



# Integrating Recognition and Reasoning in Smart Environment

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# Overview

- Motivation
- Related Work
- Current Prototype
- Framework
- Evaluation Mechanisms
- Contributions and Future work



## Motivation

- ▶ Recognizing a user is at the core of provisioning context-aware services in smart environments.
  
- ▶ Develop smart *indoor* environments that
  - identify and track occupants *unobtrusively*
  - Support spatial and temporal queries, such as:
    - the location of an occupant in the facility;
    - time of entry/exit of an occupant;
    - the first/last person to enter/leave the facility;
    - the current occupants present in the facility;
    - tracking the path followed by an occupant ; etc



## Motivation (contd.)

- ▶ Develop an *abstract framework* that will
  - accommodate multiple biometric modalities (face, voice, gait, etc) in a unified manner; **Recognition**
  - incorporate spatio-temporal reasoning based upon declarative knowledge of the environment as well as the occupants; **Reasoning**
  - facilitate answering queries about the occupants; **Retrieval**
  - provide a basis for characterizing the performance of the smart environment.

**3 R's of  
Smart  
Environments**

# Related Work

## Location Estimation and Tracking

	Methodology	Estimation Method	Non-Obtrusive
<ul style="list-style-type: none"> <li>•Krumm, J. et al.: Multi-Camera Multi-Person Tracking for EasyLiving. In: Proc. of the 3rd IEEE Intl. Workshop on Visual Surveillance (VS'2000). (2000)</li> </ul>	Visual Surveillance	Internally system generated	Yes
<ul style="list-style-type: none"> <li>• Bui, H. H. et al.: Tracking and surveillance in wide-area spatial environments using the Abstract Hidden Markov Model. Intl. Journal of Pattern Recognition and AI (2002)</li> </ul>	Abstract HMM (Predictive Model)	Simulation	n/a
<ul style="list-style-type: none"> <li>• Schulz, D. et al.: People tracking with anonymous and id-sensors using Rao-Blackwellised particle filters. IJCAI (2003)</li> </ul>	Bayesian Models involving particle filters, Kalman filters	Id-Sensors	No
<ul style="list-style-type: none"> <li>•Das, S. K. et al.: Context-aware resource management in multi-inhabitant smart homes: A framework based on Nash H-learning. IEEE Percom (2006)</li> </ul>	Game Theoretic Models using Online Learning	RFID	No
<h2>Proposed research</h2>	State Transition model integrating multiple biometric modalities	Biometrics (Face, Voice, Gait, Height, etc)	Yes

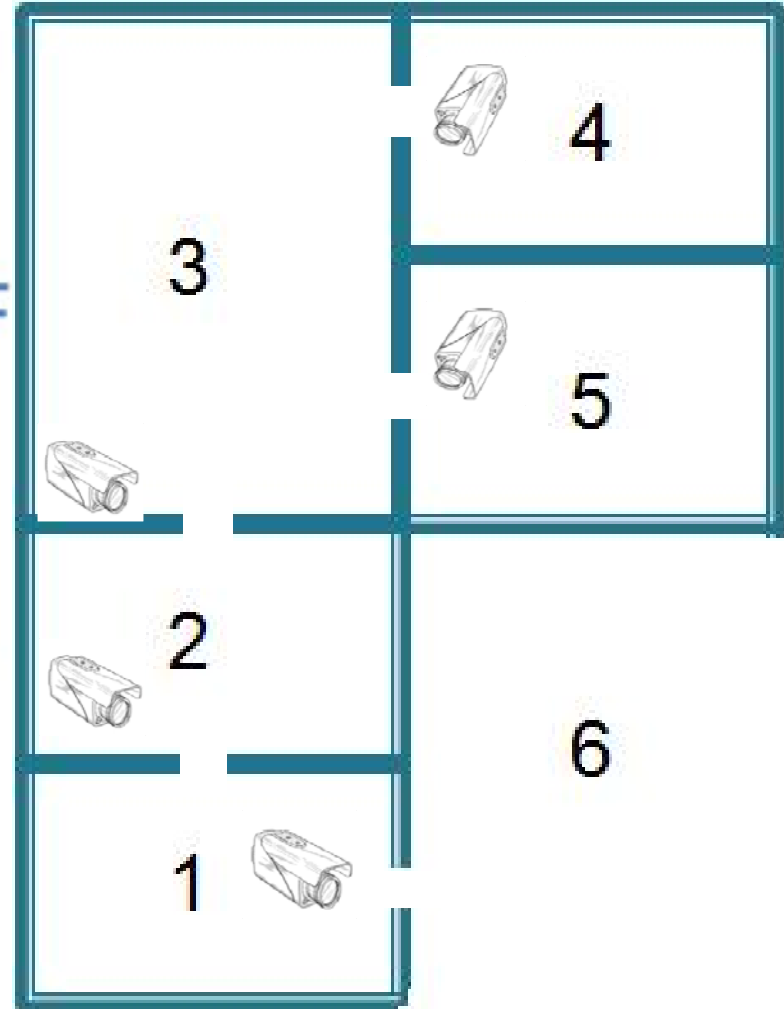
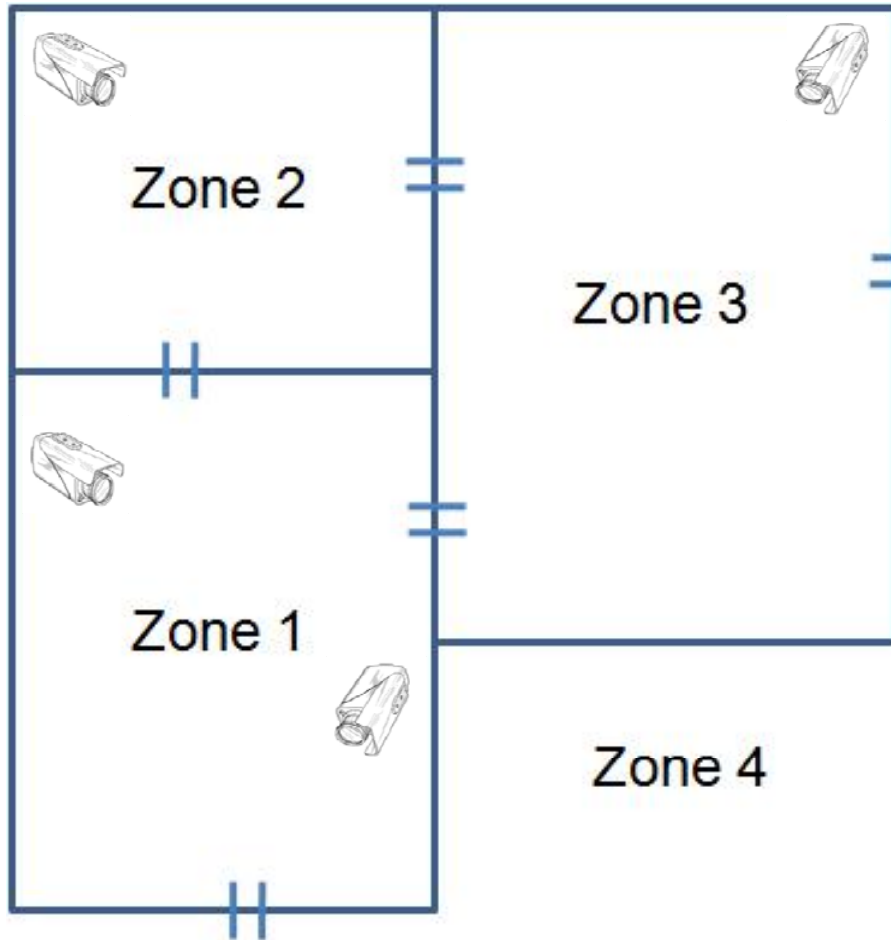
# Related Work

