A Novel Embedding Architecture and Score Level Fusion Scheme for Occluded Image Acquisition in Ear Biometrics System

Presented by:
Archishman Biswas
Authors:
Archishman Biswas, Goutham A P, Saket Pateriya, Divyang S. Jadav, Satish Mulleti and Vikram M. Gadre

Department of Electrical Engineering, Indian Institute of Technology Bombay, India 400076

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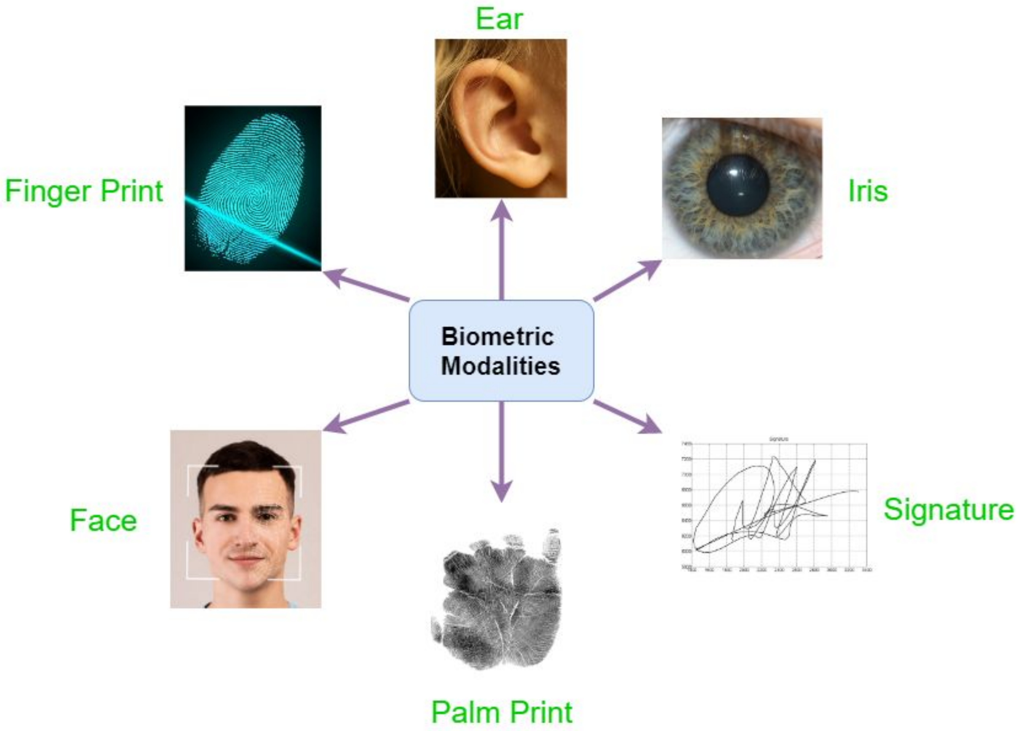
Introduction to Ear Biometrics

Biometrics
(Bio=life; Metrics=measurement)

- Biometric is the science of determining an individual's **unique identity** based on one or more **distinguishing physical or behavioural characteristics.**



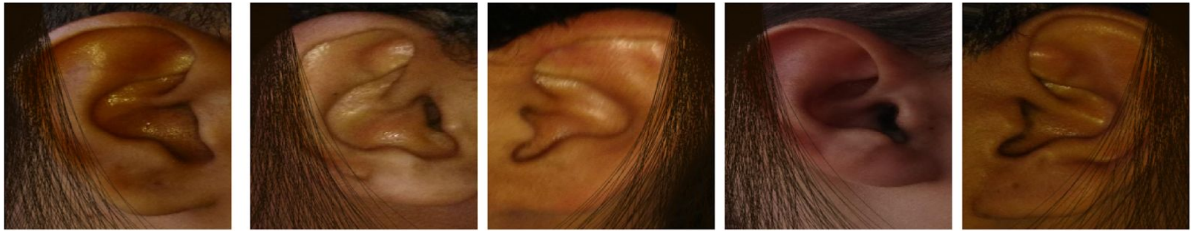
Ear Biometrics

- ❑ Past studies have shown that ears are **unique** for each individual.
- ❑ Ear image acquisition process is **contactless** and **non-intrusive**.
- ❑ Ear is **consistent** and doesn't change with expressions.

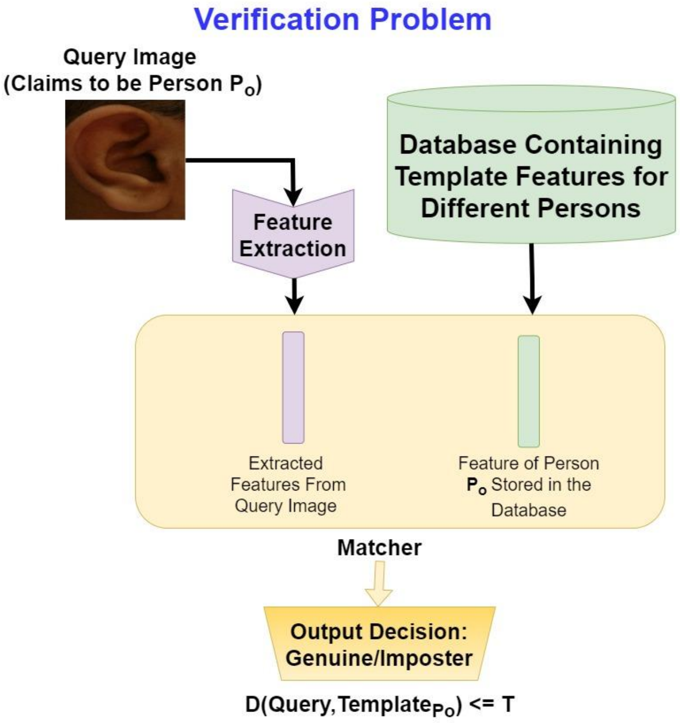
We use our own IITB-dataset for studying ear based biometrics

