On Co-training Online Biometric Classifiers

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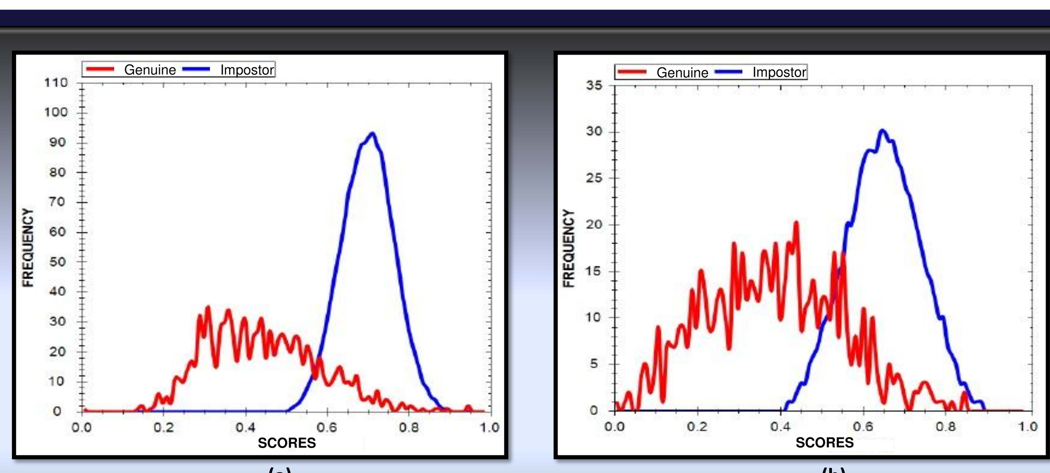
Motivation

In large scale biometric systems, such as UIDAI, US VISIT, and FBI AFIS, thousands of new users are enrolled on a daily basis. To maintain the performance and accommodate variations caused due to new data, biometric systems require frequent re-training.

Challenges

- Re-training with existing and new information in *batch-mode* requires large amount of time.
- Obtaining large number of labeled data is quite expensive. However, large number of unlabeled data is easily available



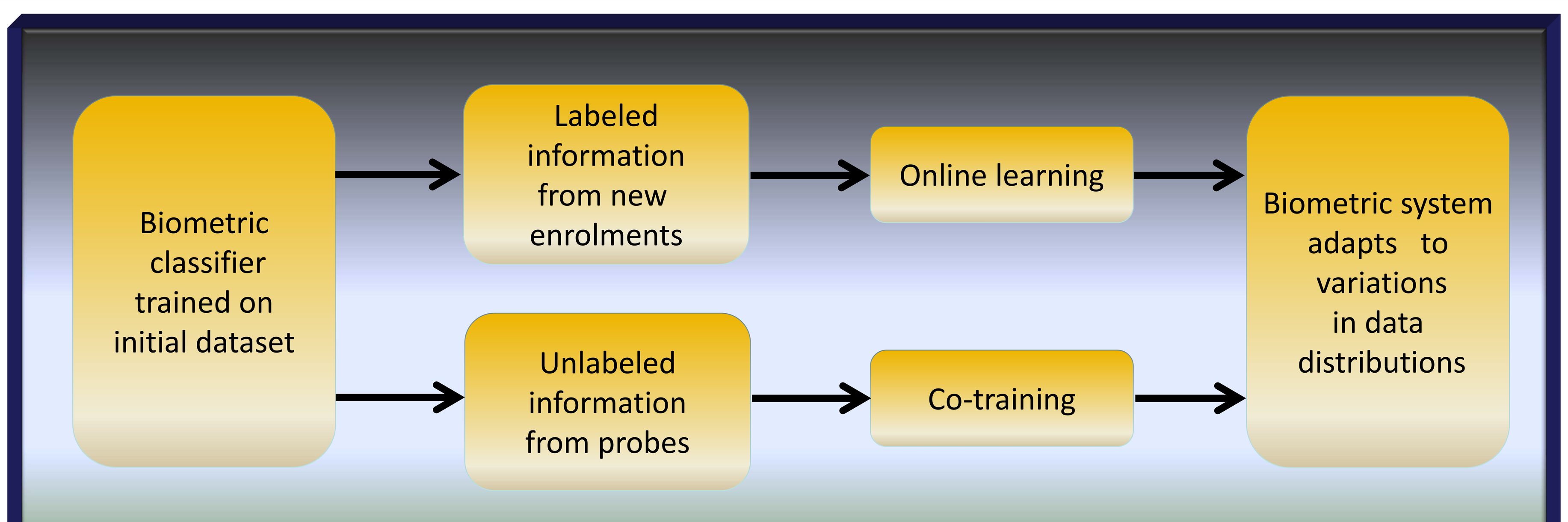
Illustrates how genuine-impostor match score distribution varies as new users are enrolled into the biometric system.