## Biometrics in Smart Environments

	Recognition	Reasoning	Approach
<ul style="list-style-type: none"><li>•Gao, Y. et al., A Multi-View Facial Analysis Technique for Identity Authentication. IEEE Pervasive Computing (2003)</li></ul>	Fusion of multiple views of face	-	-
<ul style="list-style-type: none"><li>•Zhang, S. et al.: Continuous Verification Using Multimodal Biometrics. In: Zhang, D., Jain, A.K. (eds.) ICB 2006, LNCS vol. 3832, pp. 562–570, Springer, Heidelberg (2005)</li></ul>	Face and Fingerprint	Temporal	Bayesian
<ul style="list-style-type: none"><li>• Ekenel, H.K. et al.: Multi-modal Person Identification in a Smart Environment. In: Proc. of 2007 CVPR Biometrics Workshop, pp. 1–8. IEEE (2007)</li></ul>	Face and Voice	-	Score normalization, modality weighting combination schemes
<ul style="list-style-type: none"><li>•Bernardin, K., Stiefelhagen, R.: Audio-visual multi-person tracking and identification for smart environments. In: Proc. of the 15th ACM Multimedia, pp. 661–670. (2007)</li></ul>	Face and Voice	-	Incremental multimodal identification
<b>Proposed research</b>	Probabilistic recognition using Face, Voice, Gait, Height etc	Spatio-Temporal Declarative Knowledge	Unified framework as a State Transition System