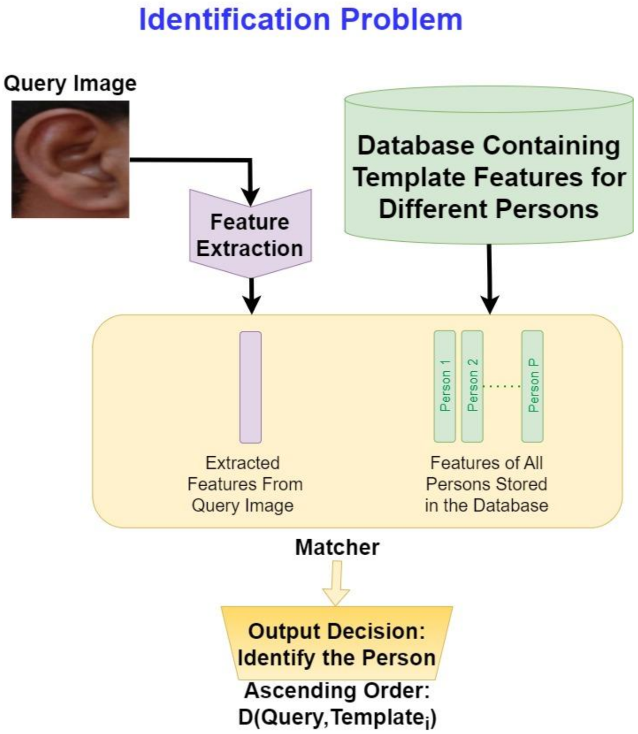
- ❑ 1000 ear images of 100 subjects, 5 images of each side ear, all of size (224,224,3)

- ❑ We have also studied the effect of occlusions due to hair, for this, we have added artificial random occlusions (covering 35% of the image on average)



Verification and Identification Problems in Biometrics





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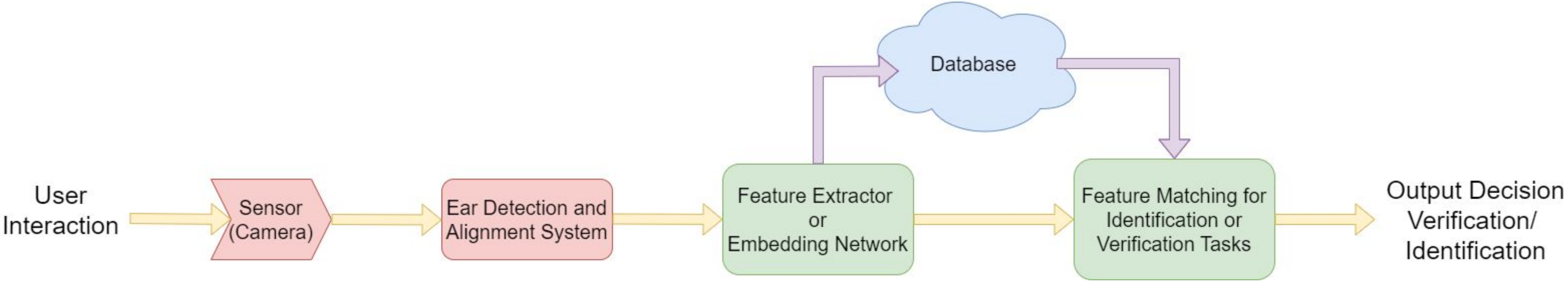
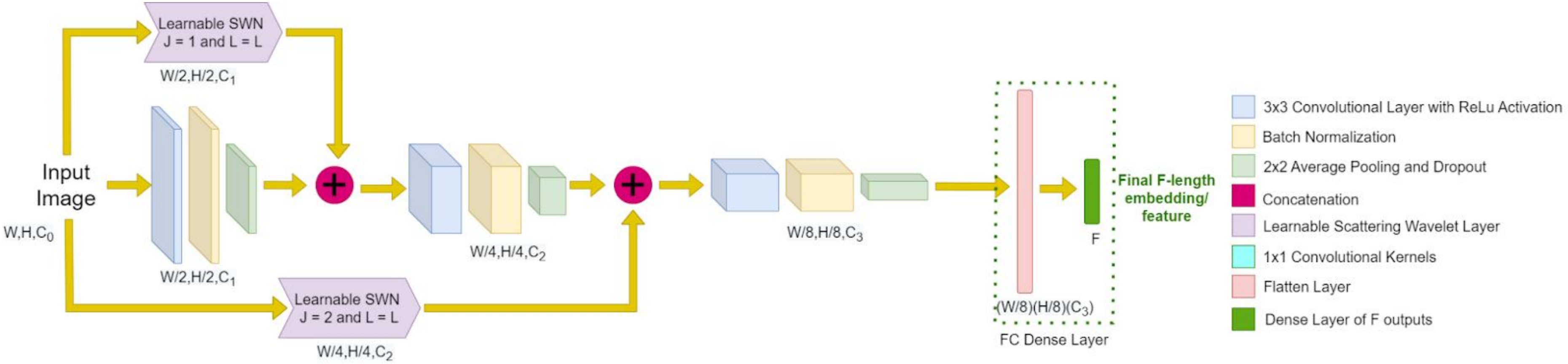
Embedding Network and Siamese Training

