
Virtual Vision: Computer Vision in Virtual Reality

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Visual Modeling & Computing

Computer Graphics

- Synthesis:
 - *From mathematical models to images*
 - *Forward problem*

and Computer Vision

- Analysis:
 - *From images to mathematical models*
 - *Inverse problem*

Visual Surveillance

Visual surveillance is becoming ubiquitous

- London has roughly 4,000,000 cameras
- Anti-Terrorism, deterring crime, etc.
- Effective visual coverage of large spaces require multi-camera systems
- Operator monitoring infeasible in large networks
- Need *autonomous networks of smart cameras*
- Smart cameras: Visual sensor nodes
 - *On-board processing, communication*
- **Problem:** Large-scale visual sensor network research is infeasible for most computer vision and sensor networks researchers



The difficulty of Doing Large-Scale Visual Sensor Networks Research

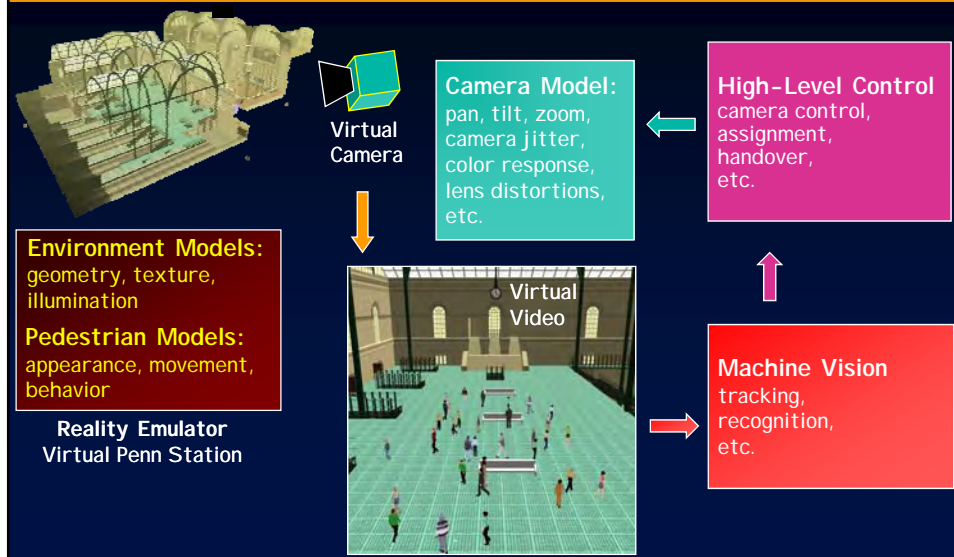
Deploying large-scale camera networks in extensive public spaces for research purposes:

- Very costly
- Privacy and legal issues
- Hardware-related technical challenges

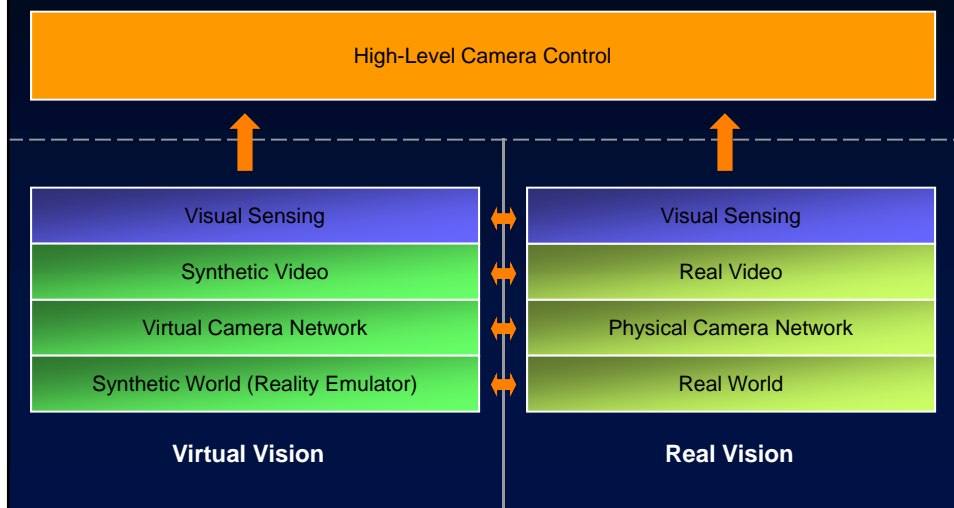
Infeasible for most computer vision researchers

Virtual Vision

Visually and behaviorally realistic simulators for designing and evaluating machine vision systems



Virtual Vision: A Tool for Visual Sensor Network Research



2007 PhD Thesis of Faisal Qureshi University of Toronto

Publications:

- Chapters in "*Distributed Video Sensor Networks*", Bhanu, et al., Springer, 2011
- 2008 Proceedings of the IEEE
- 2006 ACM Multimedia Systems Journal
- 2009 Third IEEE/ACM Intl. Conf. on Distributed Smart Cameras (*ICDSC*)
- 2008 11th Communications and Networking Simulation Symposium (*CNS*)
- 2008 ACM Symposium on Virtual Reality Software and Technology (*VRST*)
- 2007 First IEEE/ACM Intl. Conf. on Distributed Smart Cameras (*ICDSC*)
- 2007 IEEE/ACM Intl. Conf. on Dist. Comp. in Sensor Systems (*DCOSS*)
- 2007 IEEE Conf. on Computer Vision and Pattern Recognition (*CVPR*)
- 2006 ACM Intl. Wksp. on Distributed Smart Cameras (*DSC*)
- 2005 ACM Wksp. on Video Surveillance and Sensor Networks (*VSSN*)
- 2005 IEEE Intl. Wksp. on Visual Surveillance (*VS-PETS*)

2006 PhD Thesis of Wei Shao New York University

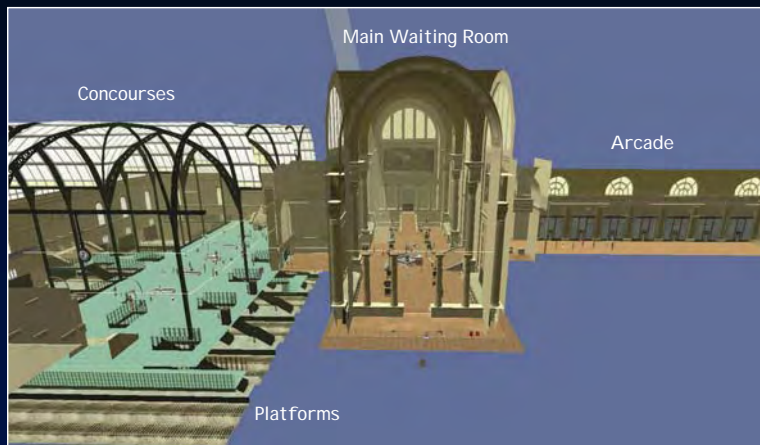
Publications:

- 2007 Graphical Models
- 2006 SAE Transactions Journal
- 2006 Int. Conf. on Intelligent Virtual Agents (IVA)
- 2005 SIGGRAPH/EG Symposium On Computer Animation (SCA)

Autonomous Pedestrian Simulation

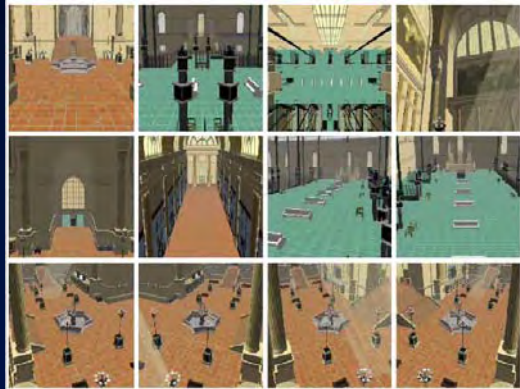
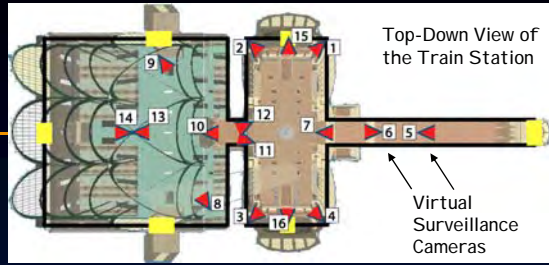