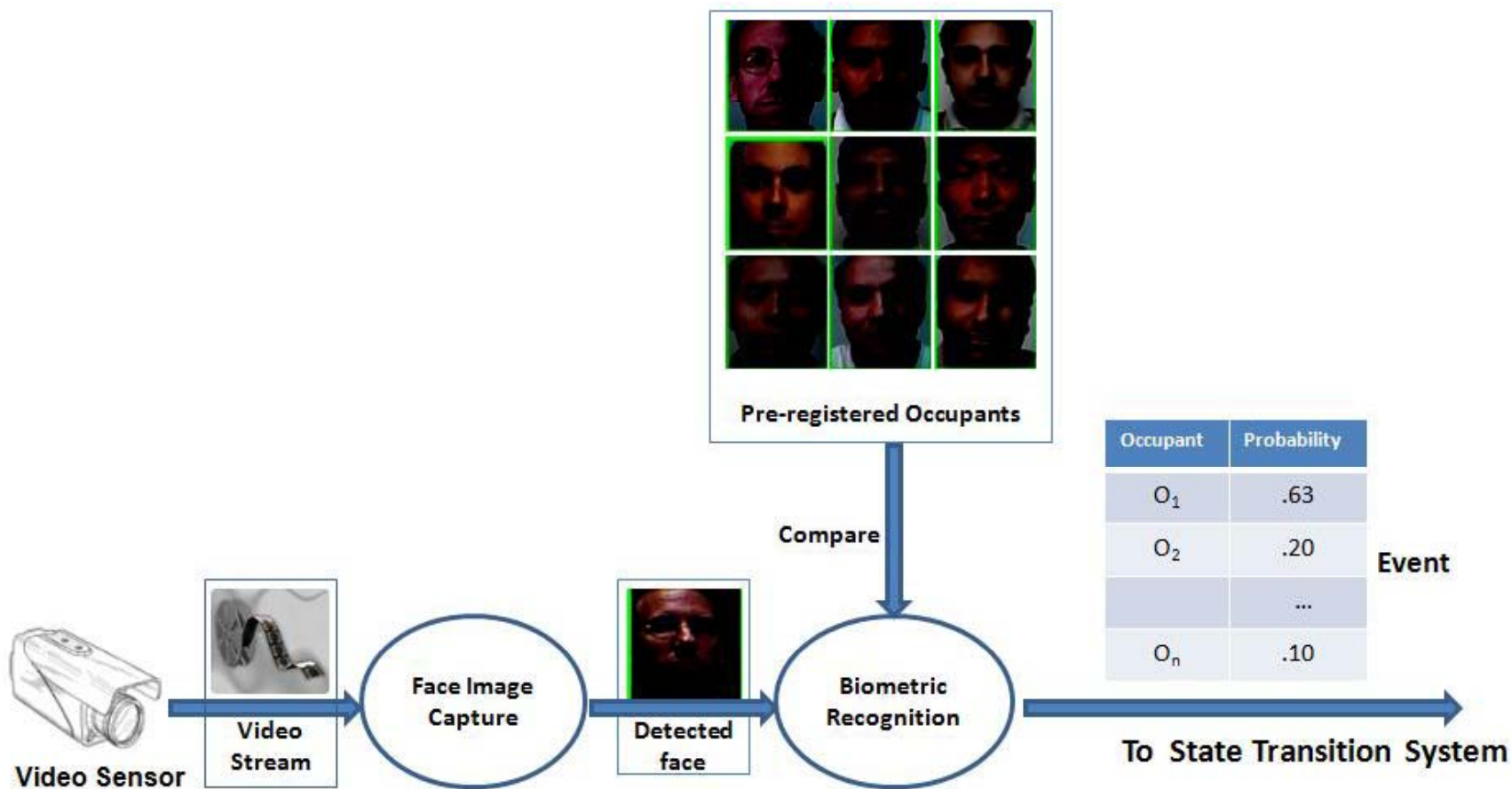


# Example Indoor Layouts



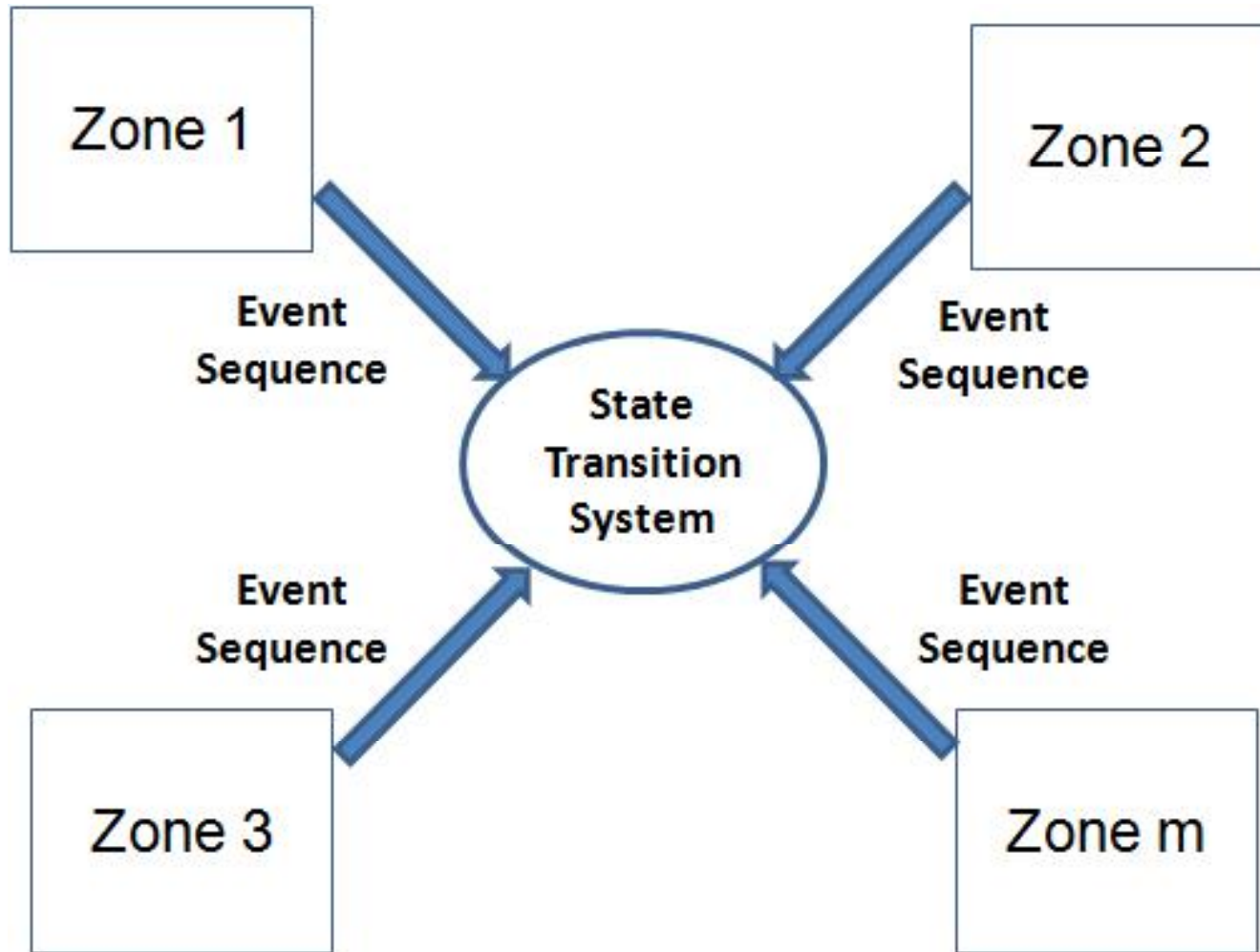


# Face Recognition Module





# Abstract Framework





# Abstraction

- A smart environment is abstracted as a **state transition system**  $(S, E, \Delta)$  where
  - $S$  is a set of states  $s_0, s_1, \dots, s_x$ ;
  - $E$  is a set of events labeled  $e_1, e_2, \dots, e_x$  and
  - $\Delta: S \times E \rightarrow S$
- State transitions encapsulate the reasoning

$$s_0 \xrightarrow{e_1} s_1 \xrightarrow{e_2} s_2 \dots \xrightarrow{e_x} s_x$$

- Event occurs at a zone, abstracts biometric recognition

# Example. - Starting State $S_0$

$$S_0 \xrightarrow{e_1} S_1 \xrightarrow{e_2} S_2 \dots \xrightarrow{e_x} S_x$$

Occupants	Z1	Z2	Z3	Z4	Z5	Z6
O1	0	0	0	0	0	1
O2	0	0	0	0	0	1
O3	0	0	0	0	0	1
O4	0	0	0	0	0	1
O5	0	0	0	0	0	1
O6	0	0	0	0	0	1
O7	0	0	0	0	0	1
O8	0	0	0	0	0	1
O9	0	0	0	0	0	1
O10	0	0	0	0	0	1
O11	0	0	0	0	0	1
O12	0	0	0	0	0	1
O13	0	0	0	0	0	1
O14	0	0	0	0	0	1
O15	0	0	0	0	0	1
O16	0	0	0	0	0	1
O17	0	0	0	0	0	1
O18	0	0	0	0	0	1
O19	0	0	0	0	0	1
O20	0	0	0	0	0	1
O21	0	0	0	0	0	1
O22	0	0	0	0	0	1
O23	0	0	0	0	0	1
O24	0	0	0	0	0	1
O25	0	0	0	0	0	1

# Sample Event Sequence

$n$  occupants,  $o_1 \dots o_n$ ;  $m$  zones labeled  $1 \dots m$

State  $s_k = \langle Z_{1k} \dots Z_{mk} \rangle$  where  $Z_{jk} = \{ \langle o_i, p_{jk}(o_i) \rangle \mid 1 \leq i \leq n \}$ ;  $\sum_{(j=1,m)} p_{jk}(o_i) = 1$

Occupants	e1 Z1	e2 Z2	e3 Z3	e4 Z1	e5 Z1	e6 Z2	e7 Z1	e8 Z4	e9 Z2	e10 Z3
O1	0.030	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.020	0.000
O2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
O3	0.458	0.420	0.528	0.005	0.000	0.001	0.000	0.481	0.001	0.000