Pipeline of Ear Biometrics System



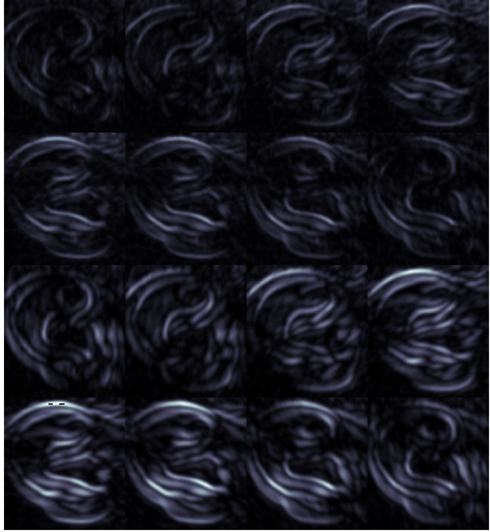
- The initial **detection and alignment system** is an important preprocessing step that gets rid of many of the irrelevant background information
- Our proposed innovations are only in the **Embedding Network** and **Feature Matching** systems/blocks

Embedding Network Used



- ❑ The architecture of the embedding network consists of conventional CNNs in the central path and **learnable Scattering Wavelet Network (SWN)** in the parallel paths
- ❑ The parallel learnable SWN paths pickup information directly from the input image and inserts them into further downstream parts of the embedding network

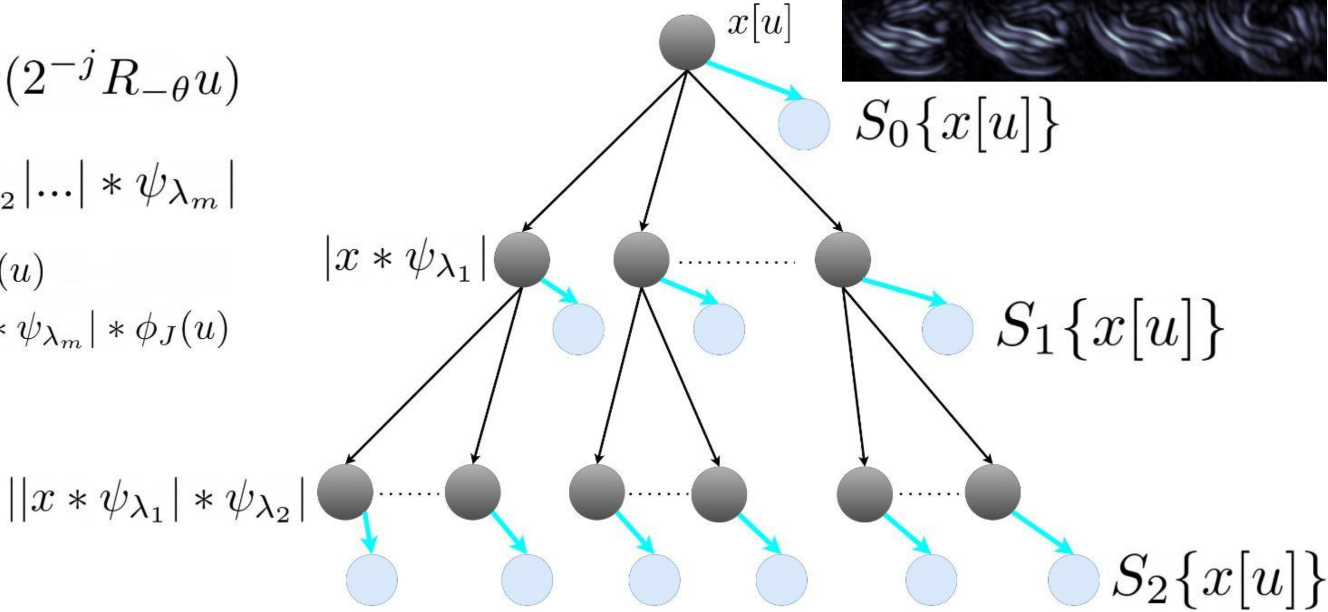
Scattering Wavelet Network



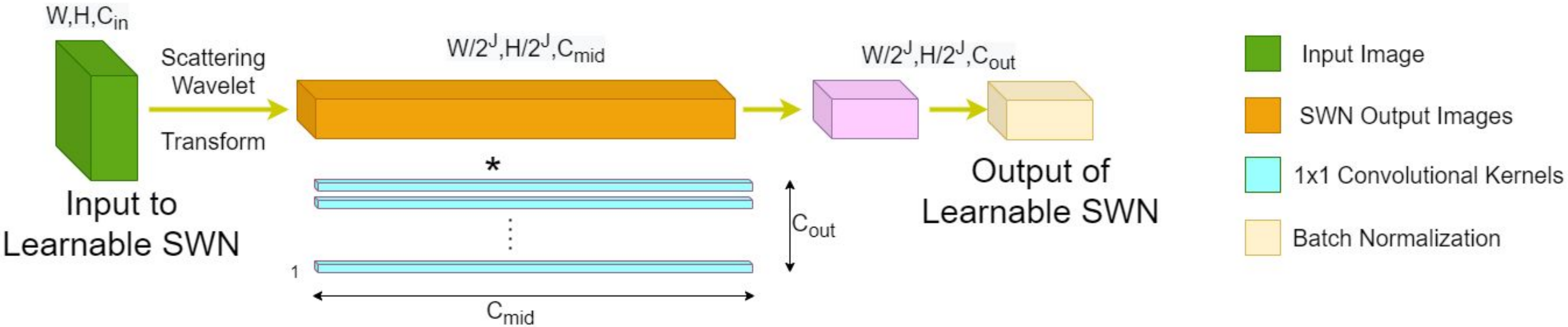
$$\psi_\lambda(u) \triangleq \psi_{j,\theta}(u) = 2^{-j}\psi(2^{-j}R_{-\theta}u)$$