Match score histogram with (a) 100 users (b) 300 users

Problem Statement

Design a framework that enables biometric classifiers to continuously adapt to the variations in data distribution. The framework utilizes both labeled and unlabeled data to maintain the recognition performance.

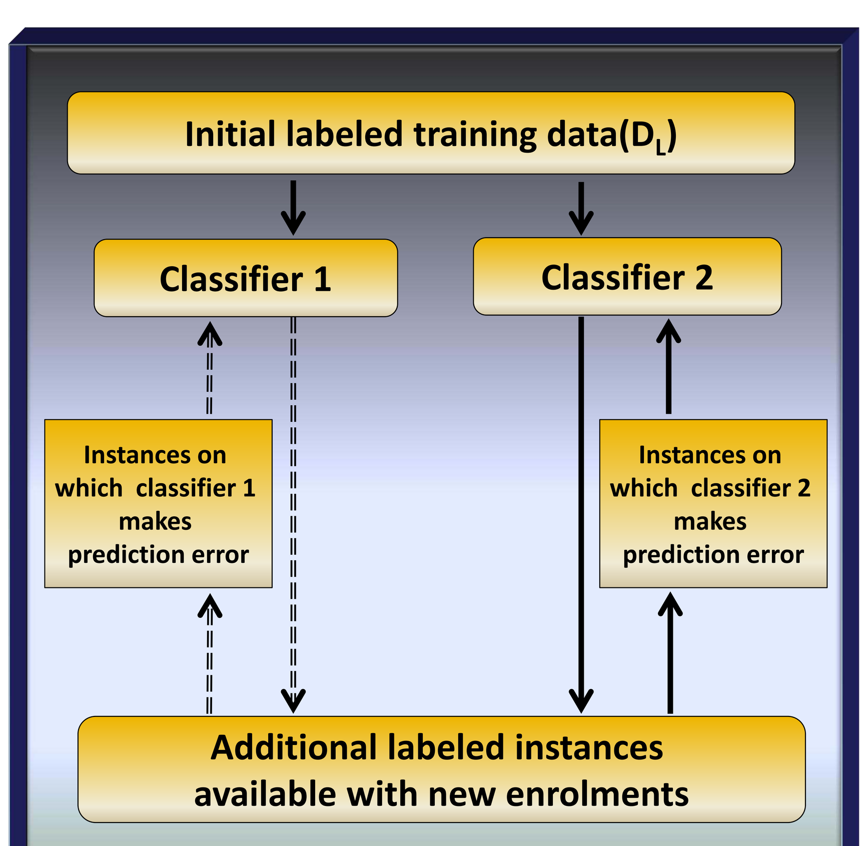
Proposed Approach



Block Diagram of the proposed Online Co-training framework

- Seamlessly use online learning and co-training for updating the classifier using both labelled enrolment data as well as unlabeled probe data as and when they arrive.