O4	0.000	0.017	0.001	0.003	0.042	0.000	0.001	0.233	0.010	0.000
O5	0.000	0.003	0.000	0.383	0.019	0.358	0.000	0.010	0.018	0.598
O6	0.011	0.000	0.000	0.045	0.017	0.309	0.426	0.000	0.003	0.000
O7	0.014	0.000	0.000	0.000	0.127	0.000	0.000	0.000	0.000	0.000
O8	0.000	0.000	0.000	0.015	0.000	0.035	0.033	0.000	0.000	0.000
O9	0.000	0.288	0.030	0.000	0.000	0.000	0.000	0.186	0.010	0.018
O10	0.344	0.100	0.014	0.000	0.493	0.000	0.000	0.006	0.552	0.000
O11	0.000	0.000	0.000	0.043	0.017	0.019	0.000	0.011	0.014	0.000
O12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
O13	0.000	0.089	0.341	0.020	0.001	0.020	0.537	0.000	0.109	0.000
O14	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.000
O15	0.000	0.054	0.077	0.013	0.004	0.014	0.000	0.000	0.005	0.000
O16	0.000	0.000	0.000	0.251	0.000	0.077	0.000	0.000	0.000	0.000
O17	0.000	0.013	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.012
O18	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
O19	0.003	0.001	0.001	0.003	0.001	0.010	0.001	0.005	0.000	0.000
O20	0.016	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.002
O21	0.002	0.012	0.003	0.004	0.000	0.003	0.000	0.000	0.000	0.000
O22	0.000	0.001	0.000	0.005	0.000	0.011	0.000	0.003	0.000	0.000
O23	0.122	0.001	0.001	0.001	0.000	0.001	0.000	0.000	0.000	0.000
O24	0.000	0.000	0.000	0.207	0.258	0.139	0.000	0.053	0.001	0.000
O25	0.000	0.000	0.000	0.000	0.019	0.000	0.000	0.000	0.256	0.369
	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Ground Truth	O3	O3	O3	O5	O10	O5	O13	O3	O10	O5



# Transition Function

## *1<sup>st</sup> Order Markov property*

▶  $\Delta: S \times E \rightarrow S$ , maps state  $s_{k-1}$  to  $s_k$  upon event  $e_k$

