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On Privacy-Protecting and Self-Organizing Cameras

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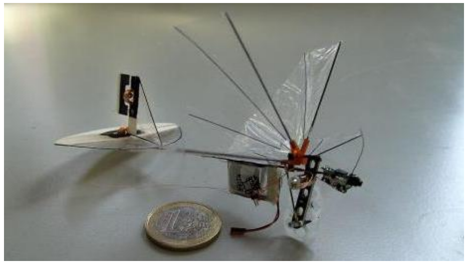
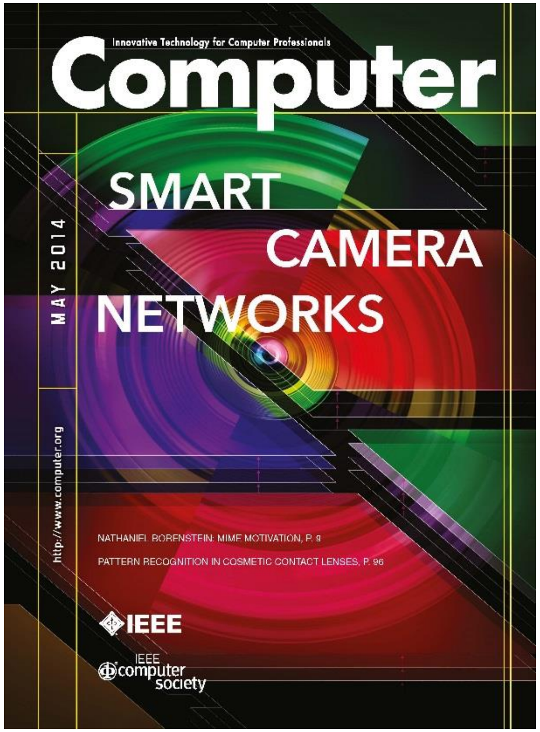
Ubiquitous Cameras

- We are surrounded by billions of cameras in public, private and business spaces
- Various well-known domains
  - Transportation
  - Security
  - Entertainment
  - Mobile
- Cameras serve a purpose and provide some utility
  - Providing documentation/archiving
  - Increasing security
  - Enabling automation
  - Fostering social interaction



Paradigma Shifts in Video Processing

- Towards online/onboard processing
- Towards distributed, in-network analysis
- Towards ad-hoc deployment and mobile and open platforms
- Towards user-centric applications

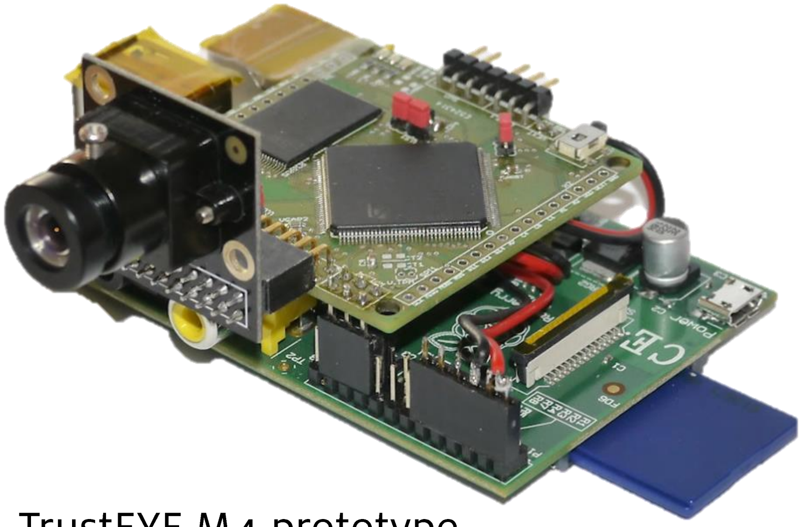


Emergence of Smart Camera Networks !

Smart Cameras as Enabling Technology

- Smart cameras combine
  - sensing,
  - processing and
  - communication

  in a single embedded device



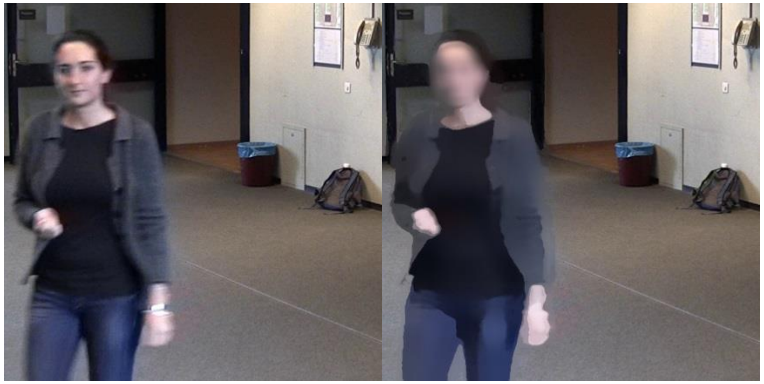
TrustEYE.M4 prototype
on top of RaspberryPI

- perform image and video analysis in real-time closely located at the sensor and transfer only the results
- collaborate with other cameras in the network

[Rinner, Wolf. A Bright Future for Distributed Smart Cameras. Proc. IEEE, 2008]

Agenda

1. Onboard privacy protection in (single) camera
   – Explore tradeoff among utility/protection/resources
   – Embed protection mechanisms close to sensor
2. Autonomous in-network analysis
   – Self-organize tracking in camera networks
   – Learn advantageous strategies of cameras