Online Learning Algorithm

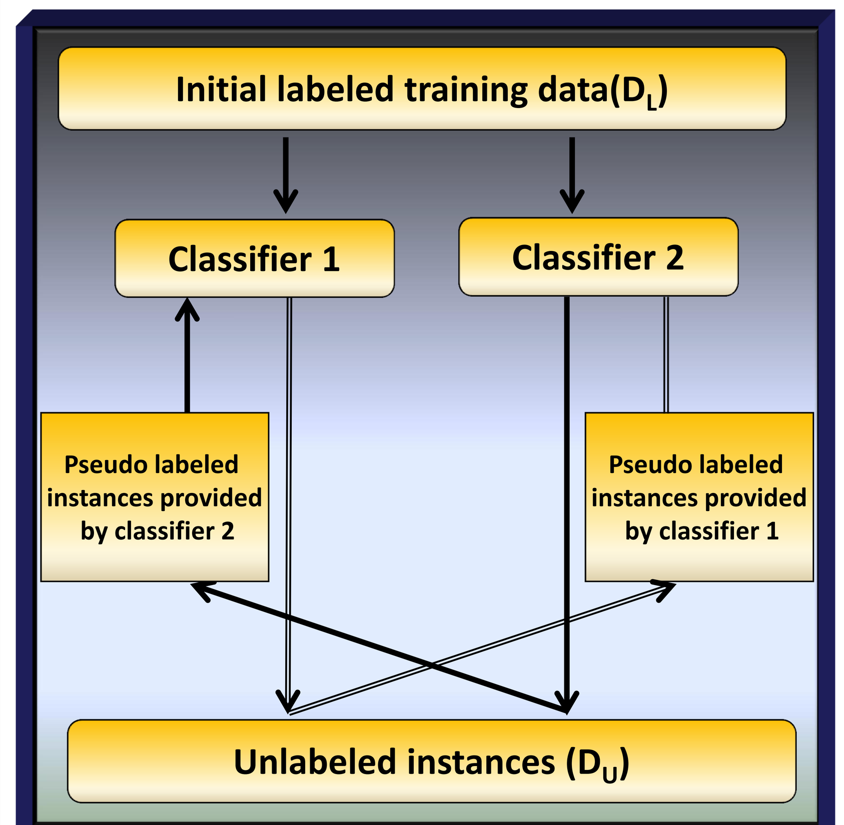


Illustrating the online learning process where each classifier learns from the incorrectly classified instances.

Algorithm 1 Online Classifier Update

Input: Initial labeled enrolment training data D_L, a set of additional labeled instances $\{u_i, z_i\}$ due to enrolments, $i = 1, 2, ...N$, where N is the number of additional instances. Each instance $u_i = (x_{i,1}, x_{i,2})$ represents two views (or scores).
Iterate: j= 1 **to** number of views (number of classifiers)
Process: Train classifier c_j on j^{th} views of D_L
for $k = 1$ **to** N **do**
  Predict labels: $c_j(x_{i,j}) \rightarrow y_i$
  if $y_i \neq z_i$ **then**
    Update c_j with labeled instance $\{x_{i,j}, z_i\}$
  end if
end for
End iterate
Output: Updated classifier c_1 and c_2.

Co-training Algorithm



Illustrates co-training where each classifier provides informative labeled instances to the other classifier.

Algorithm 2 Co-training

Input: Set of labeled training data D_L, set of unlabeled instances D_U, where each instance $\mathbf{u}' = (x_{i,1}, x_{i,2})$ represents two view/scores.
Process: Train classifier c_j on separate views of D_L. Compute confidence threshold T_j, where j = no of views
for $k = 1$ **to** sizeof(D_U) **do**
  Predict labels: $c_j(x_i) \rightarrow y_{i,j}$; α_j represents confidence of prediction
  if $\alpha_1 > T_1$ & $\alpha_2 < T_2$ **then**
    Update c_2 with labeled instance $\{x_{i,2}, y_{i,1}\}$ & recompute T_2
  end if
  if $\alpha_1 < T_1$ & $\alpha_2 > T_2$ **then**
    Update c_1 with labeled instance $\{x_{i,1}, y_{i,2}\}$ & recompute T_1
  end if
end for
Output: Updated classifier c_1 and c_2.