◦ Let  $s_{k-1} = \langle Z_{1,k-1} \dots Z_{jk-1} \dots Z_{mk-1} \rangle$  and

◦  $Z_{jk-1} = \{ \langle o_i, p_{jk-1}(o_i) \rangle \mid 1 \leq i \leq n \}$

▶ Then  $s_k = \langle Z_{1k} \dots Z_{jk} \dots Z_{mk} \rangle$  where:

▶ Let  $x_i = 1 - p_{jk}(o_i)$

◦  $Z_{jk} = \{ \langle o_i, p_{jk}(o_i) + x_i * p_{jk-1}(o_i) \rangle \mid 1 \leq i \leq n \}$  **Zone of event**

◦  $Z_{lk} = \{ \langle o_i, x_i * p_{lk-1}(o_i) \rangle \mid 1 \leq i \leq n \}$ , for  $1 \leq l \leq m$  and  $l \neq j$  **Other zones**





# Performance Measures

## Smart Environments

- Adapted from IR to suit this context; (not query based).
  - Precision captures how well an occupant is recognized ( $\pi$ )
  - Recall captures whether an occupant is recognized at all ( $\rho$ )
  - $a$ : system;  $b$ : truth

$$\pi_{jk} = a_{jk} / b_{jk};$$

$$a_{jk} = \sum \{p_{jk}(o_i) : 1 \leq i \leq n \ \& \ q_{jk}(o_i) = 1\}$$

$$b_{jk} = |\{o_i : q_{jk}(o_i) = 1 \ \& \ 1 \leq i \leq n\}|$$

$$\pi_k = \sum_{(j=1,m)} \pi_{jk} / m \text{ (zone wise)}$$

$$\Pi = \sum_{(k=1,x)} \pi_k / x$$

$$\rho_{jk} = a_{jk} / b_{jk}, \text{ where}$$

$$a_{jk} = |\sum \{o_i : 1 \leq i \leq n \ \& \ q_{jk}(o_i) = 1 \ \& \ p_{jk}(o_i) > \theta\}|$$

$$b_{jk} = |\{o_i : q_{jk}(o_i) = 1 \ \& \ 1 \leq i \leq n\}|$$

$$\rho_k = \sum_{(j=1,m)} \rho_{jk} / m$$

$$\rho = \sum_{(k=1,x)} \rho_k / x$$

# Calculation of Precision ( $\pi$ )

State : s18						
Occupants	Z1	Z2	Z3	Z4	Z5	Z6
O1	0.03	0.02	0.01	0.00	0.00	0.94
O2	0.00	0.00	0.00	0.00	0.00	1.00
O3	0.07	0.10	0.27	0.47	0.01	0.08
O4	0.09	0.02	0.01	0.21	0.00	0.66
O5	0.06	0.08	0.36	0.00	0.41	0.08
O6	0.13	0.20	0.40	0.00	0.00	0.27
O7	0.14	0.00	0.00	0.00	0.00	0.86
O8	0.20	0.20	0.47	0.00	0.00	0.13
O9	0.00	0.23	0.05	0.18	0.00	0.54
O10	0.14	0.28	0.52	0.00	0.00	0.06
O11	0.31	0.05	0.02	0.01	0.06	0.55
O12	0.00	0.00	0.00	0.00	0.00	1.00
O13	0.26	0.11	0.02	0.00	0.00	0.61
O14	0.08	0.00	0.00	0.01	0.00	0.91
O15	0.02	0.21	0.15	0.00	0.00	0.62
O16	0.21	0.07	0.00	0.00	0.08	0.64
O17	0.00	0.01	0.01	0.00	0.00	0.97
O18	0.00	0.00	0.00	0.00	0.00	1.00
O19	0.01	0.01	0.00	0.01	0.00	0.97
O20	0.02	0.00	0.00	0.00	0.00	0.97
O21	0.01	0.03	0.01	0.00	0.00	0.95
O22	0.04	0.02	0.02	0.00	0.00	0.92
O23	0.12	0.00	0.00	0.00	0.00	0.87
O24	0.24	0.08	0.01	0.03	0.35	0.29
O25	0.01	0.10	0.61	0.00	0.00	0.28
Ground Truth - O3, O5, O10, O8						

State : s18					
Z1	Z2	Z3	Z4	Z5	Z6
			0.47		
				0.41	
		0.47			
		0.52			
Ground Truth - O3, O5, O10, O8					

$\pi = 0.46$

ajk		0.99	0.47	0.41
bjk		2	1	1
pjk		0.49	0.47	0.41
m	3			
pk	0.46			





# Integrating Reasoning

## ▶ Use of multiple modalities

- E.g. Face recognition with Height estimation
- E.g. Face recognition with Voice recognition (in progress)

## ▶ Integrating declarative knowledge

- Spatial knowledge
  - Zone of events
    - Entry, Internal, and External
  - Layout and Distances
- Temporal knowledge
  - Based upon occupant schedules



## Event Definition - Revised

- *Given*
  - *n* occupants  $o_1 \dots o_n$
- *Event*  $e_k = \langle t_k, j_k, D_k \rangle$ , where
  - *t* is the time
  - *j* is the zone
  - $D_k = \{ \langle o_i, d_{jk}(o_i) \rangle \mid 1 \leq i \leq n \}$ 
    - $d_{jk}(o_i)$  is the **distance score (eigen distance)** of a registered occupant  $o_i$  from the face detected at zone *j* in event  $e_k$



## Transition Function - Revised

- ▶  $\Delta: S \times E \rightarrow S$ , maps state  $s_{k-1}$  to  $s_k$  upon event  $e_k$ 
  - Let  $s_{k-1} = \langle Z_{1,k-1} \dots Z_{jk-1} \dots Z_{mk-1} \rangle$  and
  - $Z_{jk-1} = \{ \langle o_i, p_{jk-1}(o_i) \rangle \mid 1 \leq i \leq n \}$ .
  - Note that  $e_k = \langle t_k, j_k, D_k \rangle$ 
    - where  $D_k = \langle o_i, d_{jk}(o_i) \rangle$
- ▶ In order to map scores to probabilities, we compute **a reduced database** based upon spatial and temporal knowledge of the zones and occupants.

