BioSecure Fusion Algorithm

Part II

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Participants

Short name

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- Albert Salah and Onkar Ambekar, Centrum voor Wiskunde en Informatica (CWI), the Netherlands
- John Baker, Johns Hopkins University Applied Physics Laboratory (JHUAPL), USA

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Algorithms

- AMSL-BIO
  - Weighted averaging
- GET
  - Sequential fusion strategy
  - Gaussian mixture model
- UPM
  - Linear logistic regression optimising a cost objective function
- UniS
  - Logistic regression in score/quality space
  - quality based clustering fixed rule fusion
  - naïve Bayes
- JR
  - Dempster-Shafer fusion
- CWI
  - Mixture of factor analysers
- JHUAPL
  - Bayesian network

Two types of Algorithm

- Conventional fusion

$$f : \mathbf{y} \rightarrow y_{com}$$

where $\mathbf{y} = [y_i, \ldots, y_N]'$

- Quality-dependent fusion

$$f : \mathbf{y}, \mathbf{q} \rightarrow y_{com}$$

where $\mathbf{q} = [\mathbf{q}_1, \ldots, \mathbf{q}_N]'$

and $\mathbf{q}_i \in \mathbb{R}^Q$

Naive Bayes (baseline) Logistic Regression, Fixed Rule and Device-specific Quality-dependent Fusion

Omalara Fatukasi and Norman Poh

University of Surrey (UniS)

Fusion Algorithms (UniS)

- Baseline (Unis): Naive Bayes $y_{com} = \prod_i P(\mathtt{C}|y_i)$

  $P(\mathtt{C}|y_i)$ is estimated using a linear logistic regression
- UniS: Quality-dependent fusion

$$y_{LR} \equiv P(\mathtt{C}|\mathbf{x}) = \frac{1}{1+\exp(-g(\mathbf{x}))}$$

linear logistic regression

where $g(\mathbf{x}) = \sum_{i=1}^{M} \beta_i x_i + \beta_0$

$\mathbf{x} \equiv [\mathbf{y}, \mathbf{q}, \mathbf{y} \otimes \mathbf{q}]'$

β's are estimated by maximum likelihood – gradient ascent

Fusion Algorithm (UniS)

Fixed-rule fusion

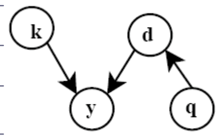
Divide scores into two groups $\{y_m^{high}\}$ $\{y_n^{low}\}$
according to quality measures then combine with the following rule:

$$y_{com} = \begin{cases} \frac{1}{M}\sum_m y_m^{high} \times \frac{1}{N}\sum_n y_n^{low} & \text{if } M > 0 \text{ and } N > 0 \\ \frac{1}{M}\sum_m y_m^{high} & \text{if } N = 0 \\ \frac{1}{N}\sum_n y_n^{low} & \text{if } M = 0 \end{cases}$$

y_i is high if q_i >mean(q_i)-std(q_i); otherwise y_i is low

Device-specific Quality-dependent Fusion

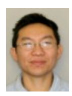
$k \in \{\mathtt{C}, \mathtt{I}\}$	Class label (*unobserved* in test)
$y \in \mathbb{R}^N$	a score (scalar)
$q \in \mathbb{R}^{N_q}$	Vector of quality measures
$d \in \{1, \ldots, N_d\}$	Device (*unobserved* in test)



$$y^{norm}_{\text{with } d} = \log \frac{\sum_d p(y|\mathtt{C}, d)p(d|q)}{\sum_d p(y|\mathtt{I}, d)p(d|q)}$$

where $$p(d|q) = \frac{p(q|d)p(d)}{\sum_* p(q|d_*)p(d_*)}$$

digital webcam

p(y,|k,d) and *p(q|d)* were estimated using GMM and its number of components was decided using cross-validation on the dev. data set

Reference: BTAS'07

Sequential Evaluation and Double Thresholding

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CWI: double-thresholding

$$P(\mathtt{C}|\mathbf{y}) = \frac{p(\mathbf{y}|\mathtt{C})P(\mathtt{C})}{p(\mathbf{y}|\mathtt{C})P(\mathtt{C}) + p(\mathbf{y}|\mathtt{I})P(\mathtt{I})}$$

Where $p(\mathbf{y}|k)$ is an incremental mixture of factor analyzers (IMOFA)

- Evaluate the modalities in the order of face, iris, fingerprint
- If the face or the iris is present, do not take the fingerprints into account
- If the probability of being a genuine user is higher than a threshold (0.5) at any time, output that probability (i.e. accept as genuine) and do not consider the rest of the modalities.
- If the probability of being a genuine user is lower than a threshold (0.025)
- Output that probability (i.e. reject as impostor) and do not consider the rest of the modalities

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CWI: SVM

- Training with only high quality data
- Quality measures are used
- Output « probabilities »

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Bayesian Belief Network

John Baker

JHUAPL

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BBN For Multi-Modal Fusion

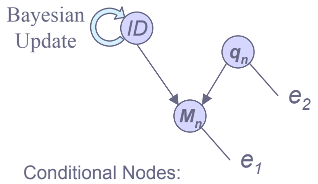
- Prior probabilities
  - Uniform Initialization:

$$p_{\text{prior}}(ID) = 0.50 \quad (ID = \textit{non-match, match})$$

  - Individual Modalities Modeled as Conditionally Independent Given ID
- Multi-Modal Update Equation:

$$p_{\text{update}}(ID) = p_{\text{prior}}(ID) \cdot \frac{p(M_n = e_1 \mid ID, q_n = e_2)}{Norm}$$

- Bayesian Update Iterated for Each Available Measurement (e.g. Each Finger) for Each Modality
  - If Correlation Exists Between Measurements or Modalities, BBN Would Need to Be Altered to Represent Appropriate Conditional Probabilities



Conditional Nodes:
- M_n n[th] Modality Score
- q_n n[th] Modality Quality

Output Nodes:
- ID Binary Random Variable (0 for Non-Match, 1 for Match)

Evidence
- e_i Measurement for i^{th} Input

$p(M_n = e_1 \mid ID, q_n = e_2)$ is the *likelihood* of observing measurement $M_n = e_1$ given observed quality $q_n = e_2$ and ID = Match or Non-Match.

Other Presentations

- GET
- JR
- UPM
- AMSL