Environmental Model of Original Penn Station in NYC



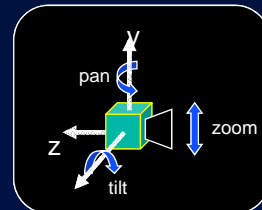
Virtual Vision

Visual sensor networks



Virtual Surveillance Camera Video Feeds

Active Pan-Tilt-Zoom Camera

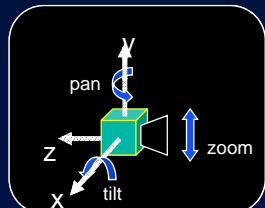


Anatomy of a Smart Camera Node

Communication subsystem:
message passing to
neighboring nodes

Task "relevance" computation
framework

Vision routines: pedestrian tracking



active pan-tilt-zoom camera

Decision logic

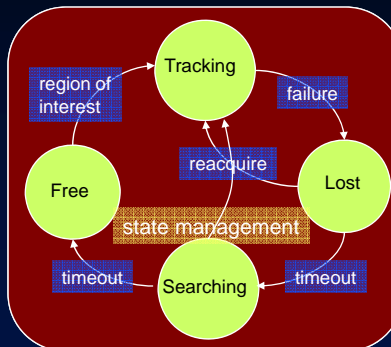


Image driven reactive behaviors:
fixation and zooming PD controllers

Synthetic Video

Model characteristics of real CCTV video

- Camera color response
- Camera distortion
- Camera noise – detector noise, data drop-out noise
- Compression artifacts
- Interlacing artifacts

Camera Noise



Compression Artifacts



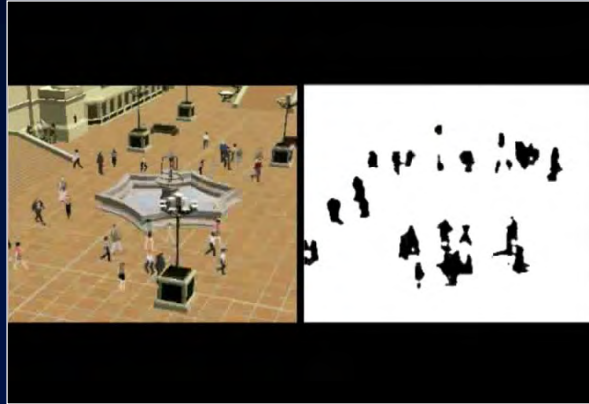
Interlacing Artifacts



Computer Vision Emulation Using Synthetic Video

Pedestrian detection

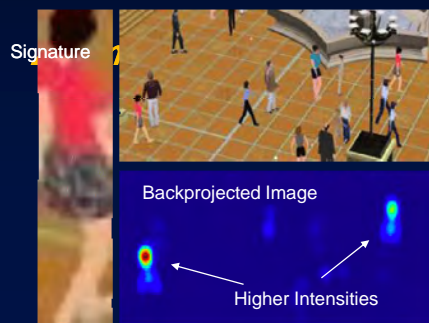
- Background subtraction using a learnt background model



Computer Vision Emulation Using Synthetic Video

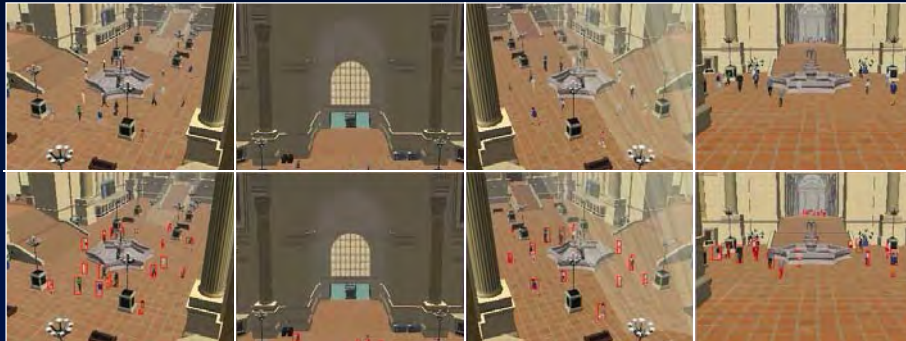
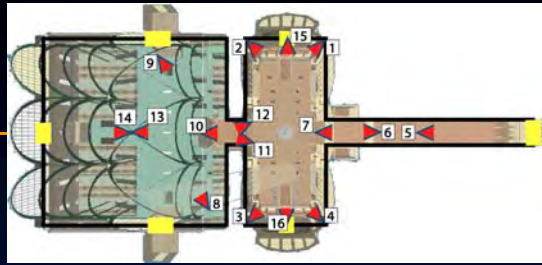
Appearance based pedestrian tracker

- Swain & Ballard 91



Visual Tracking of Pedestrians

Low-level computer vision



Automatic, Persistent Multicamera Surveillance: Active PTZ Camera Assignment and Grouping



Network Model

- Does not require camera or network calibration
 - *Can take advantage of calibration information, if available*
 - *Ad hoc deployment*
- Camera grouping is a strictly local negotiation
 - *Typically camera groups are spatially local arrangements*
- Camera groups are dynamic arrangements
- Camera handoffs occur naturally during negotiations
- Camera nodes can be added/removed during a task

Network Model

- It can gracefully handle node and message failures
- Even assuming perfect sensing, the proposed model can still fail if
 - *a significant number of messages are lost*
 - *catastrophic node failure*
 - *group evolution can't keep up with a fast-changing observation task*
- Scalability
 - *Small group sizes*
 - *Conflict resolution is viable as long as the number of relevant sensors for each task remains low (< 10)*
- Optimal sensor assignment

Benefits of Virtual Vision for Camera Networks Research

- Emulates the characteristics of a physical vision system
- Flexibility during system design and evolution
- Readily available ground truth
- Online operation and testing
- No legal impediments
- No special hardware
- Repeatability
- Inexpensive

QuickTime™ and a
H.264 decompressor
are needed to see this picture.

Camera Sensor Network #1
*Active PTZ Camera
Scheduling*

Scheduling Active PTZ Cameras

Scheduling problem

- Given n PTZ cameras, and m pedestrians, persistently observe every pedestrian using one PTZ camera at a time

Goal

- Observe as many pedestrians for as long as possible

Virtual Active Camera Scheduling

Passive wide-FOV cameras

- Calibrated
- Pedestrian localization through triangulation

Active PTZ cameras

- Un-calibrated
- Learn a coarse mapping between 3D locations and internal pan-tilt settings

Reliable pedestrian identification in different cameras via appearance based signatures



Calibrated passive cameras at the four corners of the waiting room in the virtual train station

Scheduling Active PTZ Cameras

Number of Pedestrians > Number of active cameras

Task active cameras to observe pedestrians in the scene

Active PTZ camera

Passive wide-FOV camera



Active Camera Scheduling Strategy

Camera assignment via weighted round robin

First come, first served tie breaking

Multiple observation

Preemption

Close-up snapshots captured
by active PTZ cameras



Active Camera Scheduling Results

Preemption (P)

No preemption (NP)

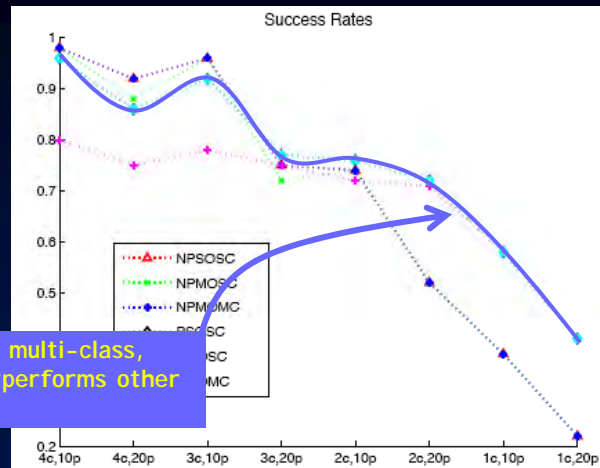
Single observation (SO)

Multiple observations (MO)

Single-class model (SC)

Multi-class model (MC)

Multiple observations, multi-class, preemption scheduler outperforms other variants