$f: \text{State} \times \text{Event} \rightarrow \text{Database}$

$$db_k = f(s_{k-1}, e_k)$$

$g: \text{Scores} \times \text{Database} \rightarrow \text{Probabilities}$

$$p_k = g(db_k, e_k)$$

- ▶ With these probabilities, the transition function is defined as before.

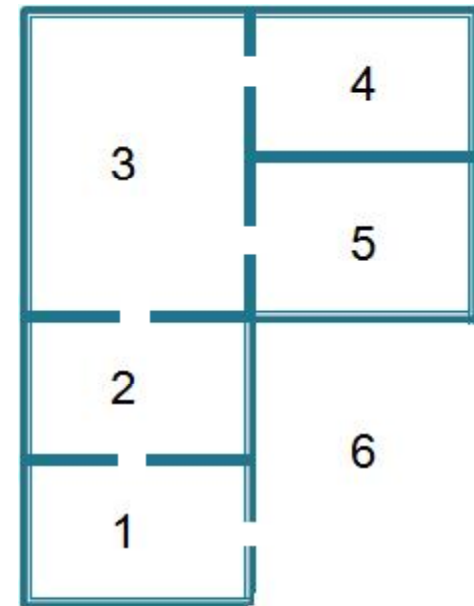


# Spatial Reasoning

- Let  $\text{thresh}(s,j)$  be a function which takes a state and a zone and returns the set of occupants with probability above threshold.
- For Internal Zones their candidate set is the union of candidate sets from their respective adjacent zones

- $\text{spatial}(s,2) = \text{thresh}(s,1) \cup \text{thresh}(s,3)$

- $\text{spatial}(s,3) = \text{thresh}(s,2) \cup \text{thresh}(s,4) \cup \text{thresh}(s,5)$





# Temporal Reasoning

- Schedule of Absence:  $\text{absent}(\text{Start}, \text{End}, \text{Occupants})$ 
  - *$\text{absent}(9:00, 13:00, \{o1, o7\})$  could denote the absence of occupants  $o1$  and  $o7$  from 9 am to 1 pm.*
- $f^{\text{tem}}(e) = 0 \quad \leftarrow \quad e = \langle t, j, D \rangle \wedge$   
 $\text{absent}(\text{start}, \text{end}, O) \wedge$   
 $\text{start} \leq t \leq \text{end}.$
- $f^{\text{tem}}(e) = \{\}$   $\leftarrow \quad e = \langle t, j, D \rangle \wedge$   
 $(\text{all } s, e) [\text{absent}(s, e, O)$   
 $\rightarrow (t < s \vee t > e)]$
- Need to generalize this approach to reflect the fuzzy nature of schedule timings



# Distance Scores to Probability

- ▶ Calculate probabilities  $\{ \langle o_i, p_{jk}(o_i) \rangle \}$  from the distance scores on the reduced database

- $g$ : Scores  $\times$  Database  $\rightarrow$  Probabilities

- $p_k = g(db_k, e_k)$

$$p(O/d) = \frac{e^{\frac{-d^2}{2\sigma^2}}}{\sum e^{\frac{-d^2}{2\sigma^2}}}$$

Summation  
across distance  
scores in the  
database

- ▶  $O$ : Occupant
- ▶  $d$ : Distance Score for Occupant
- ▶  $\sigma$ : Standard Deviation of the Distance Scores



# Precision ( $\Pi$ )

(with Spatial Reasoning)

Occupants	State : s18					
	Z1	Z2	Z3	Z4	Z5	Z6
O1	0.03	0.00	0.00	0.00	0.00	0.97
O2	0.00	0.00	0.00	0.00	0.00	1.00
O3	0.00	0.00	0.00	1.00	0.00	0.00
O4	0.10	0.00	0.00	0.00	0.00	0.90
O5	0.00	0.00	0.04	0.00	0.96	0.00
O6	0.10	0.19	0.46	0.00	0.00	0.25
O7	0.14	0.00	0.00	0.00	0.00	0.86
O8	0.14	0.23	0.54	0.00	0.00	0.09
O9	0.00	0.00	0.00	0.00	0.00	1.00
O10	0.01	0.07	0.91	0.00	0.00	0.00
O11	0.32	0.00	0.00	0.00	0.00	0.68
O12	0.00	0.00	0.00	0.00	0.00	1.00
O13	0.26	0.12	0.00	0.00	0.00	0.62
O14	0.08	0.00	0.00	0.00	0.00	0.92
O15	0.03	0.00	0.00	0.00	0.00	0.97
O16	0.22	0.13	0.00	0.00	0.00	0.65
O17	0.00	0.00	0.00	0.00	0.00	1.00
O18	0.00	0.00	0.00	0.00	0.00	1.00
O19	0.01	0.00	0.00	0.00	0.00	0.99
O20	0.02	0.00	0.00	0.00	0.00	0.98
O21	0.01	0.00	0.00	0.00	0.00	0.99
O22	0.04	0.00	0.00	0.00	0.00	0.96
O23	0.12	0.00	0.00	0.00	0.00	0.87
O24	0.33	0.23	0.01	0.00	0.00	0.43
O25	0.02	0.00	0.00	0.00	0.00	0.98
Ground Truth - O3, O5, O10, O8						

