Bayesian Multimodal Fusion in Forensic Applications

Virginia Fernandez Arguedas,

Qianni Zhang & Ebroul Izquierdo

Prof. Ebroul Izquierdo
Head of Multimedia & Vision Group
Queen Mary University of London

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Introduction

- Technological developments
- Concern about security

→ Widespread of CCTV recording 24/7

- Enormous amount of data is generated everyday
- Lack of resources
- Critical need of automatic and intelligent indexing schemes
- Forensic search

Motivation

- Surveillance cameras
  - Public/private locations
  - Un-controlled environments
  - Quality of the images
  - Availability of the images
- System requirements
  - Capable of dealing with the presence of uncertainty
  - Ensuring a continuous working-mode despite the lack of of information

Objectives

- Guarantee the system reliability despite the presence of uncertainty and the absence of information
  - Use complementary information to increase the accuracy
  - Probabilistically combine diverse-nature cues
  - Bayesian Networks
- Bayesian inference scheme
  - Decision-level multimodal fusion technique
- Surveillance object classifier exploiting the benefits of the proposed Bayesian multimodal fusion approach

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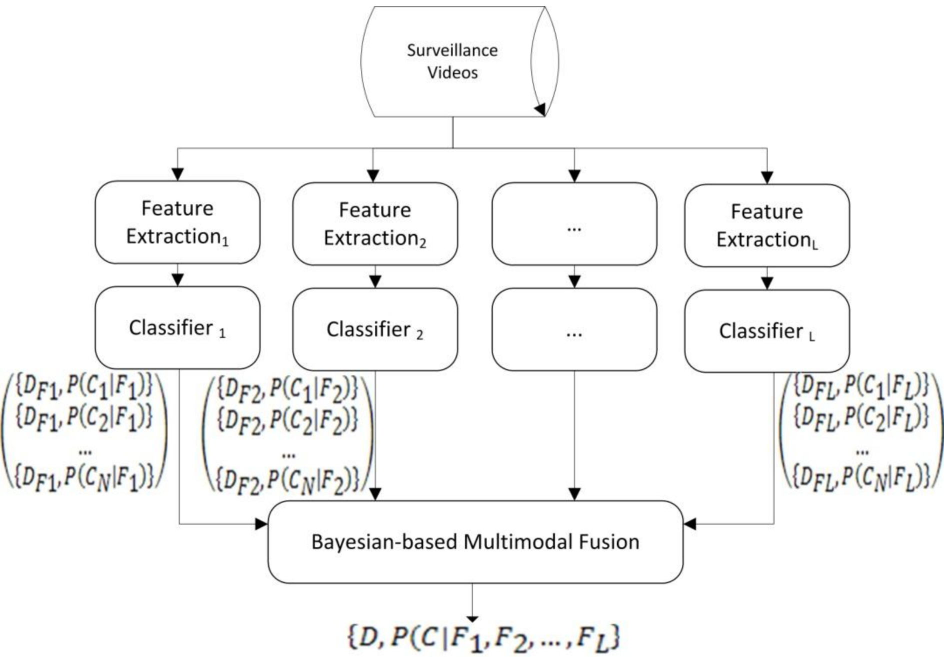
Bayesian Multimodal Fusion Technique (BMF)

- Bayesian-based Multimodal Fusion technique
  - Probabilistically combine diverse-nature cues
  - Inferring information from previously acquired knowledge
- Bayesian Networks enable the robust integration and combination of diverse-nature sources of information applying rules of probability theory
  - Allows the combination of multimodal information due to its possibility of adaptation as the information evolves as well as its capability to apply subjective or estimated probabilities when empirical data is absent
  - Hierarchical structure provides flexibility and scalability, facilitating the inclusion of additional information and enabling the degradation of the a-posteriori probability in case of the absence of information
  - Allows domain knowledge to be embedded into the structure and parameters of the networks, adjusting the fusion technique to the domain and scenario's requirements

Bayesian Multimodal Fusion Technique (BMF)



- Decision-level multimodal fusion technique
  - Independent inputs derived from different inputs
  - Unifying the output of several modules to provide a unique output in the decision-making process
- Normalised and unique representation of the information
- Combination of different nature features preserving their own feature space and unique metrics

Bayesian Multimodal Fusion Technique (BMF)

- Bayesian inference scheme can be formulated using the maximum a-posteriori criterion (MAP)

$$D = \underset{i}{argmax}\{P(C_i|F_1, F_2, ..., F_L)\} = \underset{i}{argmax}\{\prod_{j=1}^{L} P(F_j|C_i)P(C_i)\} =$$