© MediaEval

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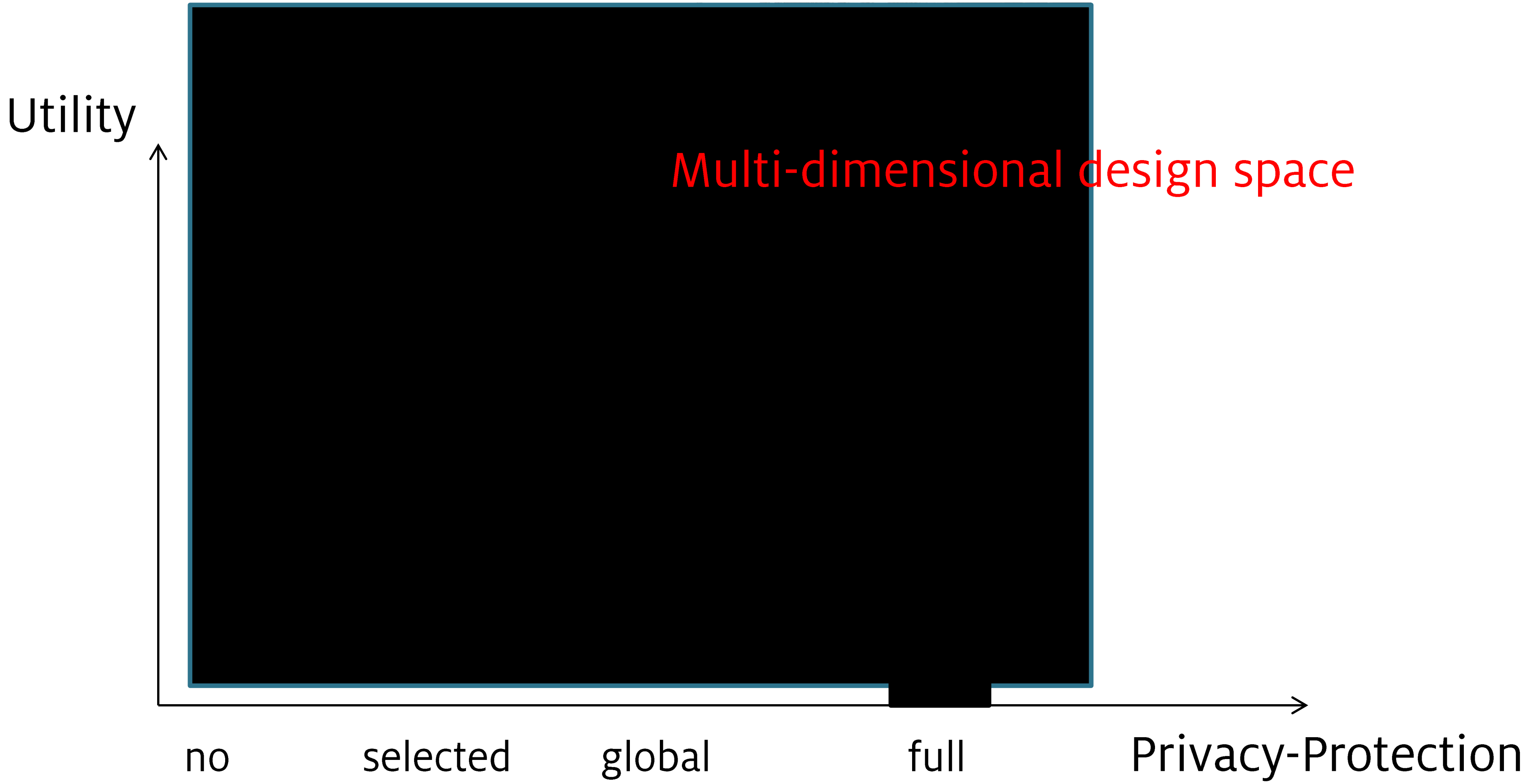
Onboard Privacy Protection

Privacy Protection in Images

Source: Wikipedia

Utility and Privacy-Protection Tradeoff



Observations and Key Challenges

- Most techniques focus on protecting sensitive regions from unauthorized access
  - Global filters protect entire frame
  - Object-based filters protect ROIs (depend on detection performance)

- No single best privacy protection method, but a large design space along protection/utility/resource dimensions
- Privacy protection goes hand-in-hand with security to provide
  - Non-repudiation
  - Confidentiality

[Winkler, Rinner. [Security and Privacy Protection in Visual Sensor Networks: A Survey](). ACM Computing Surveys, in print]

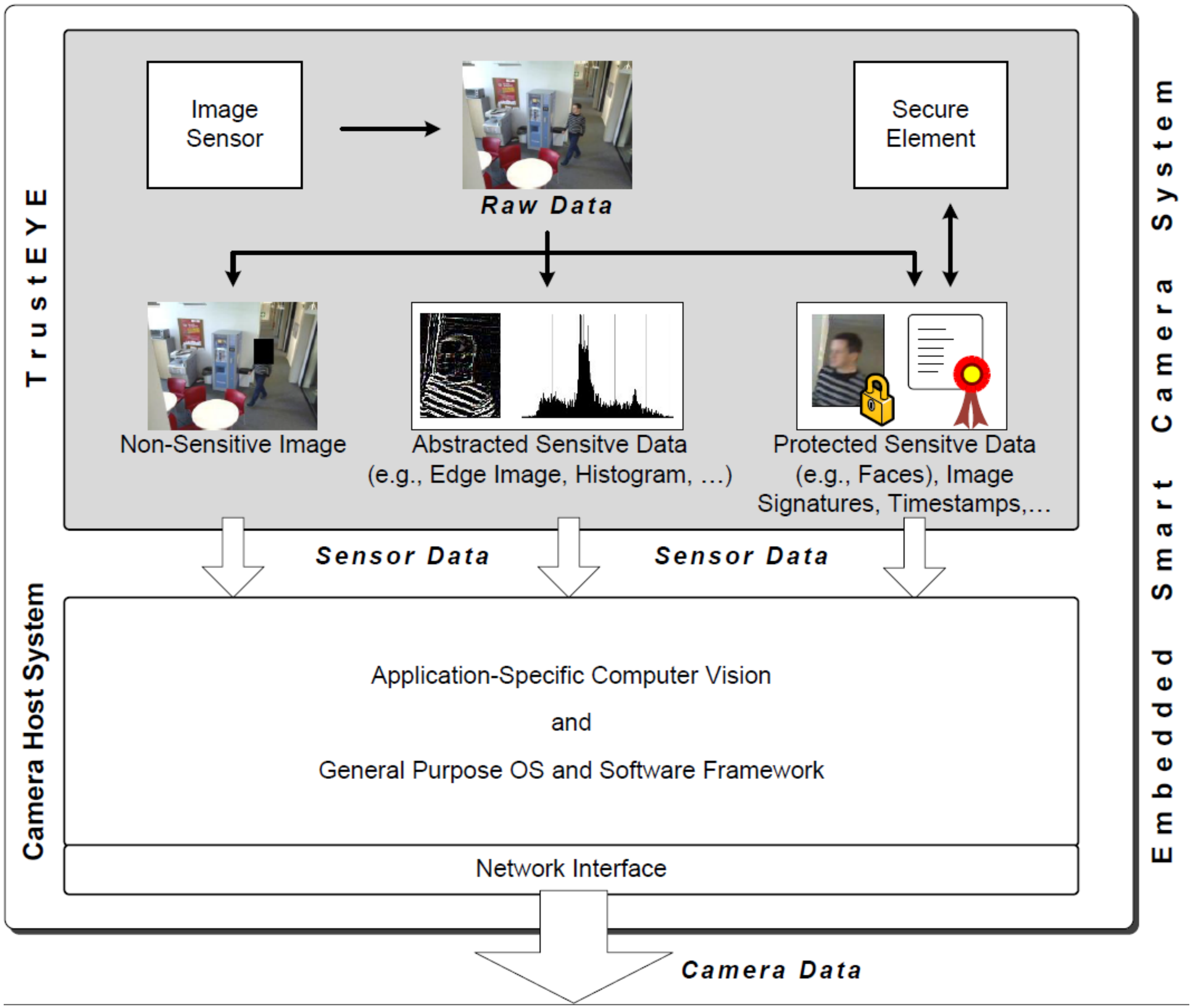
Approach: Trustworthy Sensing (TrustEYE)

