Using the smooth Receiver Operating Curve (ROC) method for evaluation and decision making in biometric systems

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IMPORTANT INFORMATIVE STATEMENTS

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The CSSP is a federally-funded program to strengthen Canada's ability to anticipate, prevent/mitigate, prepare for, respond to, and recover from natural disasters, serious accidents, crime and terrorism through the convergence of science and technology with policy, operations and intelligence.

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Abstract

This report presents the use of the smooth ROC method for evaluation of biometric systems, which can be used in developing decision making rules for face recognition triaging. From a performance evaluation perspective, the problem can be decomposed into two subproblems: the first deals with detecting the presence or absence of a specified person of interest (POI) in a given video frame, and the second measures the strength of matching between the POI image and the face found in the video frame. The former can be viewed as a binary decision of detecting (or the lack there of), and the latter is based on a score that depicts the strength of matching. Ideally, the objective of the system is to measure the agreement between higher matching scores with the presence of POI in the video frame based on the assumption that a higher matching score corresponds to a higher likelihood of the POI being present in the frame. The accumulation of this performance information across the stream of video frames will yield information required for performance assessment analysis of the system as a whole.

Keywords: video-surveillance, face recognition in video, instant face recognition, watch-list screening, biometrics, reliability, performance evaluation

Community of Practice: Biometrics and Identity Management

Canada Safety and Security (CSSP) investment priorities:

1. Capability area: P1.6 – Border and critical infrastructure perimeter screening technologies/ protocols for rapidly detecting and identifying threats.
2. Specific Objectives: O1 – Enhance efficient and comprehensive screening of people and cargo (identify threats as early as possible) so as to improve the free flow of legitimate goods and travellers across borders, and to align/coordinate security systems for goods, cargo and baggage;
3. Cross-Cutting Objectives CO1 – Engage in rapid assessment, transition and deployment of innovative technologies for public safety and security practitioners to achieve specific objectives;
4. Threats/Hazards F – Major trans-border criminal activity – e.g. smuggling people/ material

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Disclaimer

The results presented in this report were produced in experiments conducted by CBSA, and should therefore not be construed as vendor's maximum-effort full-capability result. In no way the results presented in this paper imply recommendation or endorsement by the Canada Border Services Agency, nor do they imply that the products and equipment identified are necessarily the best available for the purpose.

Release Notes

Context: This document is part of the set of reports produced for the PROVE-IT(FRiV) project. All PROVE-IT(FRiV) project reports are listed below.

- Dmitry Gorodnichy, Eric Granger "PROVE-IT(FRiV): framework and results". Also published in Proceedings of NIST International Biometrics Performance Conference (IBPC 2014), Gaithersburg, MD, April 1-4, 2014. Online at http://www.nist.gov/itl/iad/ig/ibpc2014.cfm.
- Dmitry Gorodnichy, Eric Granger, "Evaluation of Face Recognition for Video Surveillance". Also published in Proceedings of NIST International Biometric Performance Conference (IBPC 2012), Gaithersburg, March 5-9, 2012. Online at http://www.nist.gov/itl/iad/ig/ibpc2012.cfm.
- E. Granger, P.Radtke, and D. Gorodnichy, "Survey of academic research and prototypes for face recognition in video,"
- D. Gorodnichy, E.Granger, and P.Radtke, "Survey of commercial technologies for face recognition in video,"
- E. Granger and D. Gorodnichy, "Evaluation methodology for face recognition technology in video surveillance applications,'
- D. Gorodnichy, E. Granger, E. Choy, W. Khreich, P.Radtke, J. Bergeron, and D. Bissessar, "Results from evaluation of three commercial off-the-shelf face recognition systems on Chokepoint dataset,"
- S. Matwin, D. Gorodnichy, and E. Granger, "Using smooth ROC method for evaluation and decision making in biometric systems,"
- D. Gorodnichy, E. Granger, E. Neves, S. Matwin, "3D face generation tool Candide for better face matching in surveillance video,"
- E. Neves, S. Matwin, D. Gorodnichy, and E. Granger, "Evaluation of different features for face recognition in video,"

The PROVE-IT(FRiV) project took place from August 2011 till March 2013. This document was drafted and discussed with project partners in March 2013 at the Video Technology for National Security (VT4NS) forum. The final version of it was produced in March 2014.