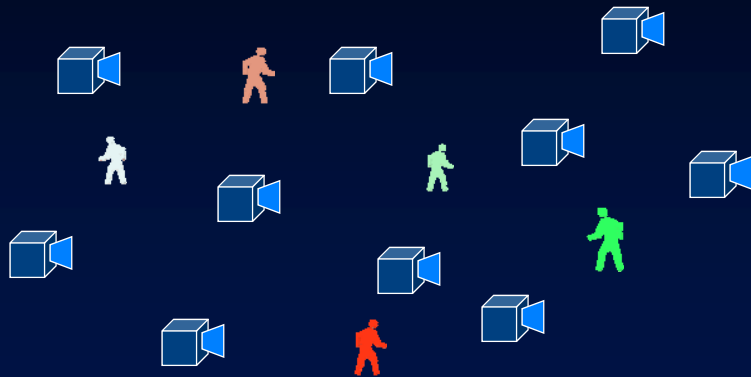
Up to 4 Cameras; 10, 20 Pedestrians

Camera Sensor Network #2

Active PTZ Camera Assignment and Grouping

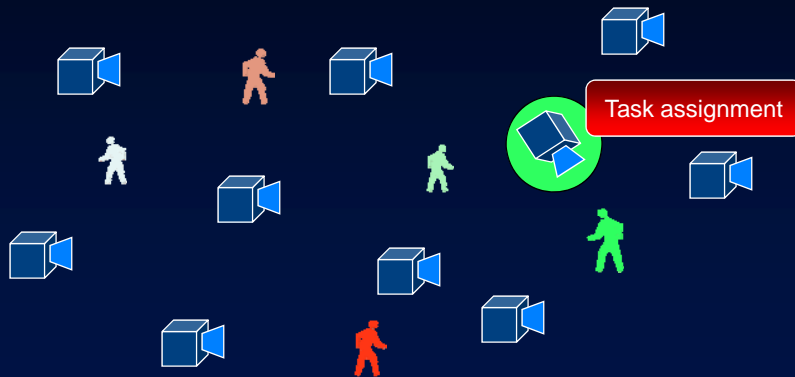
Vision and Goal

Ad hoc deployment



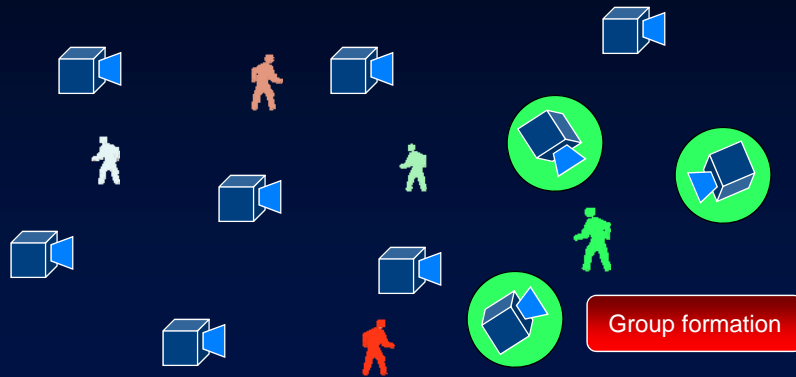
Objective

Cameras work towards common sensing goals



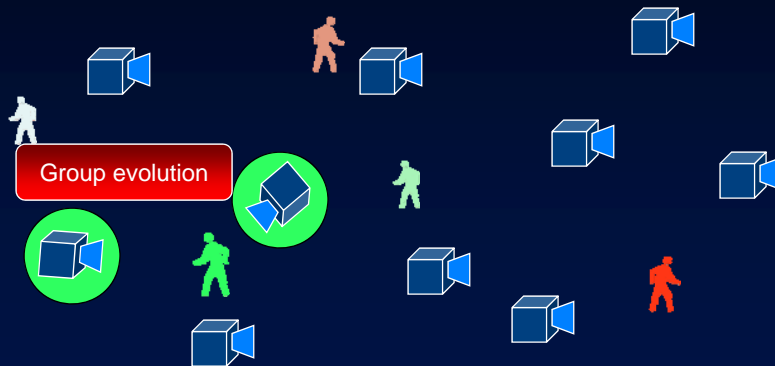
Vision and Goal

Cameras work towards common sensing goals



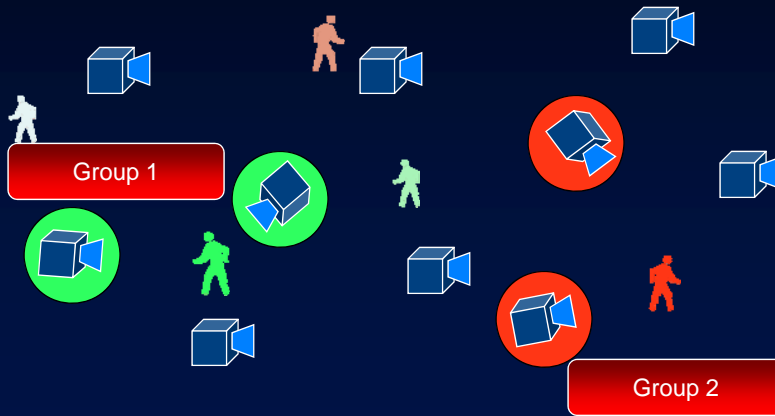
Vision and Goal

Cameras work towards common sensing goals



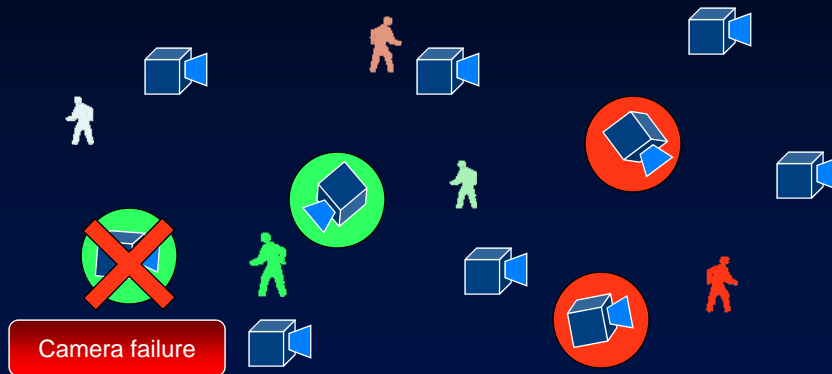
Vision and Goal

Cameras work towards multiple common sensing goals



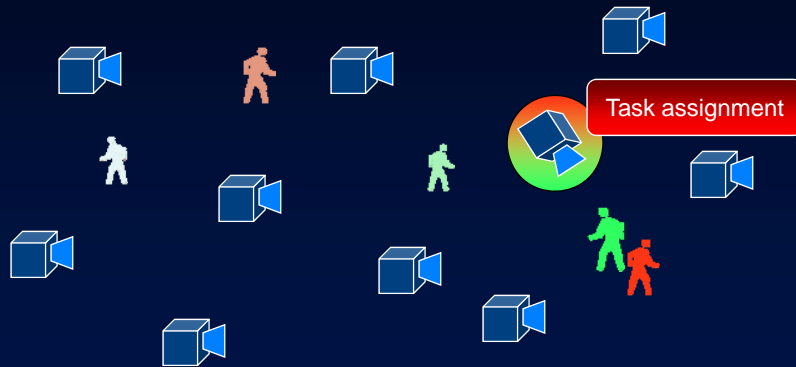
Vision and Goal

Cameras work towards multiple common sensing goals



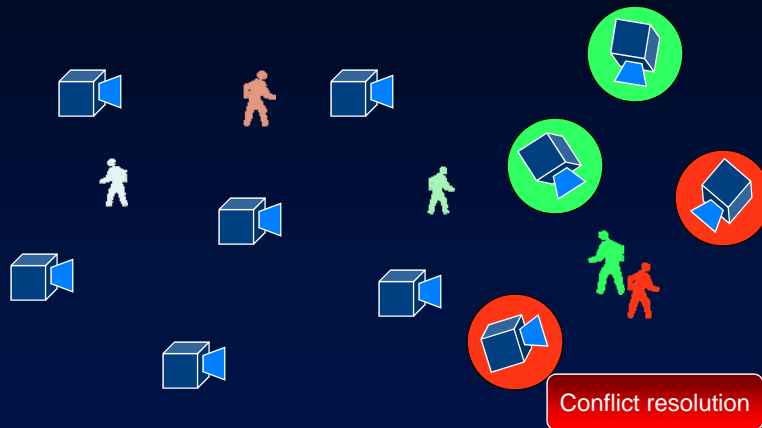
Vision and Goal

Cameras work towards multiple common sensing goals

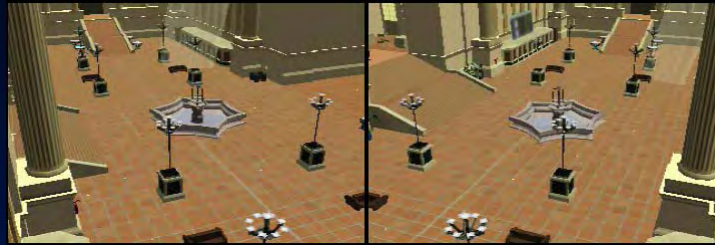


Vision and Goal

Cameras work towards multiple common sensing goals



Camera Grouping and Reassignment



Camera 1

Camera 2

(This video has sound)