- Objective:
  - Protect access to sensor via a trusted component “TrustEYE”
  - Make security and privacy protection an inherent feature of the image sensor
  - Provide resource-efficient and adaptable privacy protection filters

- Benefits:
  - Sensor delivers protected and pre-filtered data
  - Strong separation btw. trusted and untrusted domains
  - Camera software does no longer have to be trustworthy
  - Security can not be bypassed by application developers
  - TrustEYE is anchor for secure inter-camera collaboration

[Winkler, Rinner. [Sensor-level Security and Privacy Protection by embedding Video Content Analysis](). In Proc. DSP 2013]
http://trusteye.aau.at/

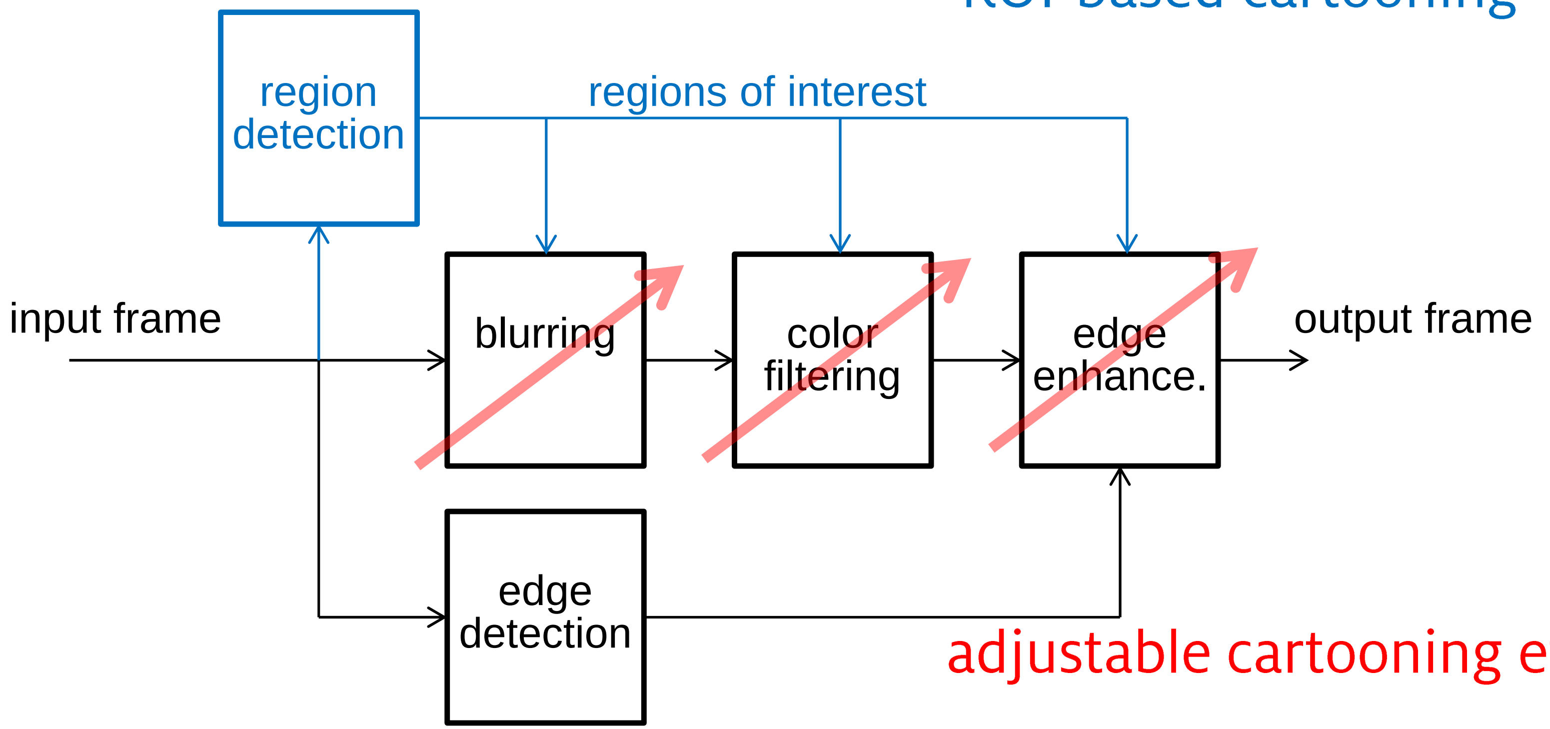
TrustEYE Overview



Privacy Protection by Cartooning

- Abstract parts or entire image by blurring and color filtering
- Cartooning pipeline

ROI-based cartooning



adjustable cartooning effect

- Embed cartooning as privacy feature into smart cameras

ROI-based Cartooning

(c) MediaEval Dataset

Cartooning of detected faces

– Privacy protection depends on performance of region detectors (faces, persons etc.)
– Adapting the filter characteristic beneficial

[Erdelyi et al. Serious Fun: Cartooning for Privacy Protection. In Proc. MediaEval 2013.]

Adjustable Global Cartooning

original

cartooning (small)

cartooning (std)

cartooning (strong)

(c) MediaEval Dataset

Evaluating Privacy/Utility Tradeoff

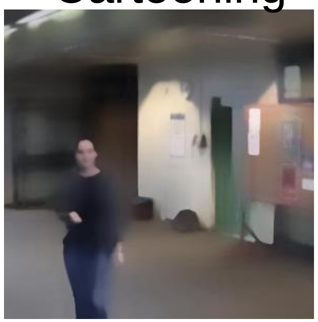
- Establish an objective evaluation framework among key dimensions, i.e.,
  - Privacy protection — Identification of objects of interest
  - Utility — Detection/tracking of objects
  - Appearance — Structural similarity with unprotected frame
  - Resource consumption — Achievable frame rate
- Measure the performance using standard CV algorithms with protected videos (and use labeled test data as ground truth)
  - Independently for each frame
  - Measure protection among object's traces

[Erdelyi et al. Adaptive Cartooning for Privacy Protection in Camera Networks. In Proc. IEEE AVSS, 2014]