Appendices: This report is accompanied by appendices which include the presentations related to this report at the VT4NS'11 and VT4NS'13 forums.

Contents

1 Problem definition

Given a stream of frames $F = \{F_t\}$ obtained from a camera source and given a list of images of particular persons of interest (POIs), call it list $L = \{L_i\}$, the objective of the system is to detect the presence of the target image L_i^* in F. First, let us reduce the problem to a single frame F_t extracted from the stream F. If a face is detected in frame F_t, the facial recognition system computes a matching score S_i for each image of interest in L_i against every video frame F_t. This means that a given face in F_t may be matched to several images of interest of L_i potentially generating multiple hits most of which are likely to be false positives – only one image of interest is an exact match to the face in frame F_t. Therefore, it is crucial that the system produces S_i scores whose magnitudes reflect the strength or quality of the matching. Using the magnitudes of these matching scores, the system will be able to prioritize the strongest matches to decide an appropriate course of action. The objective of the evaluation is to assess how the magnitudes of these S_i scores produces the desired hits in the video stream.

2 Performance analysis method

The evaluation of the overall performance of the system becomes intuitive with the use of the smooth ROC method [1]. Ideally, the system should detect all instances of strong matches whilst raising the least number of false alarms. However, the performance of this system depends on the ability of the matching scores S_i to capture the desired matching based on their magnitudes. Therefore, the use of the smROC performance metric is advantageous due to its ability to measure the agreement between the magnitude of continuous value scores S_i and a binary decision, the latter can represent the decision of whether the recognized face is of interest or not, and the former is the score S_i of matching a face in frame F_t to the image of interest L_i. The smROC method plots individual instance of matching $L_i \in F_t$ as line segments which collectively form the smROC curve. The corresponding S_i scores are used to determine the slope of the corresponding line segments so that scores equal to 1 are represented by vertical line segments, matching scores S_i of zero are plotted as horizontal line segments, and line segments of slopes between 1 and 0 represent S_i scores between zero and one. In other words, decreasing S_i scores results in line segments being rotated clockwise, from vertical to horizontal slopes proportionally to the magnitude of S_i.

3 Interpreting the results

Plotting the above line segments, which correspond to individual instances of matchings, in a decreasing order of their corresponding scores for a given set of matchings, produces the smROC curve. When the curve is convex up, it means that the strongest positive matches (where the POI is indeed in the video frame) have been assigned higher scores, and the weakest negative matches (where the POI is not in the video frame) are assigned low scores. Therefore, the ideal performance will have an smROC curve placed towards the north-west corner of the plot, which also produces the highest area under the smROC curve. Thus, calculating this area under the curve can provide a scalar (numeric) summary of the overall performance of the system on the given set of matchings.

4 A sample analysis

For illustration, consider the sample matching scores S_i listed in Table 1. In this example, instances of detecting any POI are recorded in the Table 1. The top row shows instance numbers (a unique identifier), the second row lists the corresponding labels indicating whether the matched image is that of a POI or not (a label entry of *yes/no* corresponds to the ground truth of image L_i being in frame F_t), and S_i is the matching score between the POI image and the image in frame i as calculated by the system. For the purpose of performance evaluation, these instances of matchings are sorted in a decreasing order of their matching scores (from left to right in Table 1). The corresponding smROC curve is presented in Figure 1. Plotting the smROC curve and calculating the area under it follow Algorithm 2 published in [1].

Table 1: Sample matching scores S_i of POI images L_i in video frames

i	7	3	13	12	9	5	10	6	4	1	8	11	14	2
$L_i \in F_t$	yes	yes	yes	yes	yes	yes	yes	no	yes	no	no	yes	no	no
S_i	1	1	1	1	.96	.93	.89	.66	.49	.43	.30	.29	.04	.01

When the S_i scores are assigned in a perfect agreement with the ground truth labels, the curve is expected to follow the blue line depicting a vertical rise followed by a horizontal run. In this case, the curve shows that the positive and negative matchings are assigned high and low scores respectively demonstrating a correct performance of the system because high scores (vertical line segments) precede the low ones. In addition, the area under the blue curve is maximal at value of 1.0 indicating perfect ranking performance. Alternatively, when the score magnitudes fail to depict the strength of correct matching, the performance is said to be random and is expected to follow the dotted black diagonal line in the same figure. If we consider the red curve in Figure 1 plotted for those matchings listed in Table 1, we see that most of the high scores coincide with *yes* labels and most of the low scores are assigned to *no* labels. This suggests that the sample scores are reasonably well assigned because they are better than random although they do not achieve the perfect rankings (instances 6 and 11 are incorrectly placed in the order of score values).