$$U[p]x = ||...|x * \psi_{\lambda_1}| * \psi_{\lambda_2}|...| * \psi_{\lambda_m}|$$

$$\begin{aligned} S[p]x &= U[p]x * \phi_J(u) \\ &= ||...|x * \psi_{\lambda_1}| * \psi_{\lambda_2}|...| * \psi_{\lambda_m}| * \phi_J(u) \end{aligned}$$



Learnable Scattering Wavelet Network

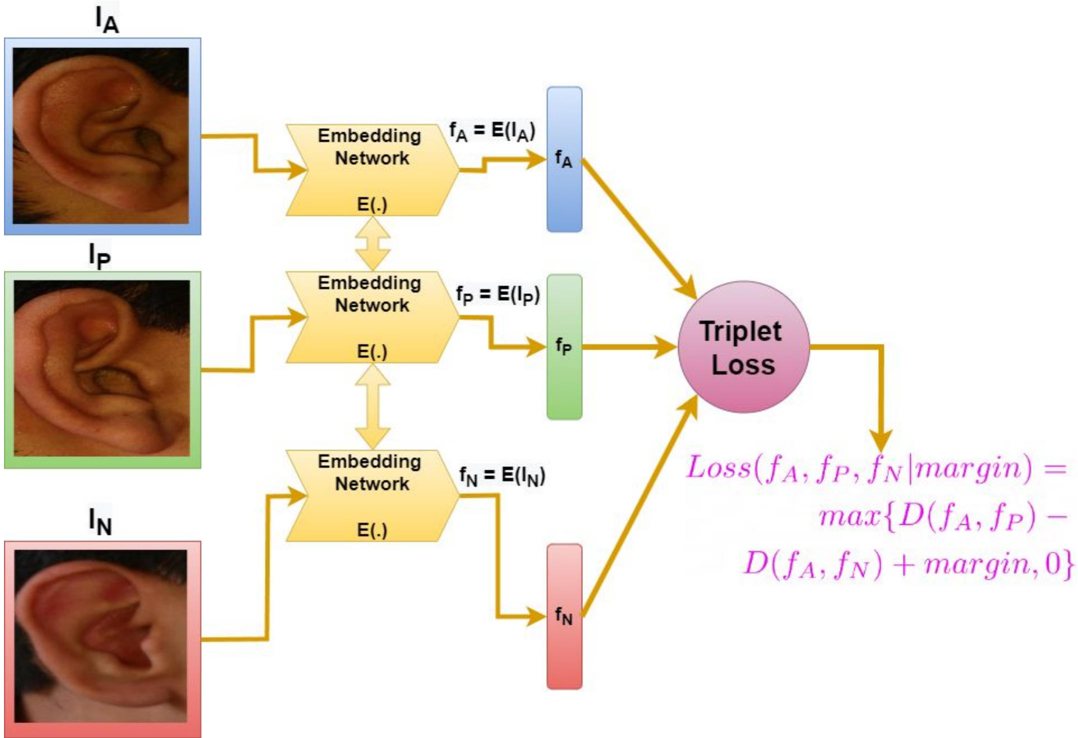


- ❑ Number of output channels (denoted by $\mathbf{C_{mid}}$) of SWN is given by:

$$C_{mid} = C_{in} \times \left(JL + \frac{J(J-1)}{2}L^2 + \ldots + \binom{J}{m}L^m\right)$$ {0th layer (low-pass) is omitted}

- ❑ Then, convolution with 1x1 kernel is carried out to learn the linear combination across the $\mathbf{C_{mid}}$ channels and finally get $\mathbf{C_{out}}$ channels.