Comparison of Global Filter Approaches

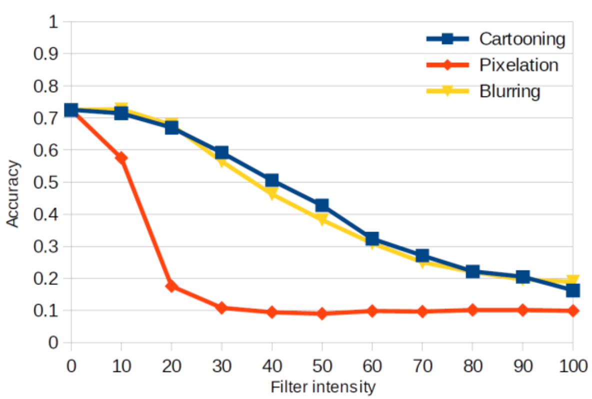
- Performance of standard CV algorithms compared to unprotected video or other protection filters

Cartooning

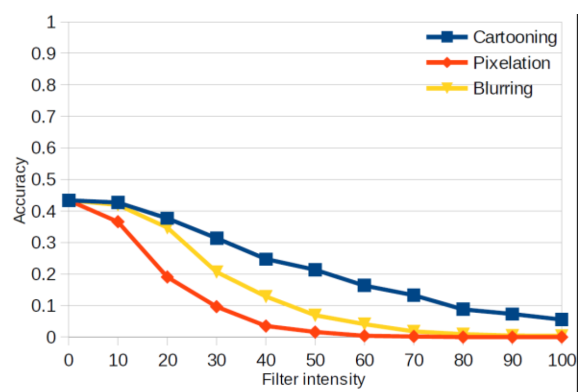


Blurring

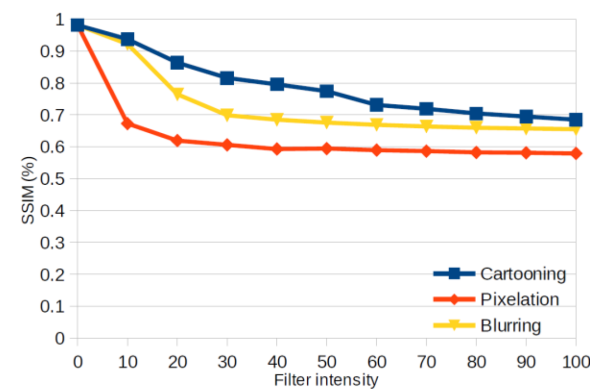
Pixelation



Protection: object re-identification performance

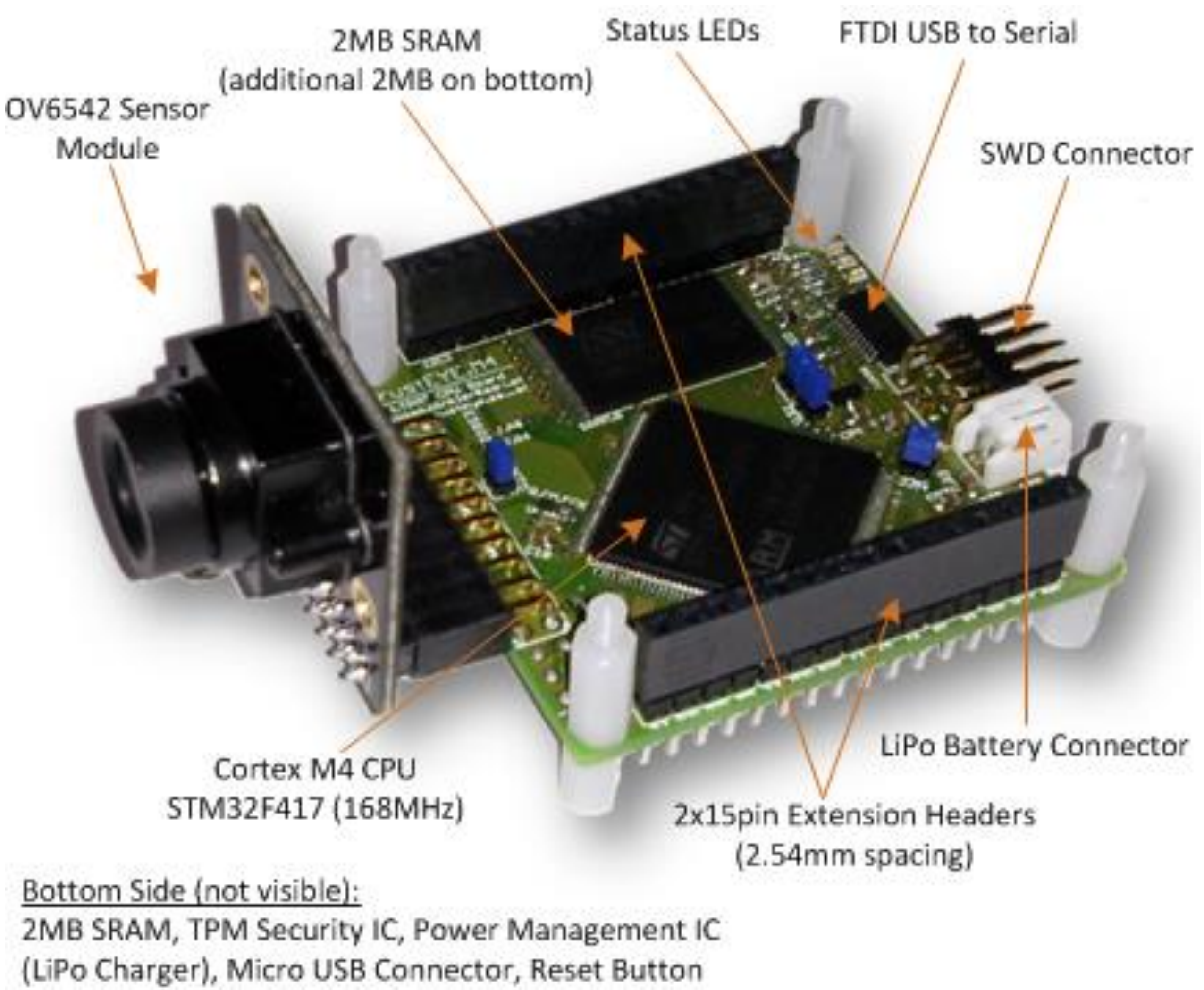


Utility: object detection performance



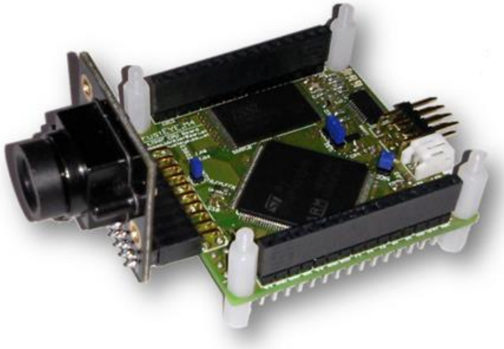
Appearance: structural similarity index

TrustEYE.M4 Architecture