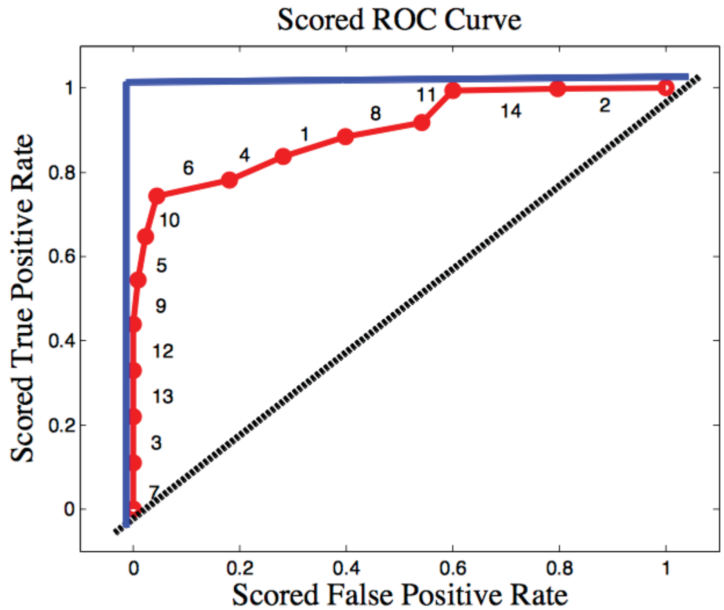

Figure 1: The smROC (or Scored ROC) curve for matchings listed in Table 1. The blue solid line depicts the ideal (perfect) performance and the black dotted line represents the random performance. The area under the red smROC curve represents a scalar summary of the performance of the system on the given set of matchings.

Furthermore, the score values are not all ones (for the *yes* labels) and instances with *no* labels have a non zero score. To this effect, the area under the red curve fails to achieve the 100% level depicted by the blue solid curve, however, it remains above the random performance indicated by the 0.5 area under the dotted black diagonal line. Comparing the scalar values of the areas under the three curves (blue, red and black) will produce the desired performance comparison.

The area under the smROC curve represents a scalar summary of the performance of the matching scores as assigned to matching instances. However, further examination of the curve itself can identify individually interesting instances. For instance, the numbers shown next to individual line segments along the red curve in the figure correspond to the unique identifiers of matching instances listed in Table 1. If we visually inspect individual line segments, we can see that instances 7, 3, 13, and 12 result in vertical line segments indicating a very strong match. The next group of instances 9, 5 and 10 are more vertical than the remaining instances but are not completely vertical either. And finally, line segments 4 and 11 are the most vertical among the remaining instances but compared to the previous two groups, they appear horizontal. If we examine the labels of these three groups of instances, we can see that they are all labeled with *yes* indicating that the associated video frame matches the corresponding image of the POI involved. Therefore, these three groups of instances represent positive matches detected by the system. Furthermore, it is clear that there is a significant change of direction along the curve between line segments 10 and 6. Setting the operational alarm threshold at that point will result in high number of hits (7 out of 9 *yes* are captured) with no false alarms.

Effectively, the same approach can be used for the detection of true positive matchings among the many matchings executed for the stream of video frames. This suggests an added benefit of using the smROC to fine tune and monitor the performance of the proposed system, it provides a visual representation of possible thresholds which can be used for raising alarms by the system. For instance, the alarm threshold may be set to raise a red alarm for the first two groups discussed above, an amber alarm for the third group and no alarm for the remaining instances of matches.