Active PTZ Camera Assignment and Grouping

Camera selection, grouping, and handoff via an auction model

- Announcement/Bidding/Selection
- ContractNet
 - *Smith, 1983*

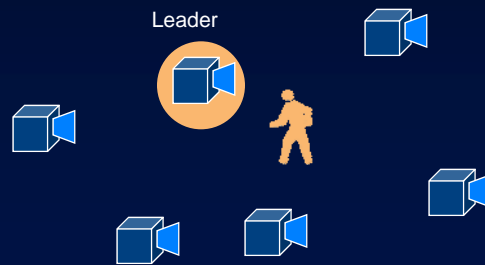
Conflict resolution within a Constraint Satisfaction Problem framework

- Partially distributed

A Camera can only perform a single task at any given time

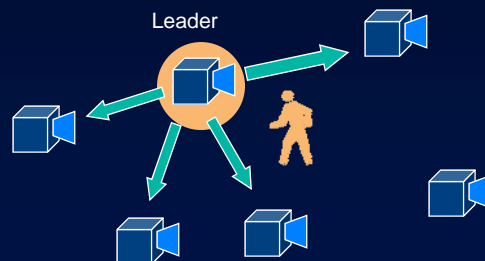
Camera Grouping: Announcement

- Start with a single camera that is tasked to observe a person



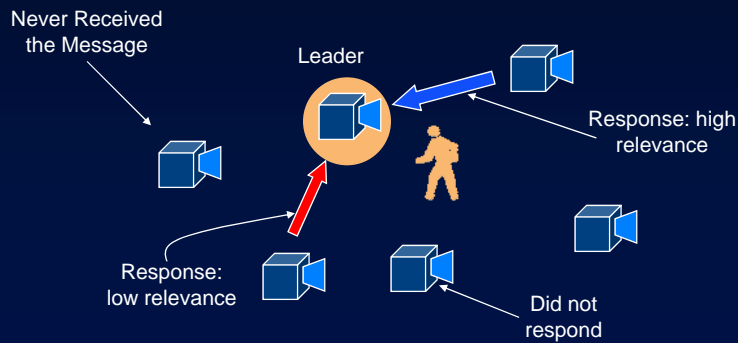
Camera Grouping: Announcement

- Seeks out other cameras in the vicinity to form a group to help it with the observation task



Camera Grouping: Bidding

- One or more cameras that receive the task announcement respond with their relevance values



Camera Grouping: Bidding

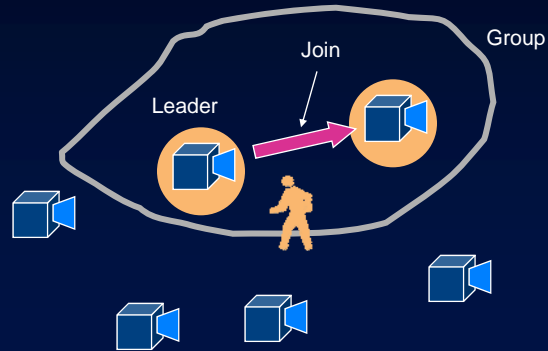
- One or more cameras that receive the task announcement respond with their relevance values
- Relevance encodes how successful a camera will be at an observation task

$$r = \begin{cases} \exp\left(-\frac{(c-1)^2}{2\sigma_c^2} - \frac{(\theta-\hat{\theta})^2}{2\sigma_\theta^2} - \frac{(\alpha-\hat{\alpha})^2}{2\sigma_\alpha^2} - \frac{(\beta-\hat{\beta})^2}{2\sigma_\beta^2}\right) & \text{when } s = \text{free} \\ \frac{t}{t+\gamma} & \text{when } s = \text{busy} \end{cases}$$

Status = $s \in \{\text{busy, free}\}$
Quality = $c \in [0, 1]$
Fov = $\theta \in [\theta_{\min}, \theta_{\max}]$ degrees
XTurn = $\alpha \in [\alpha_{\min}, \alpha_{\max}]$ degrees
YTurn = $\beta \in [\beta_{\min}, \beta_{\max}]$ degrees
Time = $t \in [0, \infty)$ seconds

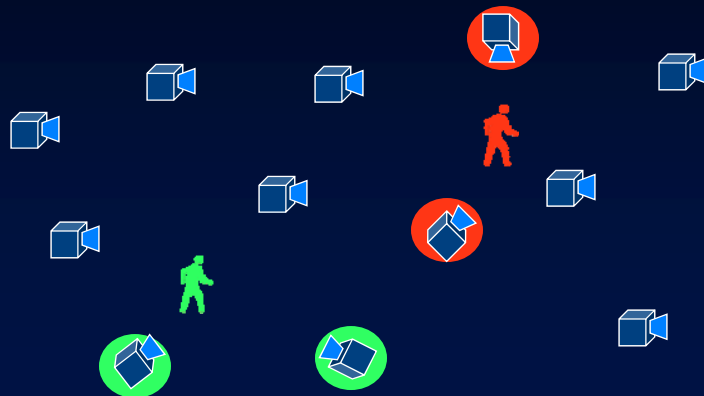
Camera Grouping: Selection

- After the leader gets relevance messages from neighboring cameras, it selects suitable cameras to join the group



Conflict Detection

- A conflict is detected when multiple tasks require the same camera node to proceed successfully



Conflict Detection

A Red group member receives a recruit query from Green group



Conflict Detection

A Red group member receives a recruit query from Green group



Conflict Detection

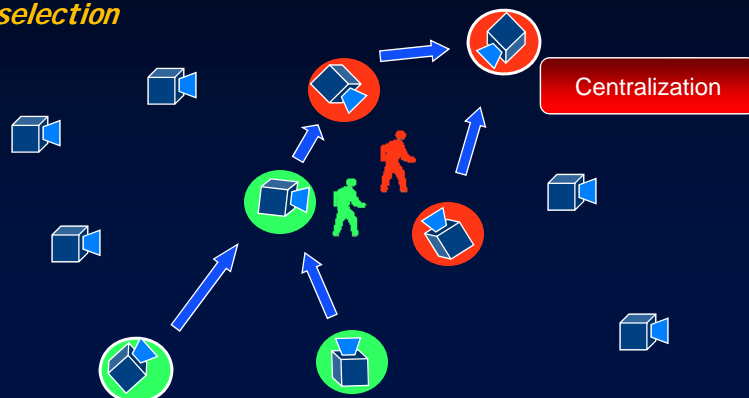
A Red group member receives a recruit query from Green group



Conflict Detection

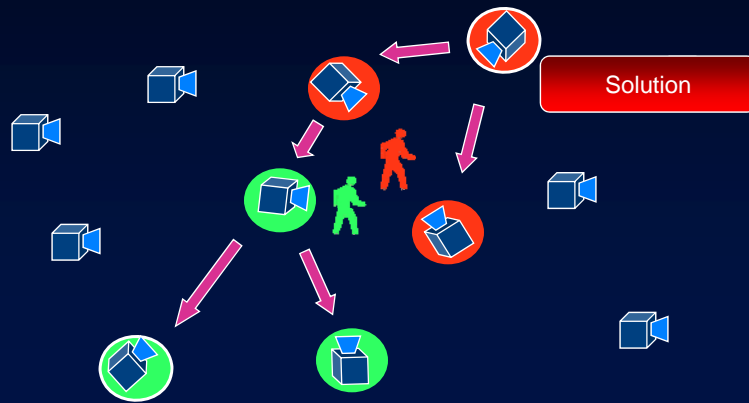
Nodes belonging to both groups send information to one of the leaders

Leader selection



Conflict Detection

The resulting node (camera) assignment is sent to the individual nodes



Conflict Detection

The resulting node (camera) assignment is sent to the individual nodes



Camera Sensor Network #3

Planning for PTZ Camera Control

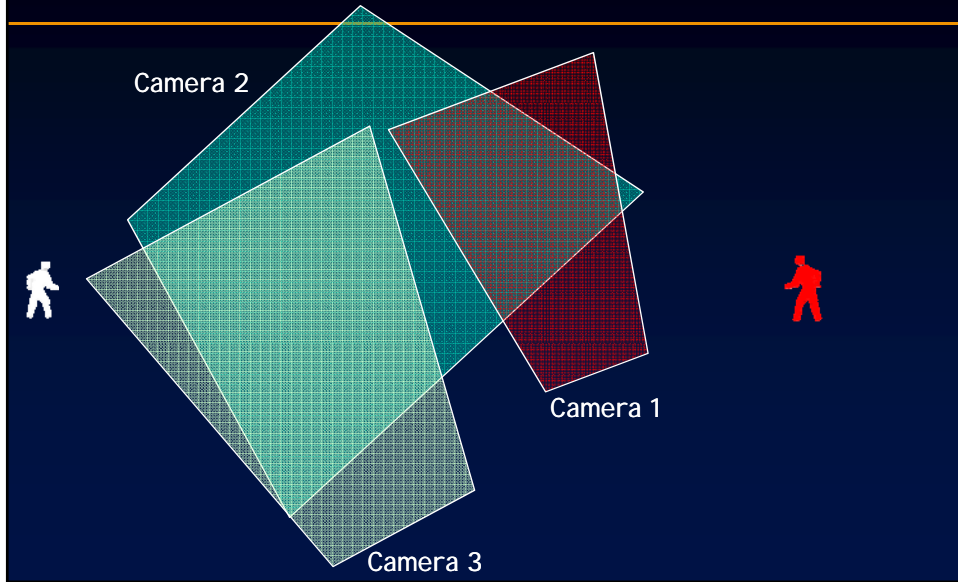
Planning for PTZ Camera Control

We formulate PTZ camera control as a planning problem whose solution achieves optimal camera utilization w.r.t. to a predefined observational goal