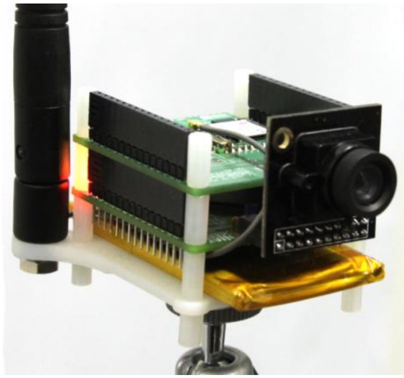


TrustEYE.M4 Prototypes

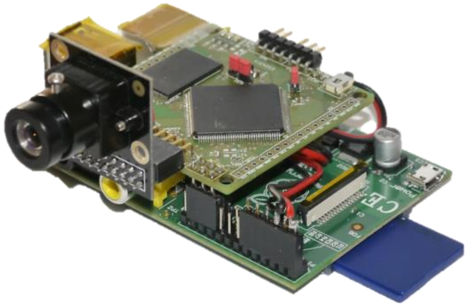
- Processing board (50x50 mm)
  - ARM Cortex M4 @ 168MHz
  - 4 MB SRAM
  - TPM IC: ST33TPM12SPI via SPI
  - Keil RTX RTOS



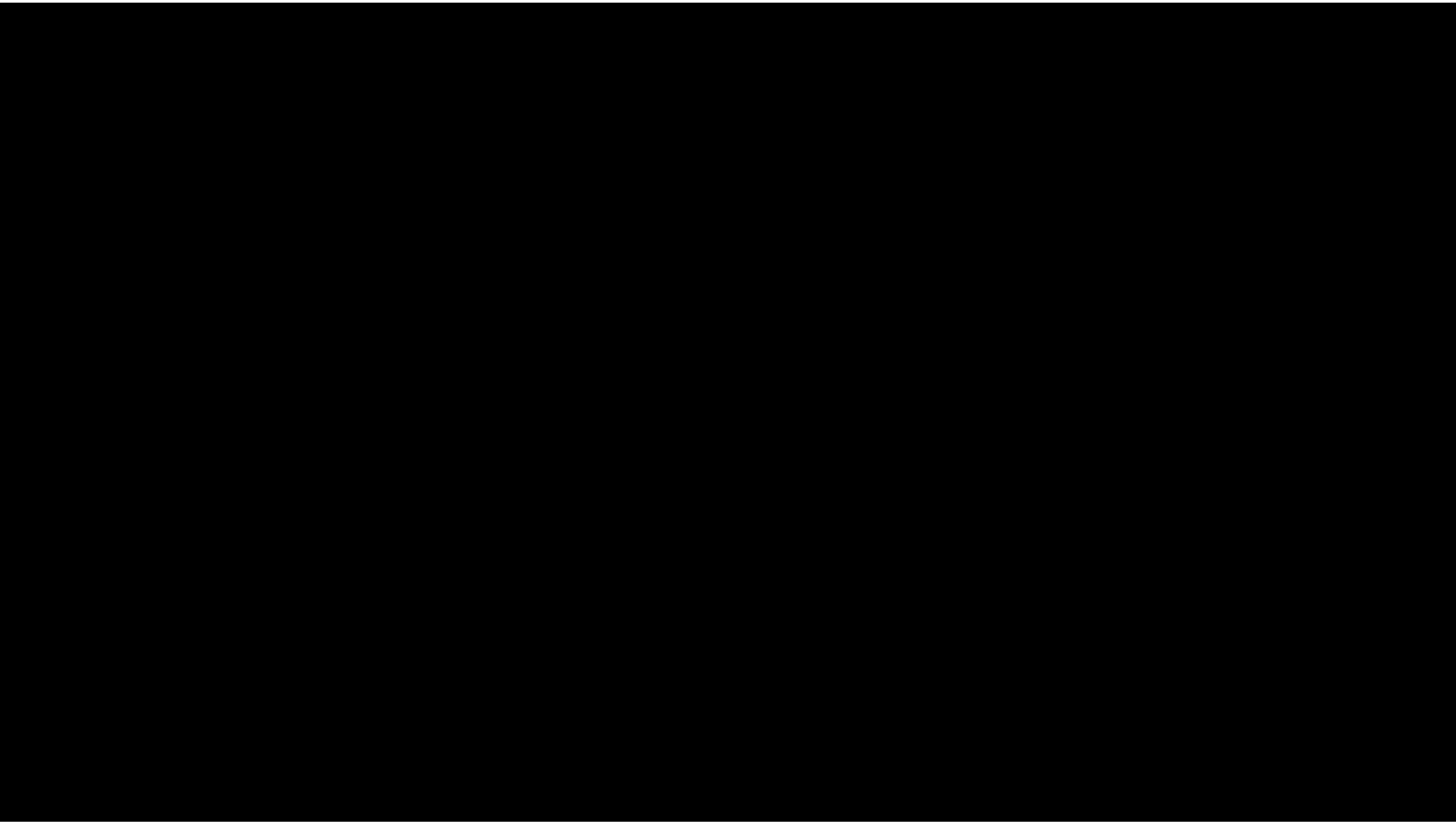
- WiFi extension board (50x50 mm)
  - Redpine Signals RS9110-N-11-02
  - 802.11 b/g/n
  - Encryption: WPA2-PSK, WEP
  - Interconnect: SPI bus on 15pin ext. header



- RaspberryPI mounting option
  - Interconnect: SPI bus via dedicated RPI
  - Daterate: 32 Mbit/s