5 Conclusions

The use of smROC curve to assess the performance of the proposed facial detection system provides several benefits particular to this problem. The correctness of image detection and balancing the trade-off between hits and alarms relies on how well the matching scores are assigned to matching instances. The magnitudes of matchings are essential for the prioritization of alarms, and they enable the system to maximally capture positive detections while raising minimal false alarms. The smROC method is the only method reported in literature that is able to incorporate the magnitudes of the scores into the analysis of hits versus alarms. Therefore, the possible use of the smROC may include measuring the detection performance in various settings, these may be:

- **Testing and validation:** for a given set of matchings, the area under the smROC curve could be used to demonstrate the ability of the system to detect the desired images. This process should be executed repeatedly on various data point sets in various testing experiments to assess the expected performance of the system. An aggregated report of the accumulated results will support a reliable conclusion of the expected overall performance.

- **Monitoring system operation:** The calculation of the area under the smROC curve provides a simplified performance summary that can be regularly monitored over a window of time. This can potentially allow for the detection of possible deterioration in system performance over time. For instance, measuring the performance over a window of 2-3 hours on a daily basis can reveal deviations from the expected performance (as estimated during testing and validation). This may be important based on the method used to calculate the matching scores because many methods assume that the underlying characteristics of the domain hardly change over time. In real life, this cannot be further from the truth. Therefore, it is important to monitor the operational performance of the matching model to detect underlying distribution changes.

- **Determining alarm thresholds:** as discussed previously, individual matching instances are represented as line segments whose slopes are directly associated with the correctness and magnitudes of matchings between images and video frames. We've illustrated how the examination of these slopes can help prioritize matching instances to determine the threshold of alarm that achieves the desired rate of hits versus alarms. Repeated thorough testing and validation of the system will reveal natural ”kinks” in the performance curves that can allow the selection of appropriate alarm thresholds.

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Machine Learning for PROVE-IT

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VT4NS 2011

Roadmap

- Exploratory character of Machine Learning in PROVE-IT
- Our research group Text Analysis & MAchine LEarning (TAMALE)
- Requirements for ML in PROVE-IT – first attempt
- What ML technologies need to be investigated in PROVE-IT
- Evaluation?

Exploratory character of ML for PROVE-IT

- Machine Learning needs to prove itself as a technology that might contribute to PROVE
- The best way – try it!
- Focus on existing techniques (learning algorithms), and on the necessary data engineering

TAMALE LAB

- More than 20 years
- Produced more than 100 graduates in the area of data and text mining
- Currently six profs, several PDFs, 25 graduate students
- Focus on applications
- Internationally recognized
- Some experience with vision data (RADARSAT, Landsat RS data)

Task: face triaging

- Given:
  - List of *k* POIs with their facial images
  - scores for each POI for a stream of frames in which a POI occurs or not:
  - 0000000000003000000000000000000000000000080000000000000000000
  - 0000000000002000000000000000000000000000090000000000000000000
  - 0000002000001000000000000000001000000000090000000000000000000
  - 0000002000001000000000000000001000000000090000000000000000000
  - 0000000000002000000000000000000000000000080000000000000000000
  - 0000002000002000000000000000000000000000090000000000000000000
  - 0000000000002000000000000000000000000000090000000000000000000
  - 0000000000003000000000000000000000000000090000000000000000000
  - 0000000000002000000000000000000000000000090000000000000000000
  - 0000000000003000000000000000000000000000080000020000000000000
- Find: raise alarm at the moment when a given POI is believed to be detected in the stream video

A preliminary solution

for each time step t

for each of the 66 faces:

- keep an incremental count of scores
- smooth the count as the t grows, eg $sm\_count_t = \sum_{i=1}^{t} \frac{score(i)}{t}$
- we test the sm_count_t against thresholds thr_Y, thr_R: when at some t it exceeds the thr_Y or thr_R threshold, then we raise Y or R alarm, respectively

The “smart” part…

- …is a good selection of the thresholds thr_Y, thr_R
- We propose to use Machine Learning for this

And also feature engineering

- What are the good features?
- How to bulid them – cooperation with CV
- Noise in features
- Feature selection?

Performance evaluation

- **Not** accuracy
- ROC or derivative?
- smROC?
- Some form of lift?
- Likely to be determined by practice

Q&A and discussion...

Smooth ROC Motivation

Scores allow:

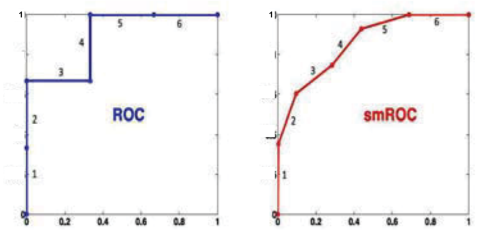
- the classifications based on decisions, ranking, and scores (confidence),
- the visualization of score margins, and
- The identification of gaps in scores.