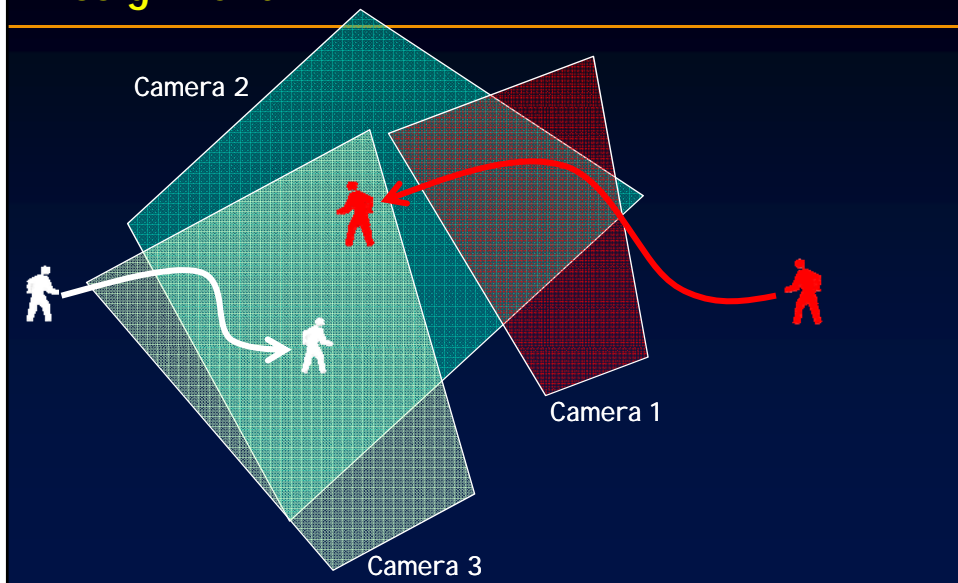


Achieve seamless closeup video of multiple pedestrians during their presence in a designated area