TrustEYE in Action



Autonomous In-Networking Analysis

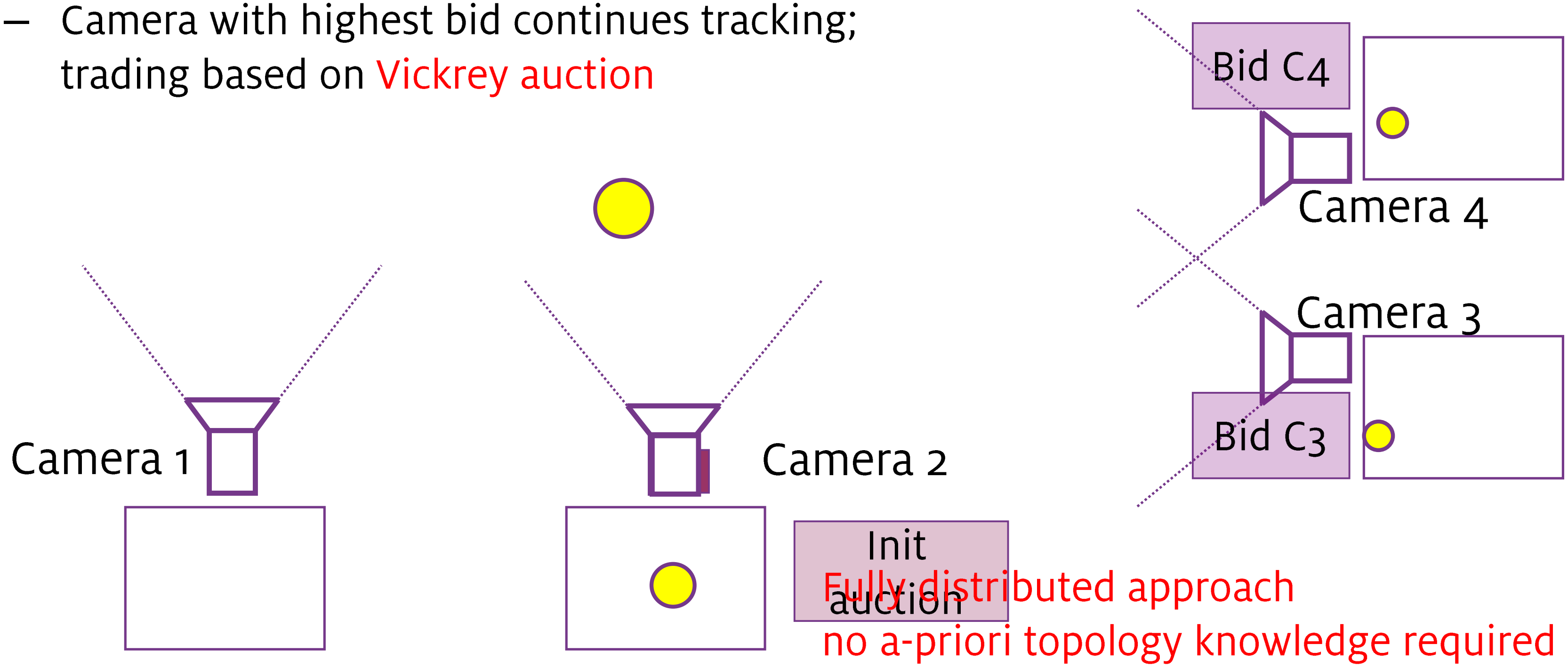
Self-organizing Camera Network

- Perform autonomous, decentralized and resource-aware network-wide analysis

- Demonstrate autonomous multi-object tracking in camera network
  - Exploit single camera object detector & tracker
  - Perform camera handover
  - Learn camera topology
- Key decisions for each camera
  - When to track an object within its FOV
  - When to initiate a handover
  - Whom to handover

Virtual Market-based Handover

- Initialize auctions for exchanging tracking responsibilities
  - Cameras act as self-interested agents, i.e., maximize their own utility
  - Selling camera (where object is leaving FOV) opens the auction
  - Other cameras return bids with price corresponding to “tracking” confidence
  - Camera with highest bid continues tracking; trading based on Vickrey auction



Fully distributed approach
no a-priori topology knowledge required

Camera Control

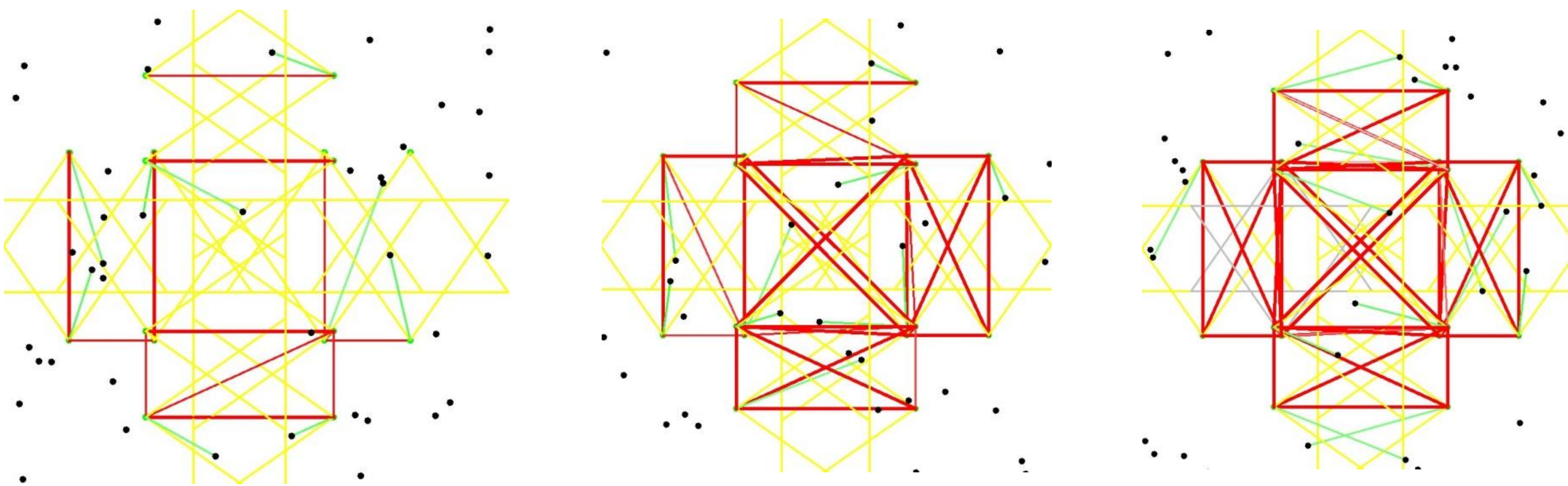
- Each camera acts as agent maximizing its utility function

$$U_i(O_i) = \sum_{j \in O_i} [c_j \cdot v_j \cdot \Phi_i(j)] - p + r$$

- Local decisions
  - When to initiate an auction (at regular intervals or specific events)
  - Whom to invite (all vs. neighboring cameras)
  - When to trade (depends on valuation of objects in FOV)
- Learn neighborhood relations with trading behavior ("pheromones")
  - Strengthen links to buying cameras
  - Weaken links over time

