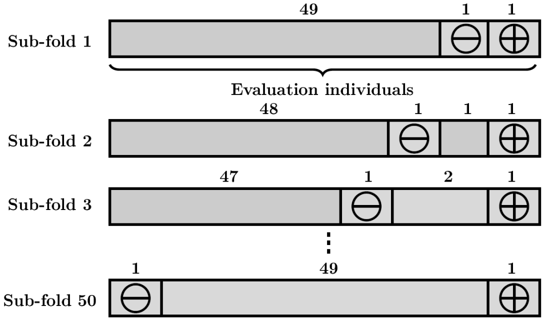

Figure 13

Experiment 1A: Rank-1 scenario

A similar 125-fold cross-validation protocol is employed within the context of the **IIT Delhi ear database** (see Figure 14).

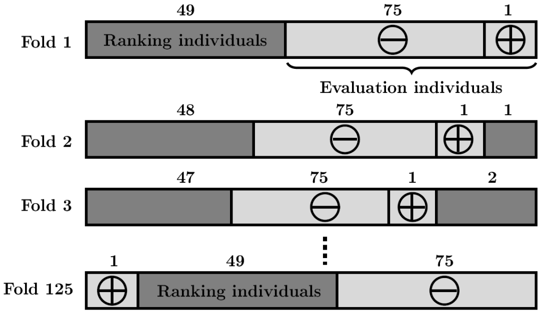

Figure 14

Furthermore, a similar data partitioning protocol to that of the AMI ear database is followed within the context of the **evaluation** individuals.

Experiment 1B: Optimal ranking scenario

In this sub-experiment, a questioned ear is accepted when it has a ranking that is better than or equal to a very specific optimal ranking, which may be greater than one.

For this sub-experiment both of the datasets are partitioned into a ranking set, an optimisation set and an evaluation set.

The proposed data partitioning and cross-validation protocol for the **AMI database** is presented in Figure 15.

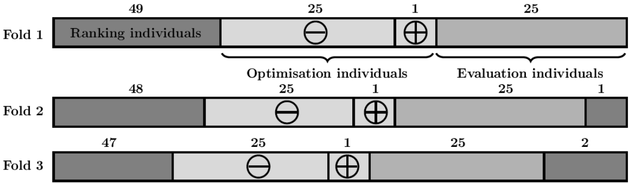

Figure 15: The first three (out of a total of 100) folds of the proposed data partitioning and cross validation protocol for the AMI ear database.

Experiment 1B: Optimal ranking scenario

The proposed data partitioning and cross-validation protocol for the **IIT Delhi database** is presented in Figure 16.

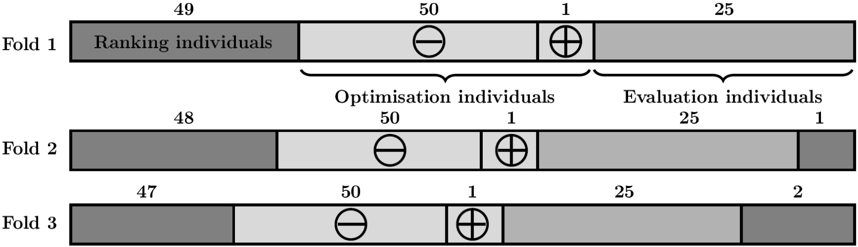

Figure 16: The first three (out of a total of 125) folds of the proposed data partitioning protocol for the IIT Delhi ear database.

Experiment 2: Automated ROI-detection

In this experiment the **manually** selected (specified) ROI serves as a ground truth for evaluating the proposed automated CNN-based ROI-detection protocol.

For both of the datasets the data is partitioned as depicted in Figure 17.

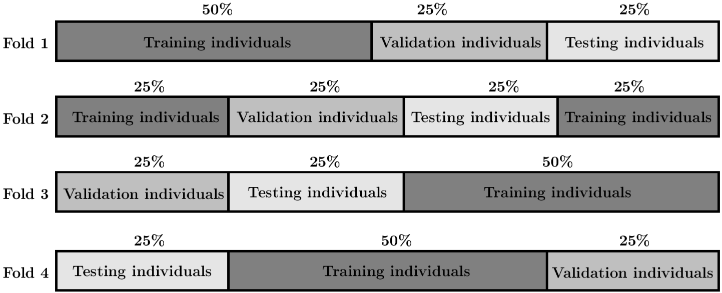

Figure 17: Conceptualisation of the 4-fold cross validation experimental protocol conducted on both the AMI and IIT Delhi ear databases.

Experiment 3: Fully automated ear-based authentication

This experiment evaluates the proficiency of the proposed fully-automated ear-based biometric authentication system, where a suitable ROI is automatically detected through deep learning.