Siamese Training Framework

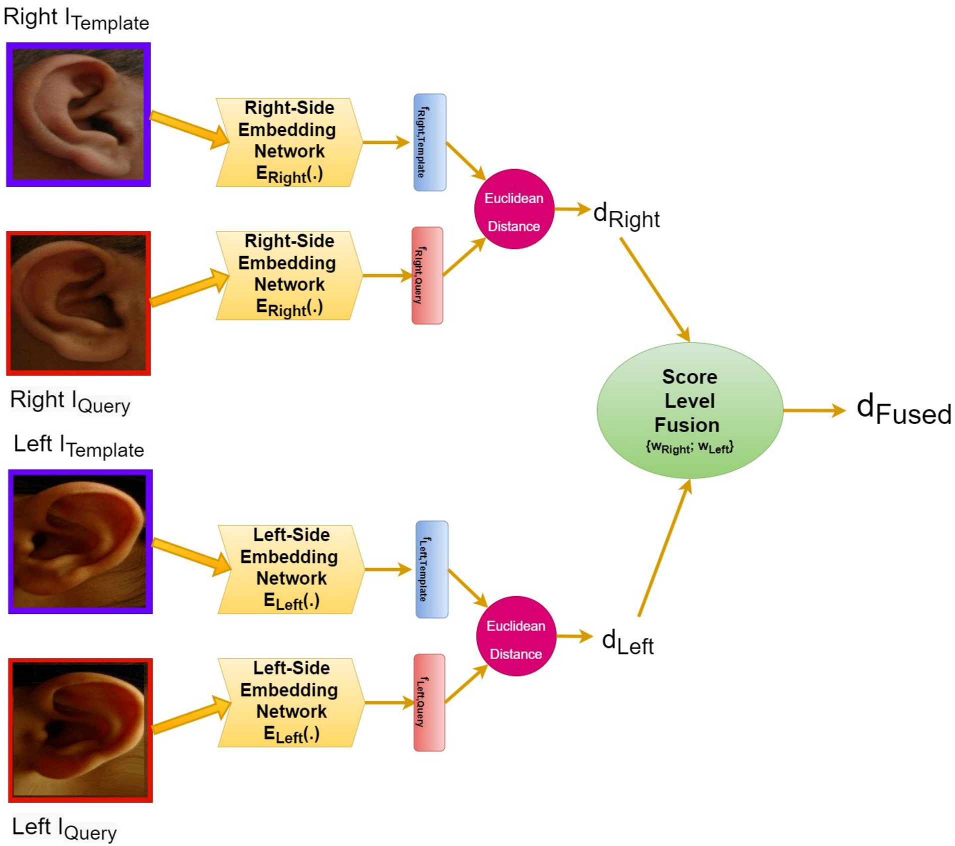


- The siamese training of the network is carried out by providing three images: Anchor(A), Positive(P), and Negative(N) together
- The distance D(,) here is taken as the Euclidean distance

Score Level Fusion: E_{Right} and E_{Left}

- For fusing information from both the right side and left side of the image, we use a score level fusion scheme

- Hence, we only need a trained left embedding network and a trained right embedding network, no separate training for the fused decision is required



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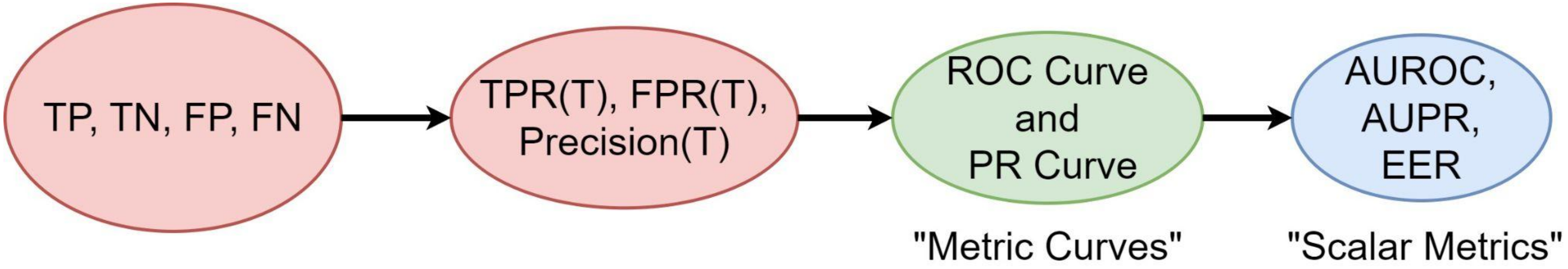
Evaluation Metrics for Biometrics System

For Verification Problem

$$\text{True Positive}: I_{query} \text{ actually belonged to person } P_n : D(f_{template}, f_{query}) \leq T$$
$$\text{True Negative}: I_{query} \text{ actually didn't belonged to person } P_n : D(f_{template}, f_{query}) > T$$
$$\text{False Positive}: I_{query} \text{ actually didn't belonged to person } P_n : D(f_{template}, f_{query}) \leq T$$
$$\text{Flase Negative}: I_{query} \text{ actually belonged to person } P_n : D(f_{template}, f_{query}) > T$$



For Identification Problem

- ❑ In identification mode the system returns ranking for the query image, I_{Query} of a person P_i. The system is working correctly in Rank-R sense if:

$$\boldsymbol{r_i \leq R}, \textbf{ for query image of } \boldsymbol{i^{th}} \textbf{ person.}$$

$$\text{Rank-R Accuracy} = \frac{\text{Number of test cases declared correct in Rank-R sense}}{\text{Total number of query images}}$$

- ❑ Using above results the plot of Rank-R Accuracy versus Rank-R called Cumulative Match Curve (***CMC***).