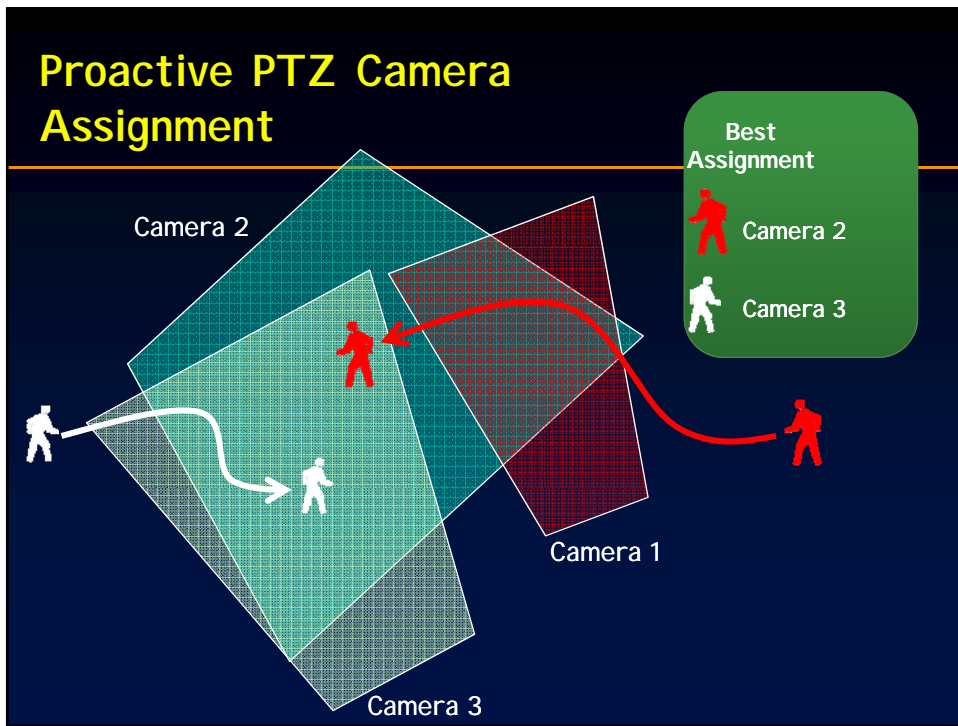
Proactive PTZ Camera Assignment



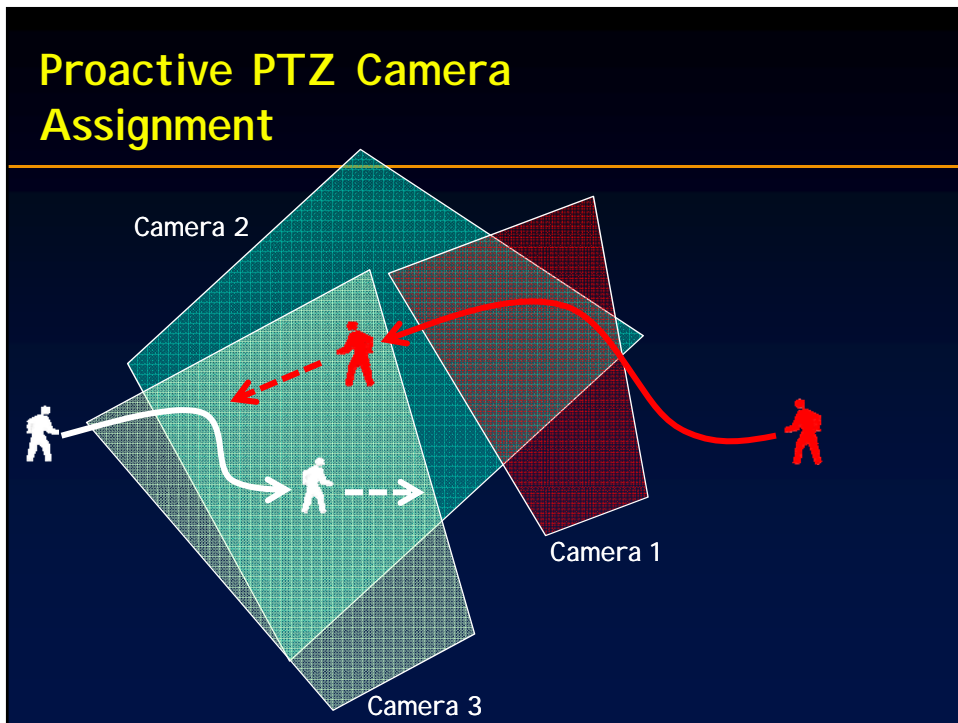
Proactive PTZ Camera Assignment



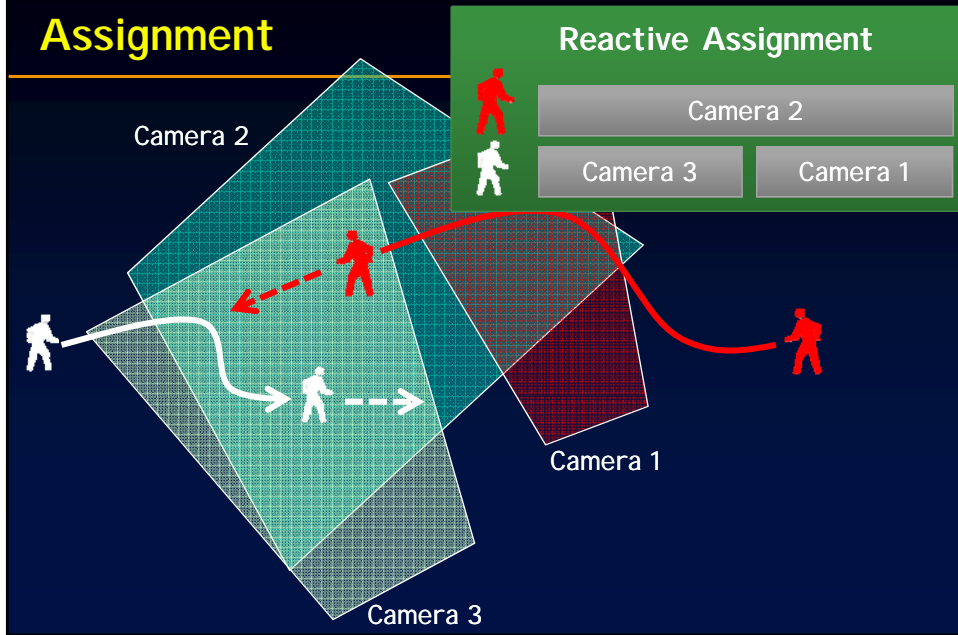
Proactive PTZ Camera Assignment



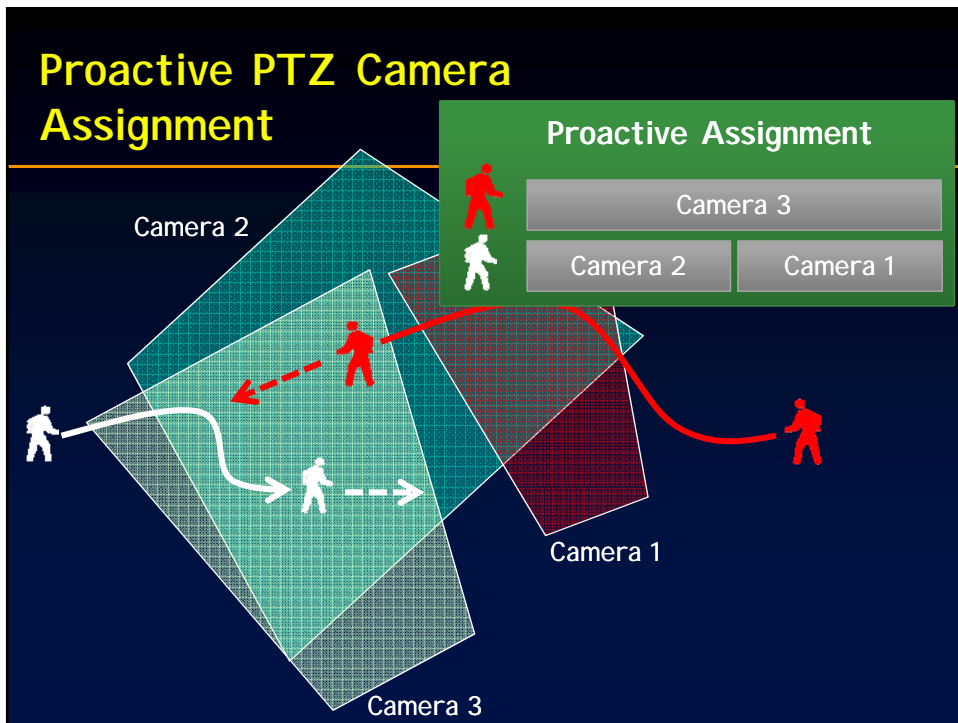
Proactive PTZ Camera Assignment



Proactive PTZ Camera Assignment



Proactive PTZ Camera Assignment



States and Actions

Planning problems are characterized by

- States
 - Actions
 - Goals
- } State space

Search for the best state sequence or action sequence

State at time t

The status of every PTZ camera at time t

- Free
- Acquiring pedestrian
- Recording pedestrian

Action taken at time t

Actions available to a single camera

- **Continue** doing whatever it is doing before
- Stop recording and be **Idle**
- Start **Acquiring** a pedestrian
- Start **Recording** a pedestrian

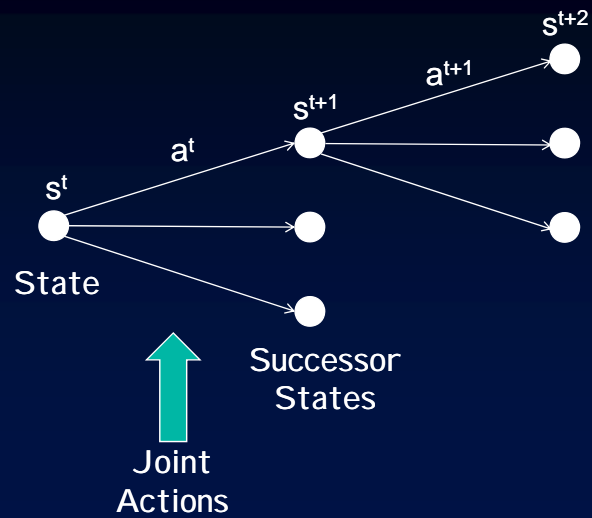
Joint Action taken at time t

Joint Action taken by cameras at time t

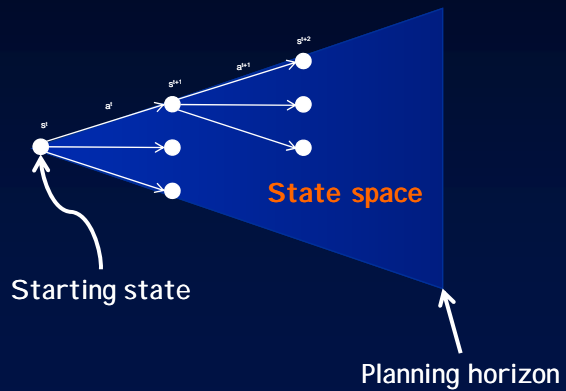
- Action taken by every PTZ camera at time t

Camera 1 is **Acquiring** pedestrian 1
Camera 2 is **Continuing** recording pedestrian 3
Camera 3 is **Recording** pedestrian 2

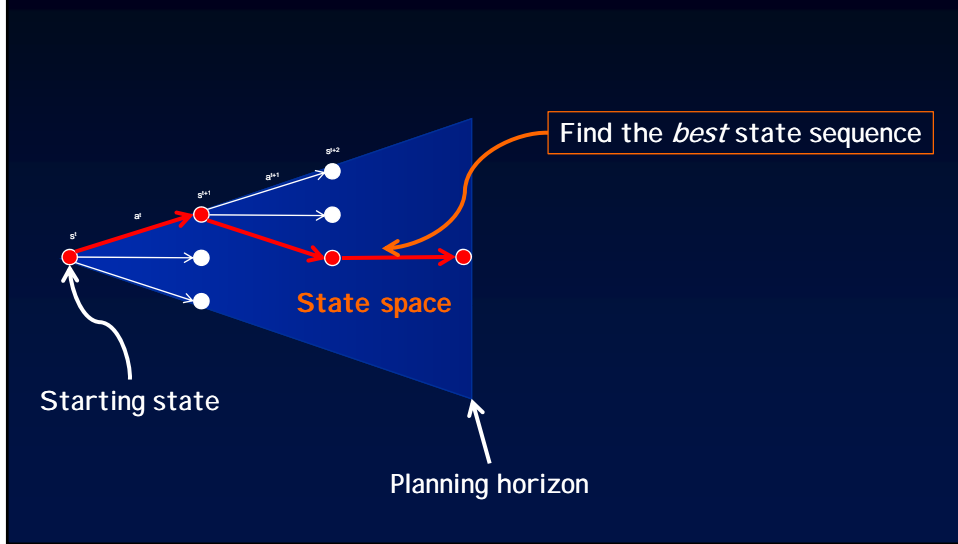
Planning Ahead for PTZ Camera Assignment



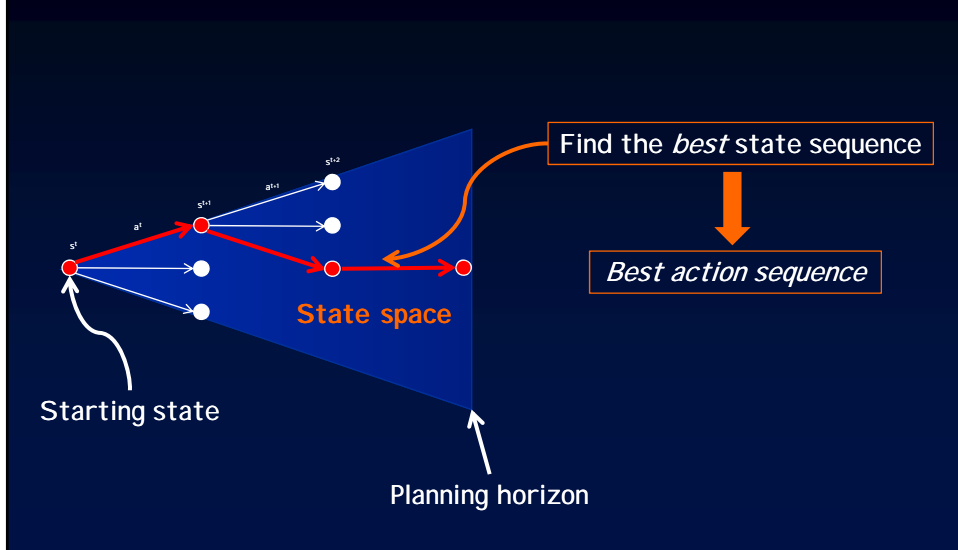
Planning Ahead for PTZ Camera Assignment