Learn Neighborhood Relationships

- Gaining knowledge about the network topology (vision graph) by exploiting the trading activities
- Temporal evolution of the vision graph



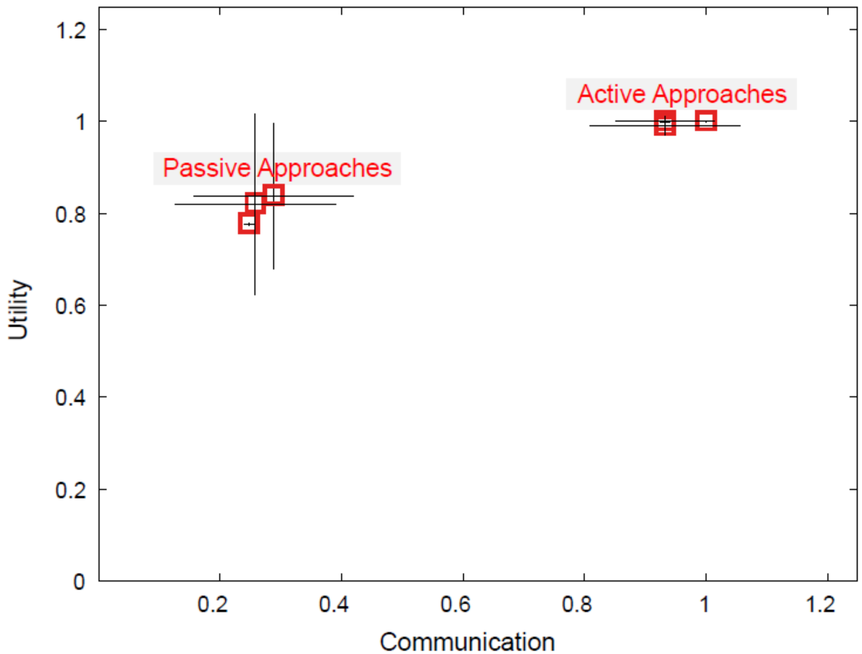
Six Camera Strategies

- Auction initiation
  - “Active”: at regular intervals (at each frame)
  - “Passive”: only when object is about to leave the FOV
- Auction invitation
  - “Broadcast”: to all cameras
  - “Smooth”: probabilistic proportional to link strength
  - “Step”: to cameras with link strengths above threshold (and rest with low probability)

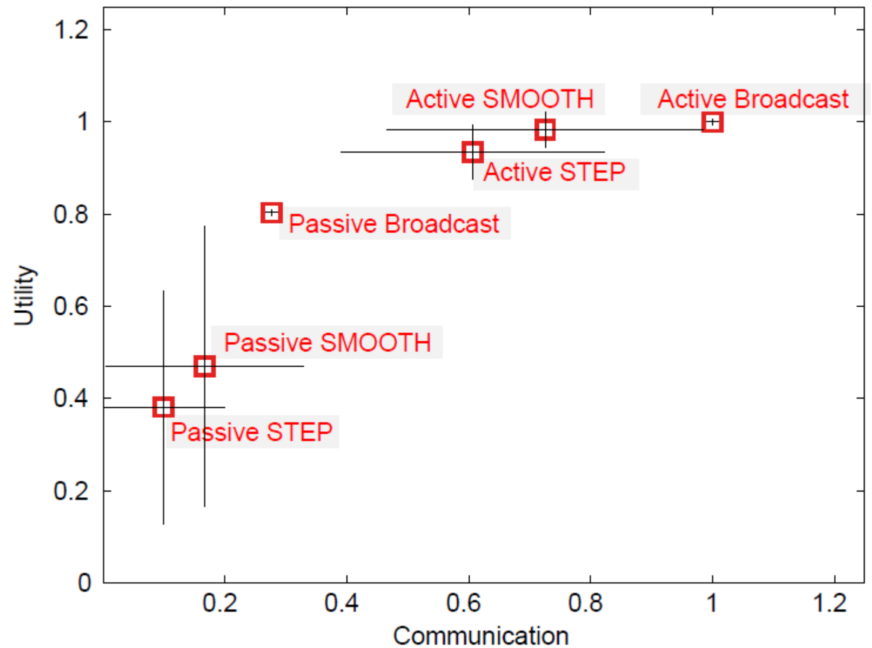
- Selected strategy influences network performance (utility) and communication effort

Tracking Performance

- Tradeoff between utility and communication effort



Scenario 1 (5 cameras, few objects)



Scenario 2 (15 cameras, many objects)

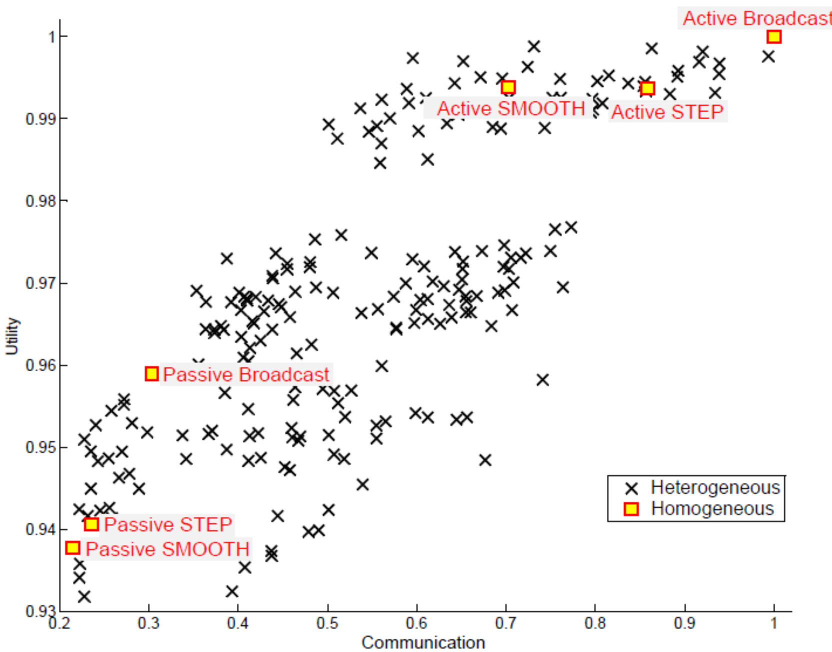
- Emerging Pareto front

[Esterle et al. Socio-Economic Vision Graph Generation and Handover in Distributed Smart Camera Networks. ACM Trans. Sensor Networks. 10(2), 2014]

Assigning Strategies to Cameras

- Identical strategy for all cameras may not achieve best result

Homogeneous strategies (3 cameras)