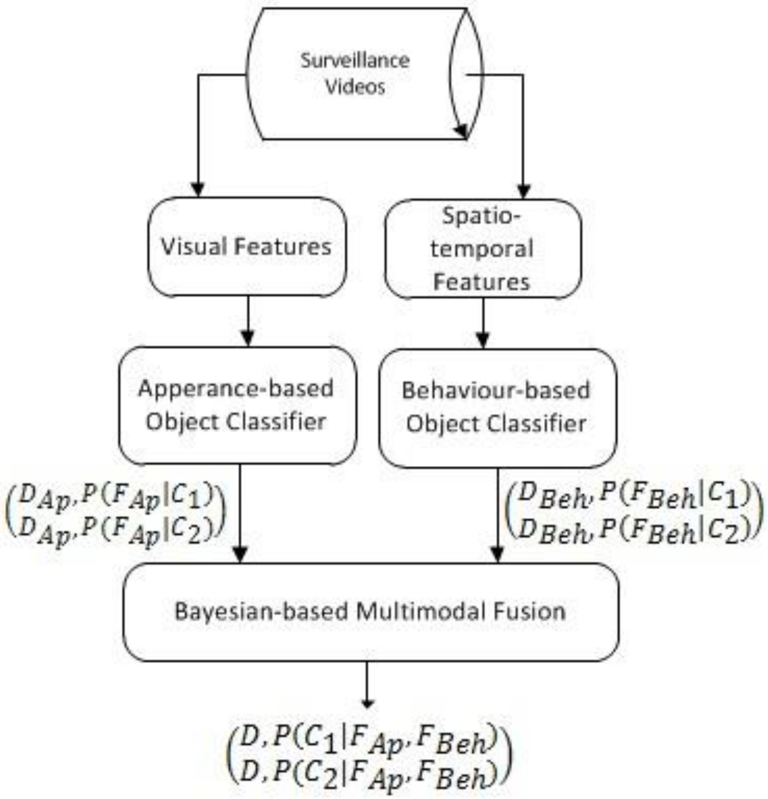
$$= \underset{i}{argmax} \begin{pmatrix} \prod_{j=1}^{L} P(F_j|C_1)P(C_1) \\ \prod_{j=1}^{L} P(F_j|C_2)P(C_2) \\ \vdots \\ \prod_{j=1}^{L} P(F_j|C_N)P(C_N) \end{pmatrix}$$

- The conditional probability matrices connecting each partial decision to the network allow the specification according to the scenario and application

Bayesian-based Object Classifier

- The scalable hierarchical structure of the Bayesian-based Multimodal Fusion technique
  - Incorporation of various classifiers
  - Enabling a high level of flexibility and adaptation to the scenario under analysis in the form of a-priori probabilities
- Each partial decision could perform automatic object classification
- The integration of several features, derived from different and uncorrelated media, addresses higher robustness, stability, flexibility and adaptation towards the scenario under analysis

Bayesian-based Object Classifier



- A tracking algorithm fed the individual classifiers with detected moving objects or observations
- Inputs
  - Visual-based Object Classifier
  - Behaviour-based Object Classifier
- Each individual classifier categorise each observation into one of the two semantic concepts defined for the scenario

Bayessian – based Object Classifier

- Each individual classifier provides
  - Partial decisions to the Bayesian inference scheme
  - Conditional probability matrix
    - Probability of a detected moving object to belong to each semantic concept
- Maximum a-posteriori criterion

$$\begin{pmatrix} P(C_1 \mid F_1) & P(C_1 \mid F_2) \\ P(C_2 \mid F_1) & P(C_2 \mid F_2) \\ \cdots & \cdots \\ P(C_N \mid F_1) & P(C_N \mid F_2) \end{pmatrix}$$

$$D = \arg\max_i \{P(C_i \mid F_1, F_2)\} =$$

$$= \arg\max_i \{\prod_{j=1}^{2} P(F_j \mid C_i) P(C_i)\} =$$

$$= \arg\max \begin{pmatrix} \prod_{j=1}^{2} P(F_j \mid C_1) P(C_1) \\ \prod_{j=1}^{2} P(F_j \mid C_2) P(C_2) \end{pmatrix}$$

- Bayesian Networks enable the continuous work of the multimodal classifier due to their reliability In the presence of missing evidence, either partially or completely
  - Rigorously decreasing the certainty on the classification

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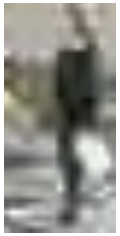
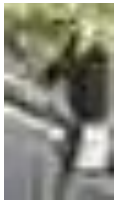
Evaluation dataset

- iLIDS dataset
- Urban environments
  - Realistic conditions
  - 3 Scenarios
- Concepts: CAR/PERSON
- Ground truth: 1576 objects
  - 6% Person, 50% Vehicles
- Interannotator agreement

Quantitative Evaluation

- A conditional probability matrix is calculated by each individual classifier
- Bayesian-based Multimodal Fusion technique combines the different partial decision to achieve a unique classification
  - Considering the diverse-nature cues
  - Preserving their individual feature spaces and metrics
- Fundamental objectives:
  - High true positive rate balanced with a low false negative rate
  - Low false positive rate

Semantic Concepts	True Positive (%)	True Negative (%)	False Positive (%)	False Negative (%)
Vehicle	97	66	34	3
Person	66	97	3	34

Performance Comparison

Semantic Concepts		True Positive	True Negative	False Positive	False Negative
Vehicle	Appearance Classifier	77	64	36	23
	Behaviour Classifier	79	57	43	21
	Bayesian Classifier	97	66	34	3
Person	Appearance Classifier	64	77	23	36
	Behaviour Classifier	57	79	21	43
	Bayesian Classifier	66	97	3	34

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Conclusions & Future Work

Conclusions

- Probabilistic multimodal fusion technique to integrate diverse-nature cues in surveillance applications
    - Scalable technique to combine multiple features while preserving their nature
    - Address the partial or total absence of information by degrading the classification results
    - Considering the scenario in the a-priori knowledge
- Bayesian-based Object Classifier

Future work

- Use the Bayesian-based Multimodal Fusion technique to combine classification results to perform event detection and classification

Thank you for your attention

Contact:
virginia.fernandez@eecs.qmul.ac.uk
qianni.zhang@eecs.qmul.ac.uk
ebroul.izquierdo@eecs.qmul.ac.uk