Of course, probabilities tell us all this plus more (theoretical), but not all scores are good estimates of probabilities!

Applications

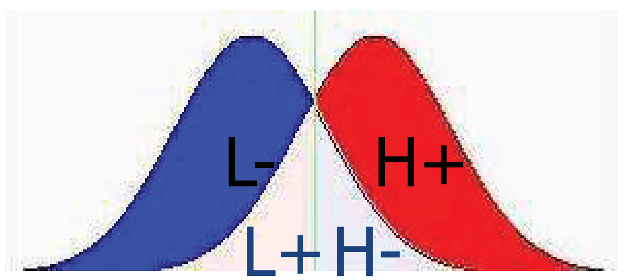
- Comparing user preferences
- Evaluating relevance in search applications (facial recognition in images)
- Magnitude-preserving ranking (Cortes et. al ICML'07)
- Research Tool
- Bioinformatics (gene expression)

Visualizing The Scores



No.	Prediction	Score
1.	+	0.99
2.	+	0.70
3.	-	0.60
4.	+	0.51
5.	-	0.20
6.	-	0.00

The Appropriateness of scores



$$\Theta(x_i) = \begin{cases} s_i & \text{if } x_i \in \{H^+ \cup L^-\} \text{ (Appropriate Scores)} \\ 1 - s_i & \text{if } x_i \in \{H^- \cup L^+\} \text{ (Inappropriate Scores)} \end{cases}$$

(Appropriateness of Scores)

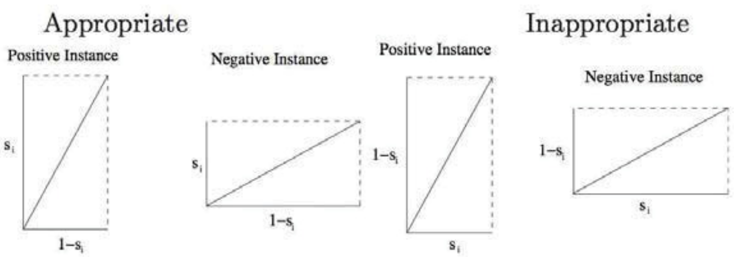
Label	Scores: High	Low
+	yes	no
−	no	yes

(Accuracy of Appropriate Scores)

Score	Label	Predicted: Y	N
High	+	correct	incorrect
Low	−	incorrect	correct

(Accuracy of Inappropriate Scores)

Score	Label	Predicted: Y	N
High	−	incorrect	correct
Low	+	correct	incorrect



Constructing The Smooth ROC Curve

$$Mid = \frac{1}{2}(m^+ + \frac{m^-}{c})$$

$$smTPR = \frac{\Theta(x_i)}{\propto_v} \qquad smFPR = \frac{\Theta(x_i)}{\propto_h}$$

$$\propto_v = \sum_{i=1}^{|H^+|} S_i + \sum_{i=1}^{|L^-|} S_i + \sum_{i=1}^{|L^+|} (1 - S_i) + \sum_{i=1}^{|H^-|} (1 - S_i) = \sum_{i=1}^{n} \Theta(x_i)$$

$$\propto_h = \sum_{i=1}^{|H^+|} (1 - S_i) + \sum_{i=1}^{|L^-|} (1 - S_i) + \sum_{i=1}^{|L^+|} S_i + \sum_{i=1}^{|H^-|} S_i = \sum_{i=1}^{n} (1 - \Theta(x_i))$$

The Area Under smROC Curves

$$smAUC = \frac{1}{\propto_v \propto_h} \sum_{i=1}^{n} \sum_{j=1}^{n} \Theta(x_i) \Psi(x_i, x_j)$$

$$\Psi(x_i, x_j) = \begin{cases} 1 - \Theta(x_i) & \text{for } (S_i > S_j) \text{ and } (i \neq j) \\ \frac{1}{2}(1 - \Theta(x_i)) & \text{for } i = j \\ 0 & \text{otherwise} \end{cases}$$

- Compare all points pairwise.
- Measure the differences in classifications weighted by the magnitu