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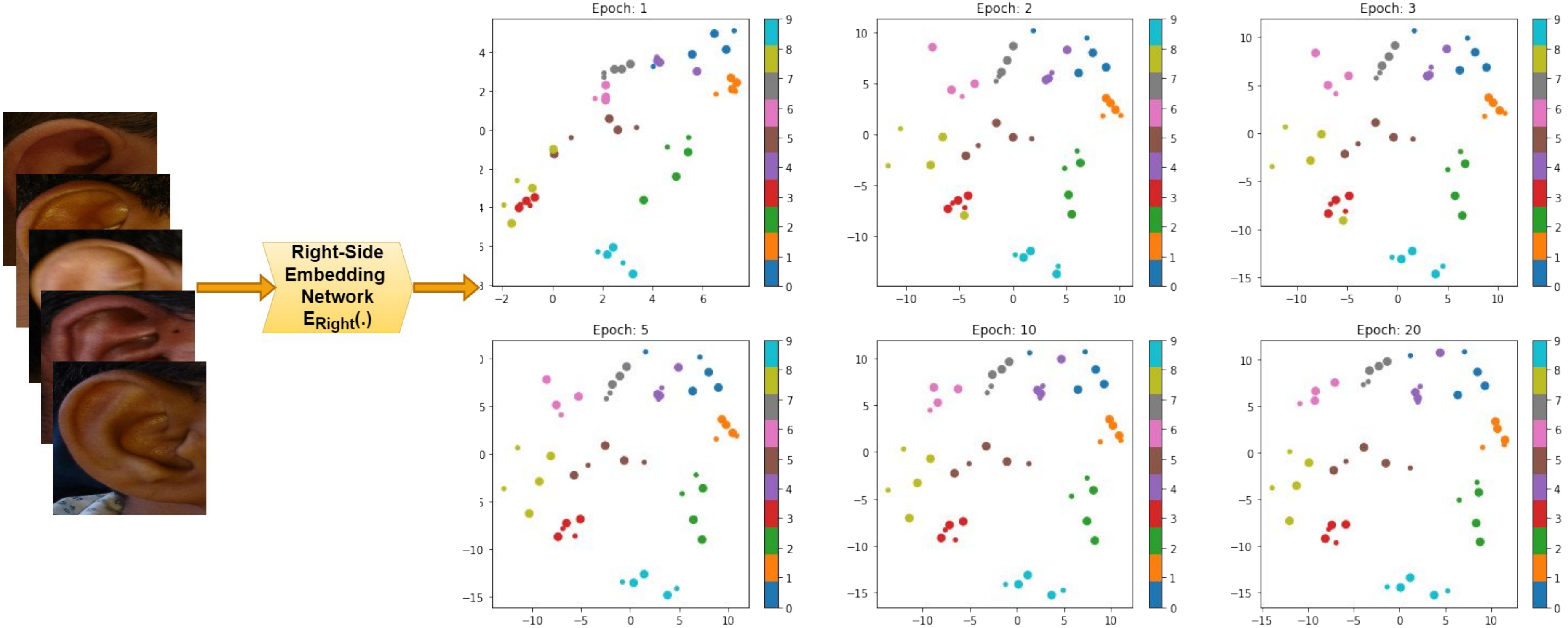
Experimental Results

Set Hyperparameters and Type of Experimental Settings

- ❑ Train the embedding network with margin = 1 using Adam optimizer in Keras library with learning rate of 1e-4 and β parameters set to default.
- ❑ Run the training for 20 epochs with a batch size of 100. Embedding network for each of the ear side is trained for 5 independent trials.
- ❑ The AUPR, EER and Rank-1 metrics are reported with mean and SD across the 5 trials in the paper for different experimental settings
- ❑ Experimental settings: "Closed" and "Open" sets; "Clean" and "Occluded" image acquisition; "Clean" and "Augmented" training of model; 3 different embedding network: no parallel paths, L = 4, L = 8

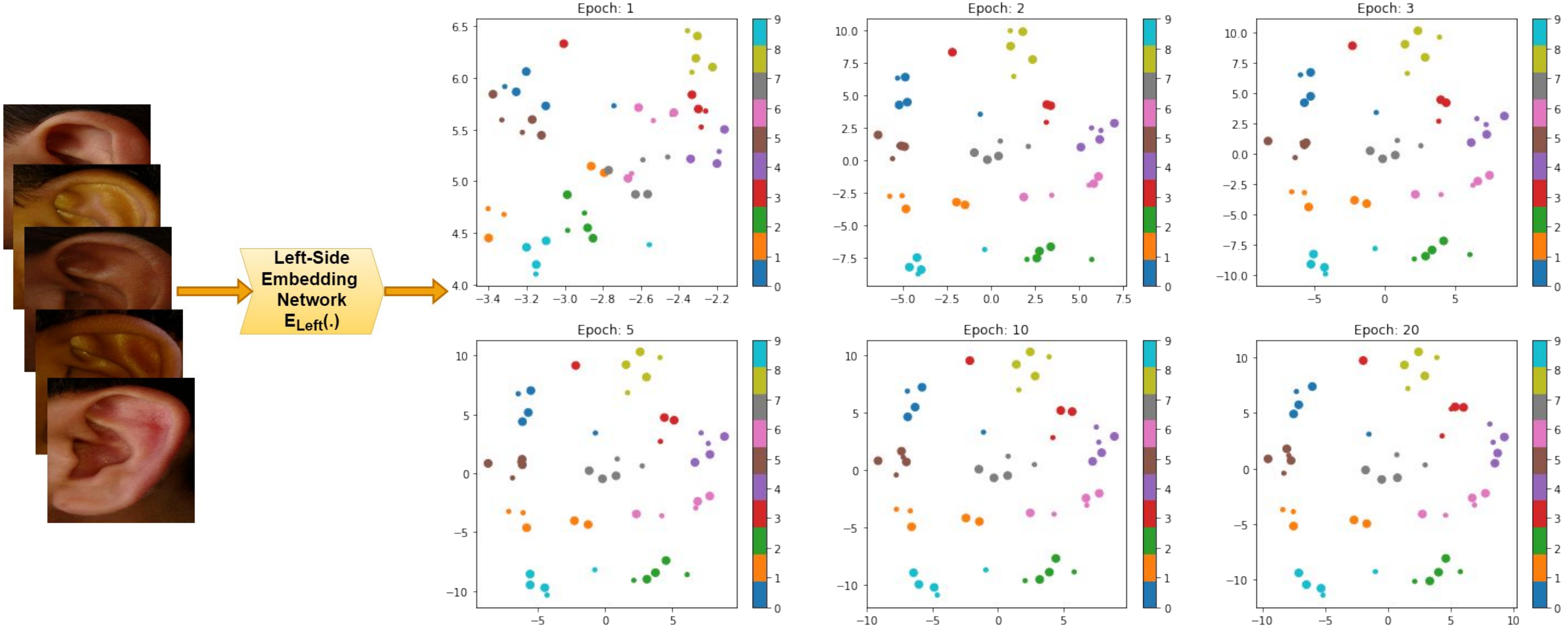
Visualizing the Extracted Features (Right Embeddings)

- The figure shows the extracted features (2D projection of 128D vector) from **10 person's right ear images**. Train: Larger dots, Test: Smaller dots.