Database and Results

Case Study: Multi-classifier SVM based face verification

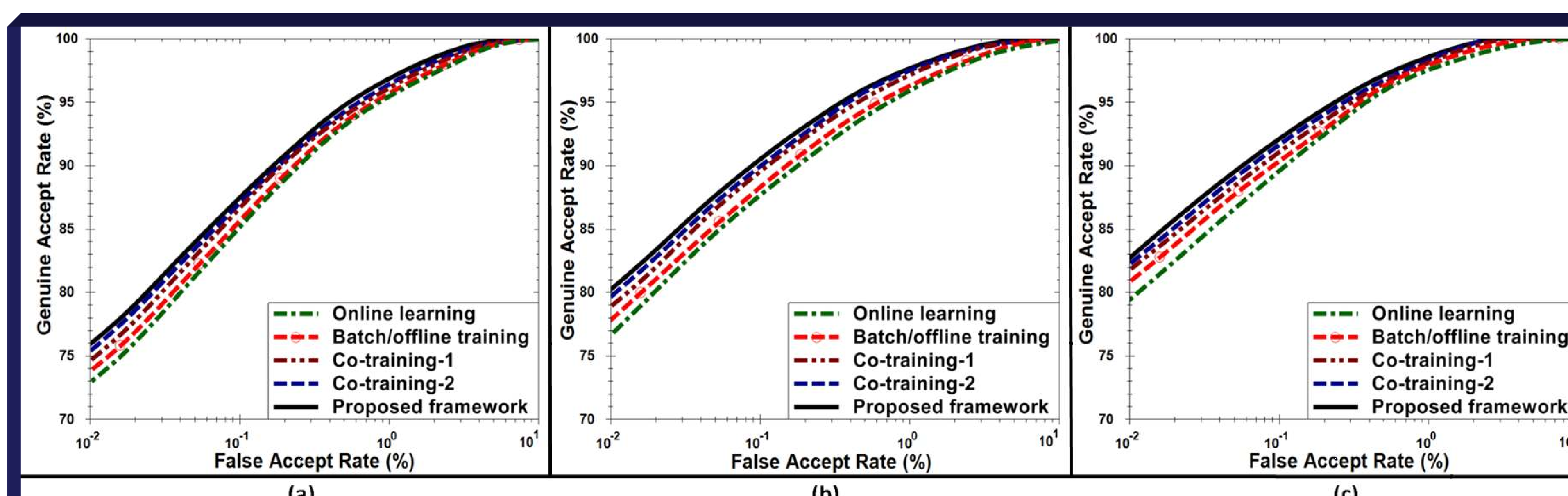
Database used in this research

Database	Number of subjects	Number of images
AR	119	714
WVU Multimodal	270	3482
MBGC v.2	446	5468
Caspeal	711	5658
CMU Multi-PIE	287	4828
Total	1833	20150

Experimental protocol

Experimental protocol	Training	
Batch/Offline training	Training on 1833	
Online learning	Initial training on 600	Online learning on 1233
Co-training-1	Initial training on 600	Co-training on 1833
Co-training-2	Training on 1833	Co-training on 1833

Results:



ROC curves for (a) Classifier1 (SURF), (b) Classifier2 (UCLBP), and (c) SVM-fusion of the two classifiers.

Verification accuracy and training time of the classifiers trained using different modes

Training Mode	Verification accuracy at 0.01% FAR (%)			Training Time (Minutes)	
	Classifier1	Classifier2	SVM Fusion	Classifier1	Classifier2
Batch/Offline training	73.82	77.88	80.78	98.62	110.84
Online learning	72.96	76.58	79.42	24.32	32.42
Co-training-1	74.64	78.92	81.86	28.25	36.18
Co-training-2	75.48	79.62	82.24	114.75	128.56
Proposed framework	76.02	80.28	82.78	45.61	54.05

Conclusion

- Updating a biometric classifier is posed as a semi-supervised learning task.
- Proposed framework improves the performance both in terms of verification accuracy and computational time.

References

- A.Blum and T. Mitchell. Combining labeled and unlabeled data with co-training. In *Proceedings of Conference on Computational Learning Theory*, pages 92–100, 1998.
- G. Cauwenberghs and T. Poggio. Incremental and Decremental Support Vector Machine Learning. In *Proceedings of Advances in Neural Information Processing Systems*, pages 409–415, 2000.
- N. Poh, R. Wong, J. Kittler, and F. Roli. Challenges and research directions for adaptive biometric recognition systems. In *Proceedings of International Conference on Advances in Biometrics*, pages 753–764, 2009.

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