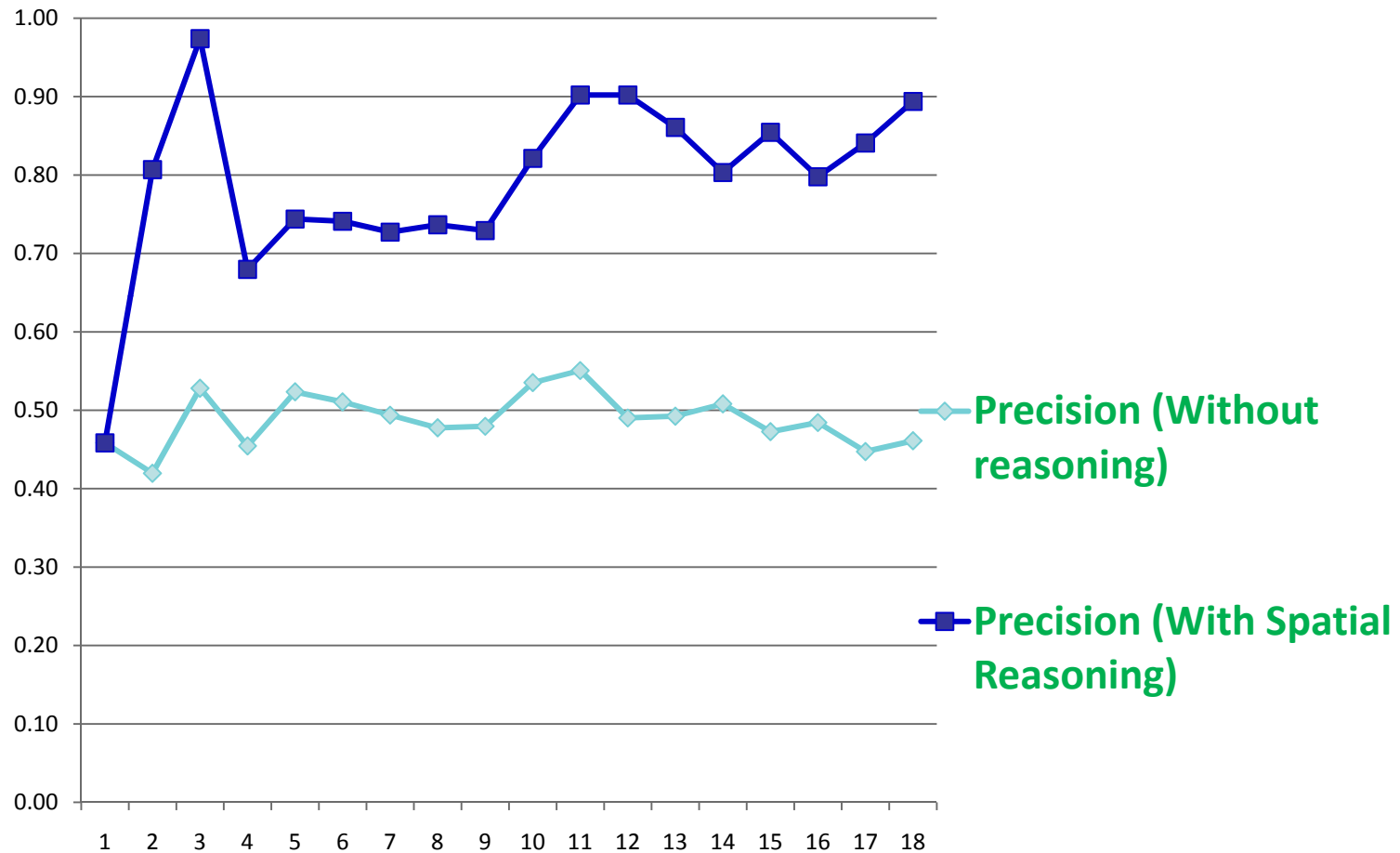
State : s18					
Z1	Z2	Z3	Z4	Z5	Z6
			1.00		
				0.96	
		0.54			
		0.91			
Ground Truth - O3, O5, O10, O8					

$\Pi = 0.46 \rightarrow 0.89$

ajk		1.45	1.00	0.96
bjk		2	1	1
pjk		0.73	1.00	0.96
m	3			
pk	0.89			



# Precision – 18 events





# Recall ( $\rho$ )

(with Spatial Reasoning)