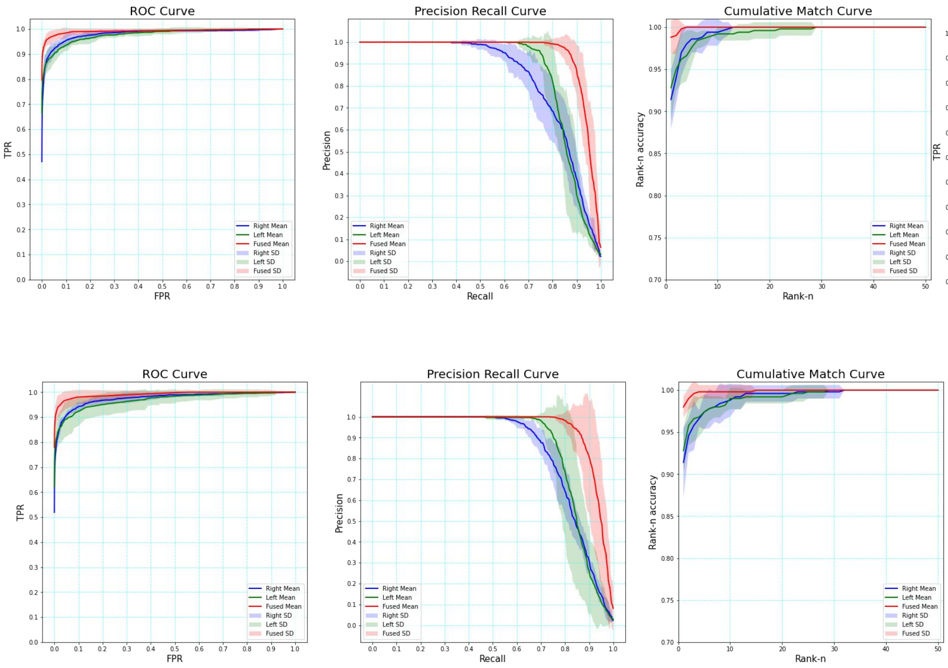
Visualizing the Extracted Features (Left Embeddings)

- The figure shows the extracted features (2D projection of 128D vector) from **10 person's left ear images**. Train: Larger dots, Test: Smaller dots.

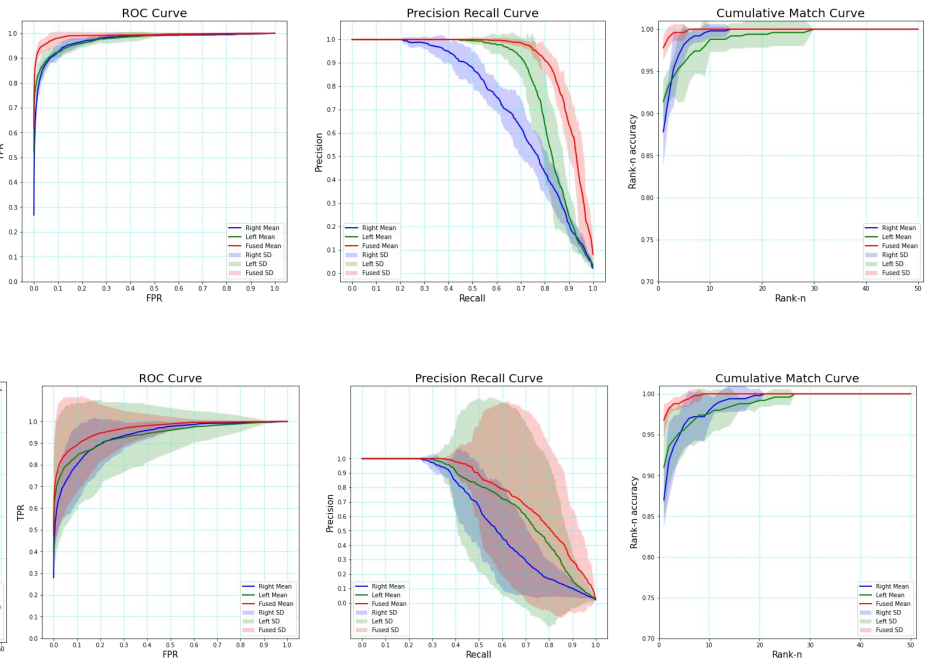


Comparing Results for L = 4 and No Parallel Paths (No Data Augmentation)