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For this experiment both of the ear datasets are partitioned into four sets, that is a training set, a validation set, a ranking set and an evaluation set.

Experiment 3: Fully automated ear-based authentication

This experiment evaluates the proficiency of the proposed fully-automated ear-based biometric authentication system, where a suitable ROI is automatically detected through deep learning.

For this experiment both of the ear datasets are partitioned into four sets, that is a training set, a validation set, a ranking set and an evaluation set.

Within the context of this experiment both the "Rank-1" and "Optimal ranking" scenarios are investigated in Experiment 3A and Experiment 3B, respectively.

Results

Table 1: The statistical performance measures employed in this study.

Performance measure	Definition
False acceptance rate (FAR)	FP/(FP+TN)
False rejection rate (FRR)	FN/(FN+TP)
Average error rate (AER)	(FAR+FRR)/2
Equal error rate (ERR)	FAR $\approx$ FRR
Precision (PRE)	TP/(TP+FP)
Recall (REC)	TP/(TP+FN)
Accuracy (ACC)	(TP+TN)/(TP+FN+FP+TN)
F_1 score	2 * PRE * REC/(PRE+REC)

Experiment 1A: Rank-1 scenario

Table 2: The results for the proposed semi-automated ear-based authentication system within the context of the rank-1 scenario for the AMI and IIT Delhi ear databases. These results constitute averages across the relevant folds according to the protocol outlined for the rank-1 scenario.

Performance measure	AMI ear database	IIT Delhi ear database
FAR	0.04	0.18
FRR	4.76	13.00
AER	2.40	6.59
ACC	95.24	89.12

Experiment 1B: Optimal ranking scenario

The AER and EER were investigated as optimisation criteria for selecting the optimal ranking.

Table 3: The results for the proposed *optimised* semi-automated ear-based authentication system within the context of (a) the AMI database (with an optimal ranking of 5) and (b) the IIT Delhi database (with an optimal ranking of 7).

Performance measure	Rank-5
FAR	1.75
FRR	0.45
AER	1.10
ACC	99.20

(a)

Performance measure	Rank-7
FAR	5.40
FRR	3.63
AER	4.52
ACC	96.06

(b)

Experiment 2: Automated ROI-detection

Table 5: Results for the proposed automated ROI detection protocol.

Performance measure	AMI ear database	IIT Delhi ear database
PRE	80.30	70.26
REC	90.88	81.86
ACC	91.01	87.93
F_1	87.66	73.40

Experiment 3A: Rank-1 scenario

Table 6: The results for the proposed fully automated ear-based authentication system within the context of the rank-1 scenario for the AMI and IIT Delhi ear databases.

Performance measure	AMI ear database	IIT Delhi ear database
FAR	1.12	2.45
FRR	20.50	39.25
AER	10.81	20.85

Experiment 3B: Optimal ranking scenario

Table 7: The results for the proposed *optimised* fully automated ear-based authentication system within the context of (a) the AMI database (with an optimal ranking of 7) and (b) the IIT Delhi database (with an optimal ranking of 10).

Performance measure	Rank-7
FAR	3.11
FRR	10.23
AER	6.67

(a)

Performance measure	Rank-10
FAR	5.38
FRR	15.45
AER	10.46

(b)

Conclusion

- In the case of the proposed **semi-automated system** AERs of 2.4% and 6.59% are reported for the AMI and IIT Delhi ear databases respectively within the context of the Rank-1 scenario. These AERs are reduced to 1.10% and 4.52% respectively by employing optimal rankings.

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- Accuracies of 91% and 88% are reported for the proposed CNN-based **ROI detection protocol** within the context of the AMI and IIT Delhi ear databases respectively.

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- Accuracies of 91% and 88% are reported for the proposed CNN-based **ROI detection protocol** within the context of the AMI and IIT Delhi ear databases respectively.
- Within the context of the **fully automated system** AERs of 10.81% and 20.85% are reported for the AMI and IIT Delhi ear databases respectively within the context of the Rank-1 scenario. These AERs are significantly improved to 6.67% and 10.46% respectively by employing optimal rankings.

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- An investigation into the feasibility of another machine learning-based approach, like a suitable support vector machine, for the second part of the fully automated system developed in this study.

Future work

- An investigation into the feasibility of an end-to-end deep learning-based approach to ear-based biometric authentication.
- An investigation into the feasibility of another machine learning-based approach, like a suitable support vector machine, for the second part of the fully automated system developed in this study.
- Evaluate the proposed systems on other datasets that may become publicly available in the near future.

I would like to express my sincere gratitude to the Ball family for funding this research.

Thank you