Planning Ahead for PTZ Camera Assignment



Planning Ahead for PTZ Camera Assignment



Finding the Best State Sequence

State sequence with the highest probability of success with respect to a given goal



Each designated pedestrian must be viewed by at least one PTZ camera at all times

Finding the Best State Sequence

Success probability
(Quality) of a state sequence



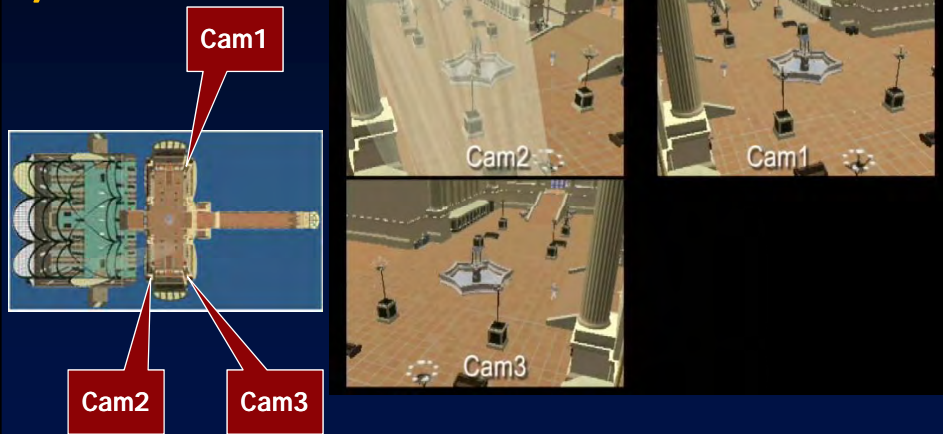
Success probability of
individual states



How successful individual
PTZ cameras are at carrying
out the tasks assigned to them

Scenario 5

7 PTZ cameras are tasked to observe two pedestrians



Multi-Human Simulation

Autonomous Pedestrians

Self-Animating Virtual Humans in a Large-Scale Indoor Urban Space

Autonomous pedestrian simulation



Concourses

Main Waiting Room

Virtual Train Station

Autonomous Pedestrians

PhD thesis work of Wei Shao

Artificial life modeling approach

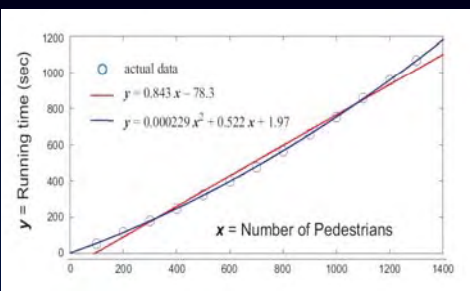
- Decentralized, autonomous, highly capable *individuals*
- Comprehensive human model with motor, perceptual, behavioral, and cognitive components
- Hierarchical environment model

Each Pedestrian is a Capable Behavioral / Cognitive Individual

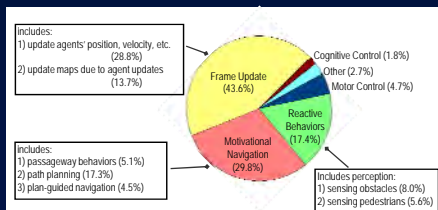
Following an Autonomous Pedestrian

(this video has sound)

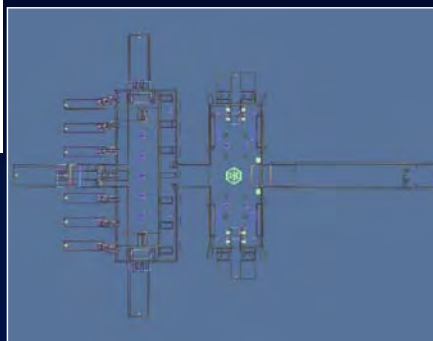
Performance



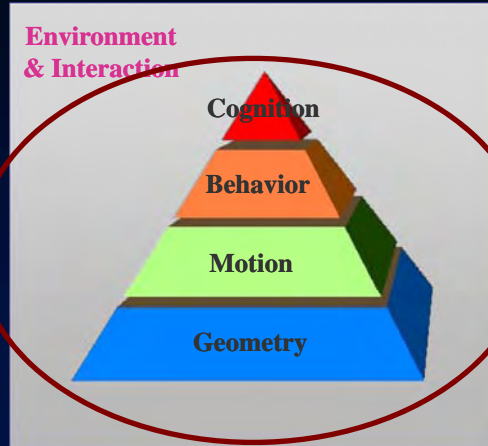
Intel Xeon 2.8GHz, 1GB Memory



Large-Scale Pedestrian Kinetics



Architecture of Pedestrian Model



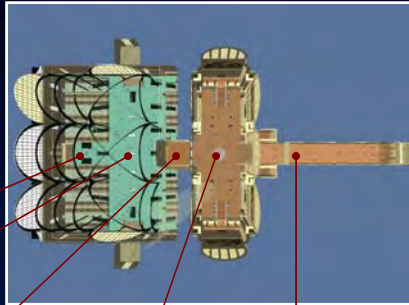
Penn Station Model

200m×150m×20m

43 regions

>500 objects (stairs, ticket booths, portals, ...)

90MB memory



*Lower Concourse
And Platforms*

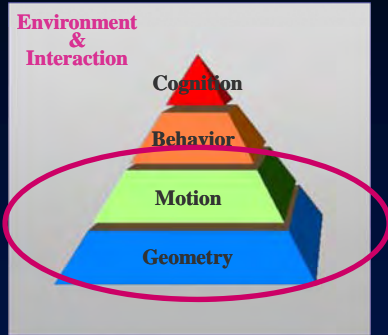
Upper Concourse

Halls

Main Waiting Room

Arcade

Geometry and Motor Control



DI-Guy (Boston Dynamics, Inc.)

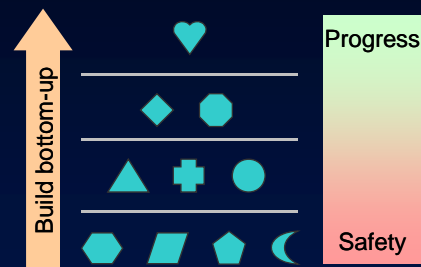
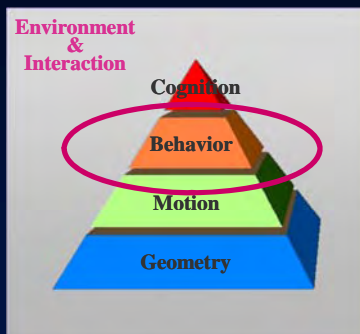
- Customized motion repertoire
- More responsive motion transitions