- ❑ Top Row: For no parallel Paths
- ❑ Bottom Row: With L = 4



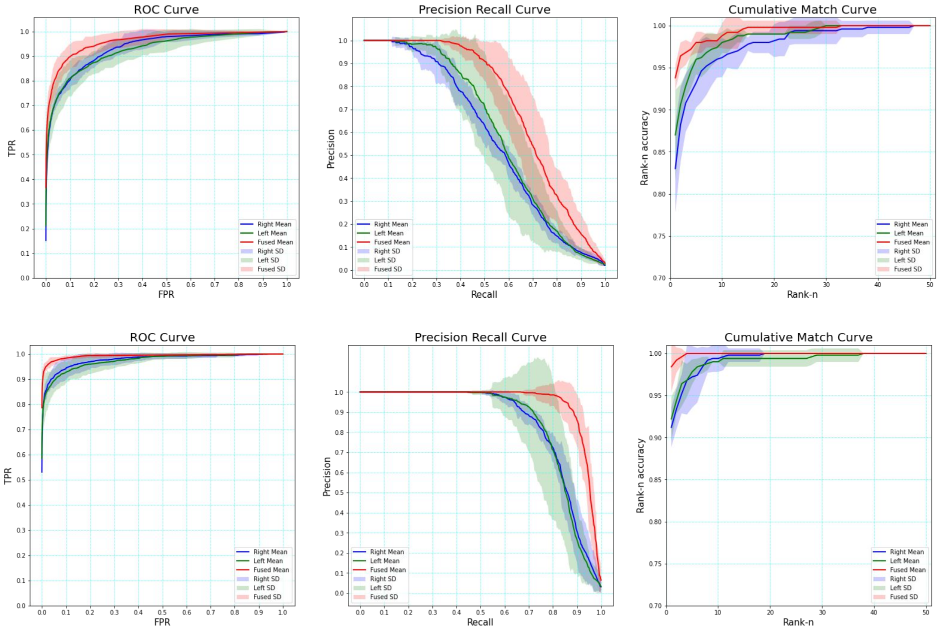
Test Data is Clean



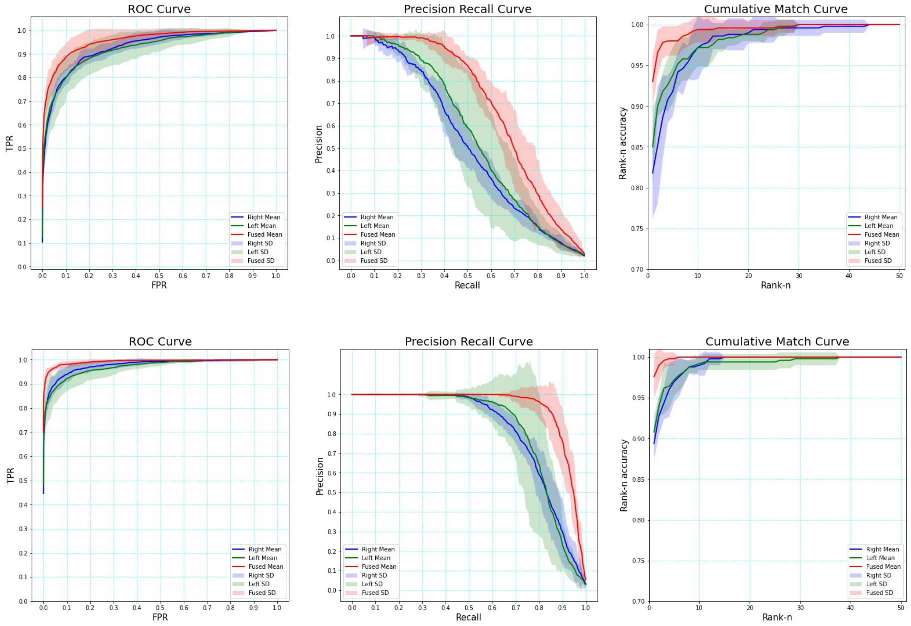
Test Data is Occluded

Comparing Results for L = 4 and No Parallel Paths (With Data Augmentation)

- Top Row: For no parallel Paths
- Bottom Row: With L = 4



Test Data is Clean



Test Data is Occluded

Numerical Results

Test set with no occlusions

	Clean Training			Augmented Training		
	AUPR	EER	Rank-1 Acc.	AUPR	EER	Rank-1 Acc.
No Parallel	**94.23, 0.69**	**3.53, 0.34**	**98.8, 0.40**	76.88, 3.19	8.64, 1.17	97.20, 1.16
Parallel L = 4	93.94, 1.35	3.47, 0.65	98.20, 1.16	93.58, 1.28	3.62, 0.63	**99.40, 0.49**
Parallel L = 8	93.50, 1.34	3.70, 0.51	97.60, 1.02	**95.05, 0.82**	**3.08, 0.76**	98.60, 0.80

Numerical Results

Test set with occlusions

	Clean Training			Augmented Training		
	AUPR	EER	Rank-1 Acc.	AUPR	EER	Rank-1 Acc.
No Parallel	**89.73, 1.24**	**5.09, 0.37**	**98.80, 0.40**	72.67, 2.42	9.56, 1.11	95.40, 1.50
Parallel L = 4	69.34, 14.33	13.59, 8.35	96.4, 1.35	92.38, 1.54	4.24, 0.76	**99.00, 0.63**
Parallel L = 8	84.79, 3.94	5.85, 1.42	97.20, 1.17	**94.01, 0.89**	**3.54, 0.74**	98.00, 0.89

Size of embedding networks used and the corresponding average training time required per step for a batch-size of 100

Embedding Architecture	# trainable params	training time per step
CNN + Parallel SWN with L = 8	562343	374.5 ms/step
CNN + Parallel SWN with L = 4	560603	287.5 ms/step
Baseline with only CNN	560858	80.3 ms/step

- There is very low increment in the number of trainable parameters as the learnable SWN blocks adds very little amount to the number of parameters.

- The training time increases for parallel paths as backpropagation has to pass through multiple paths.

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Future Scope

Conclusion and Future Scope

- The results show an **agility of a system to recognize occluded and non-occluded images using a common framework**. We believe that it will perform equally with other biometric modalities.

- The score-level fusion technique used in the research can also be used for **multimodal biometric recognition systems**.

- As a part of future work, we will explore the **utility of other types of wavelets** and **advanced information fusion** methods.

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Thank You

Questions?