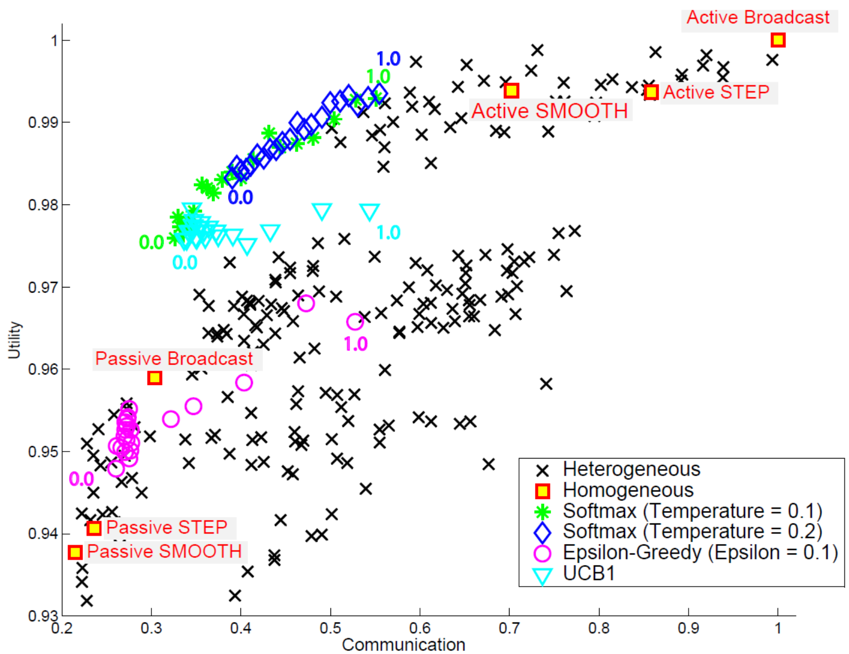


Heterogeneous strategies (3 cameras)

- Strategy depends on various parameters (FOV, neighbors, scene …)
  - Let cameras learn their best strategy

Decentralized Multi-Agent Learning

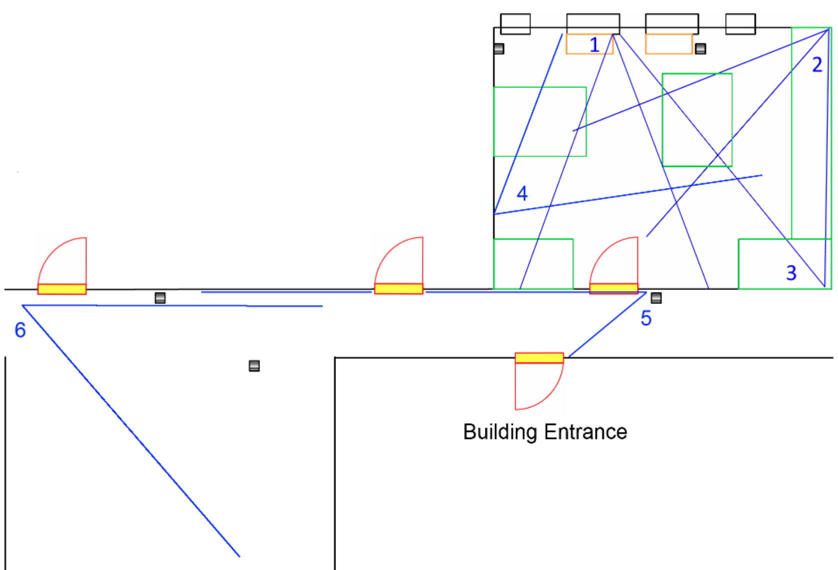
- Exploit bandit solver framework to maximize global performance
  - Co-dependency among agents' performance
  - Complex relationship between local reward global performance

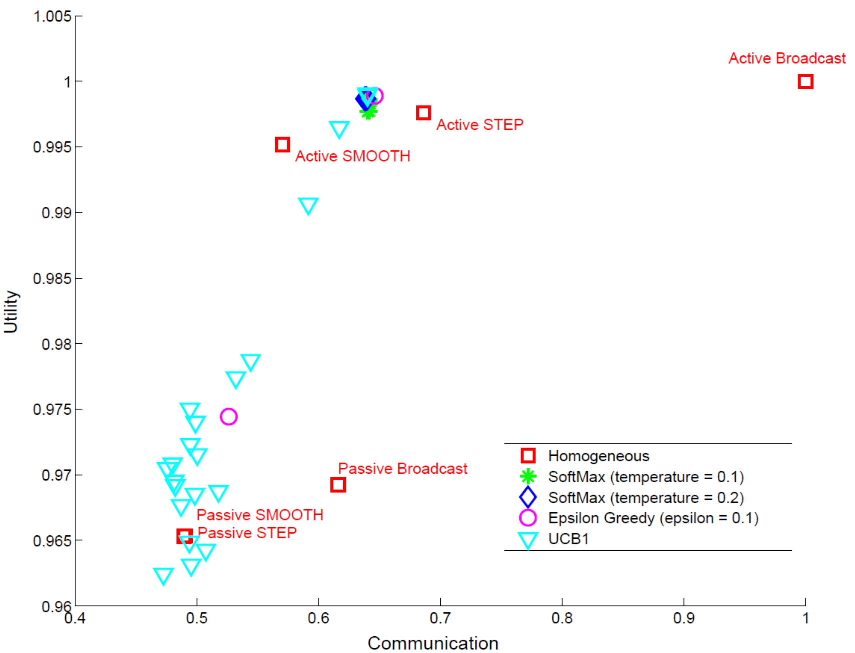


[Lewis et al. Static, Dynamic and Adaptive Heterogeneity in Socio-Economic Distributed Smart Camera Networks. ACM Trans. Autonom. Adapt. Syst. 2014 (accepted)]

Multi-camera Experiment

- Indoor demonstrator with 6 cameras tracking 6 persons
- Each camera performs
  - Color-based tracking
  - Fixed or adaptive handover strategies (bandit solvers)
  - Exchange of color histograms for person re-identification





Conclusion

- Smart cameras process video data onboard and collaborate autonomously within the network
- Our cartooning approach protects image data "at the sensor" but stills provides reasonable utility with low resource usage
- We apply socio-economic techniques to learn control strategies for autonomous multi-camera tracking
  - Global configurations emerge from local decision using local metrics
  - Adaptive strategies extend Pareto front of best static configurations
- Techniques applicable to various decentralized networked systems (e.g., Internet of Things)

Acknowledgements & Further Information

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Institute of Networked and Embedded Systems

http://nes.aau.at

http://bernhardrinner.com

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