Motor control interface

- Verify motor control commands
- Hide underlying details

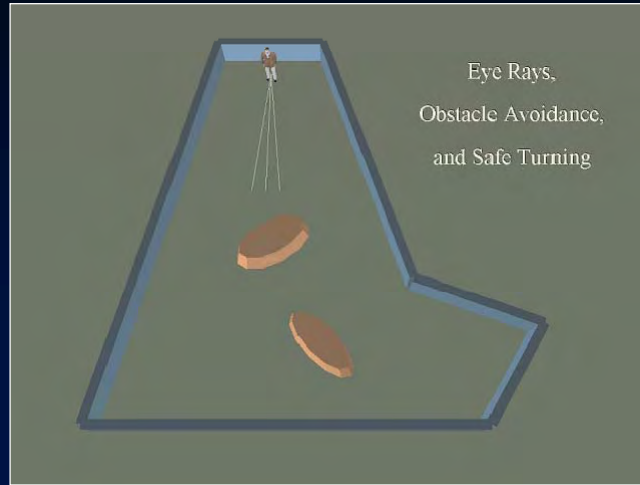
Behavior

An ethological approach



Behavior modules as building blocks

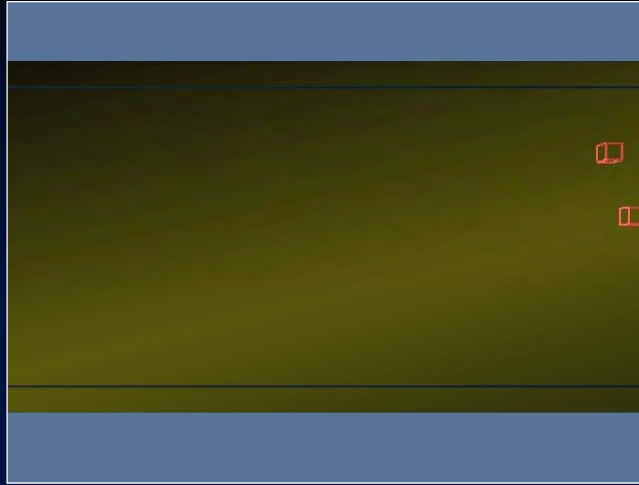
Perception-Guided Obstacle Avoidance



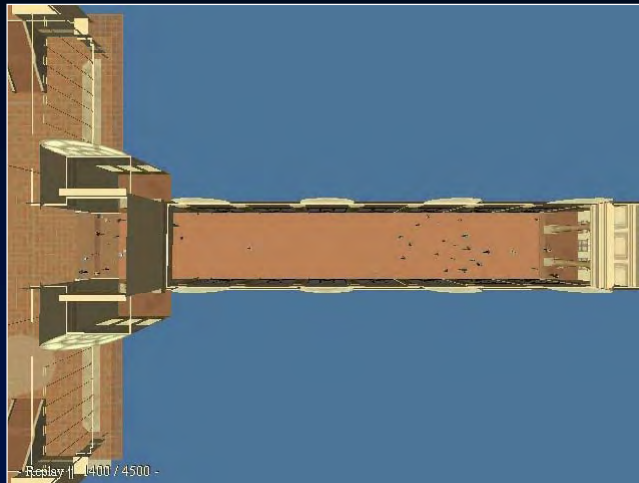
Perception-Guided Path Navigation



Corridor Navigation



Corridor Navigation



Other Motivational Behaviors

Select an unoccupied seat and sit down

Queue at ticket booths and purchase tickets

Approach artists and watch performances

Approach vending machines and purchase food

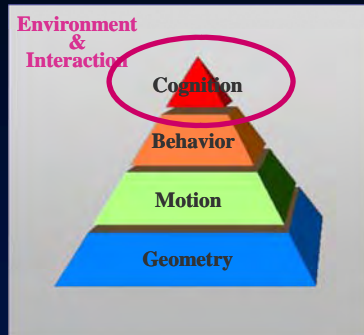


Social Conventions

Stay to the Right



Cognition



Global Path Planning

- Iteratively set intermediate goals at different levels
- Re-plan continuously

Heuristics

- Divide and conquer
- Think globally and act locally
- Be flexible

Related Virtual Vision Work

Active vision in (virtual) humans (and lower animals)

- 1999 PhD thesis of Tamer Rabie,
University of Toronto

Visual Perception in Virtual Humans

Left
Retinal
Image



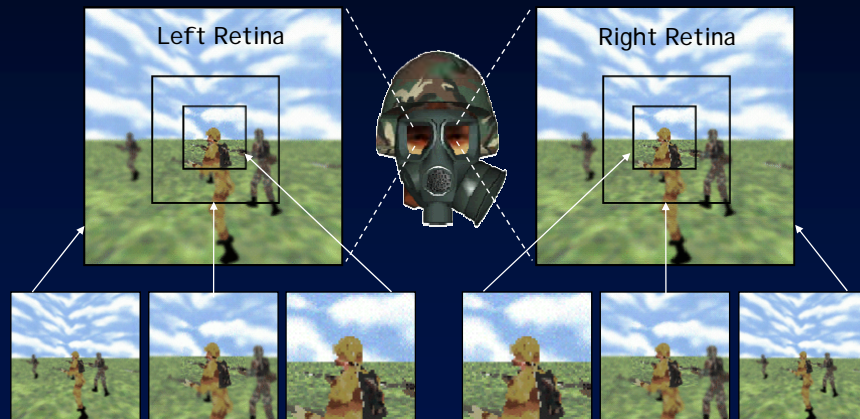
Right
Retinal
Image

Top
View

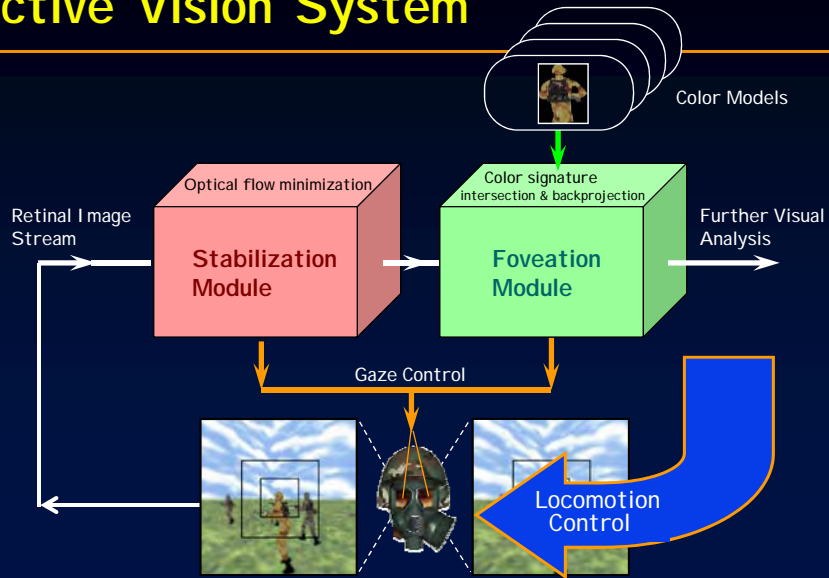


Oblique
View

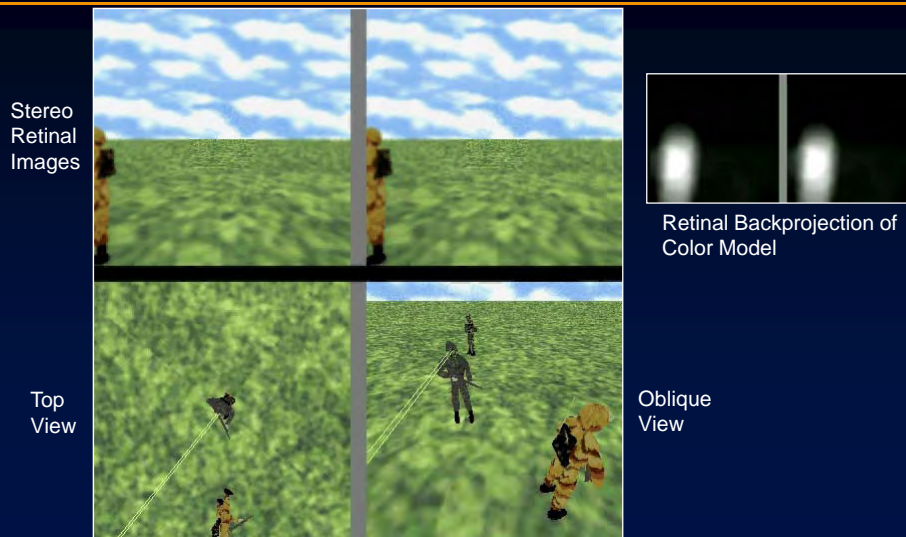
Virtual Eyes



Active Vision System



Visual Tracking and Sensorimotor Control



Conclusion

Advanced simulators are useful for computer vision research

- Particularly for research in intelligent, autonomous visual sensor networks
- Acceleration of the design/test cycle and scientific method

The gap between virtual reality and physical reality will continue to close over time

- The two should be indistinguishable in the long run, even though physical reality is extremely complex and the challenges in emulating it remain formidable

Future Work

Physical sensor networks

- Transfer these algorithms to physical multicamera systems and validation
 - NSF-funded project with the University of California, Riverside

Better virtual camera sensor networks

- Consistent labeling of pedestrians - Who, What, Where, When?
- Smarter networks through better cognitive modeling

Bigger, better reality emulators

- Higher-fidelity synthetic video
- Virtual sensor networks in the sky?
- An entire city ...

Virtual Los Angeles

*Virtual outdoor
urban environment*

UCLA Urban Simulation Lab



Virtual LA

Building level of detail



Virtual LA

Interior spaces



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Thank You !

For papers and videos:

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