State : s18						
Occupants	Z1	Z2	Z3	Z4	Z5	Z6
O1	0.03	0.00	0.00	0.00	0.00	0.97
O2	0.00	0.00	0.00	0.00	0.00	1.00
O3	0.00	0.00	0.00	1.00	0.00	0.00
O4	0.10	0.00	0.00	0.00	0.00	0.90
O5	0.00	0.00	0.04	0.00	0.96	0.00
O6	0.10	0.19	0.46	0.00	0.00	0.25
O7	0.14	0.00	0.00	0.00	0.00	0.86
O8	0.14	0.23	0.54	0.00	0.00	0.09
O9	0.00	0.00	0.00	0.00	0.00	1.00
O10	0.01	0.07	0.91	0.00	0.00	0.00
O11	0.32	0.00	0.00	0.00	0.00	0.68
O12	0.00	0.00	0.00	0.00	0.00	1.00
O13	0.26	0.12	0.00	0.00	0.00	0.62
O14	0.08	0.00	0.00	0.00	0.00	0.92
O15	0.03	0.00	0.00	0.00	0.00	0.97
O16	0.22	0.13	0.00	0.00	0.00	0.65
O17	0.00	0.00	0.00	0.00	0.00	1.00
O18	0.00	0.00	0.00	0.00	0.00	1.00
O19	0.01	0.00	0.00	0.00	0.00	0.99
O20	0.02	0.00	0.00	0.00	0.00	0.98
O21	0.01	0.00	0.00	0.00	0.00	0.99
O22	0.04	0.00	0.00	0.00	0.00	0.96
O23	0.12	0.00	0.00	0.00	0.00	0.87
O24	0.33	0.23	0.01	0.00	0.00	0.43
O25	0.02	0.00	0.00	0.00	0.00	0.98
Ground Truth - O3, O5, O10, O8						

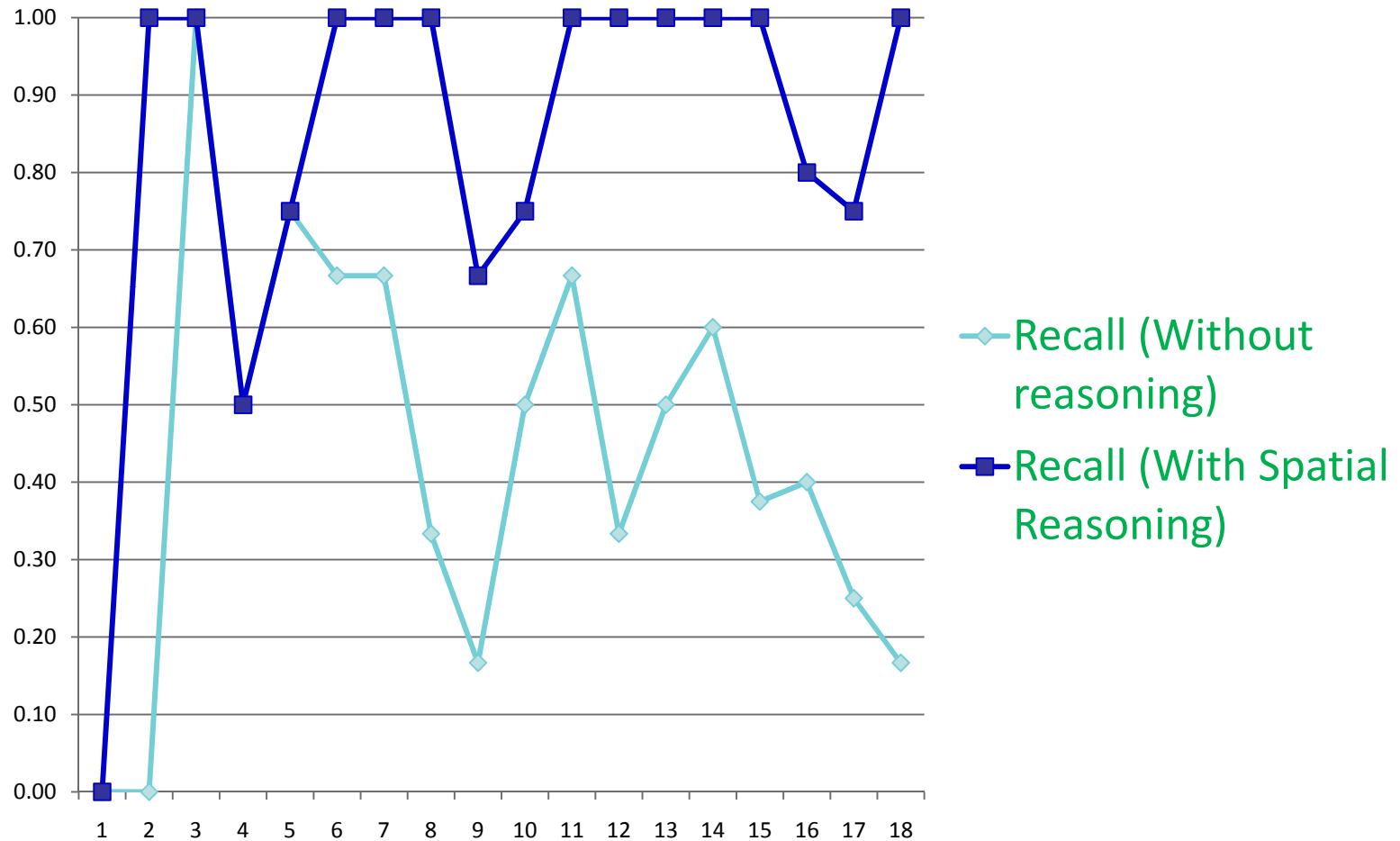
State : s18					
Z1	Z2	Z3	Z4	Z5	Z6
			1.00		
				0.96	
		0.54			
		0.91			
$\rho = 0.17 \rightarrow 1$					
Ground Truth - O3, O5, O10, O8					

ajk		2	1	1
bjk		2	1	1
rjk		1.00	1.00	1.00
m	3			
rk	1.00			



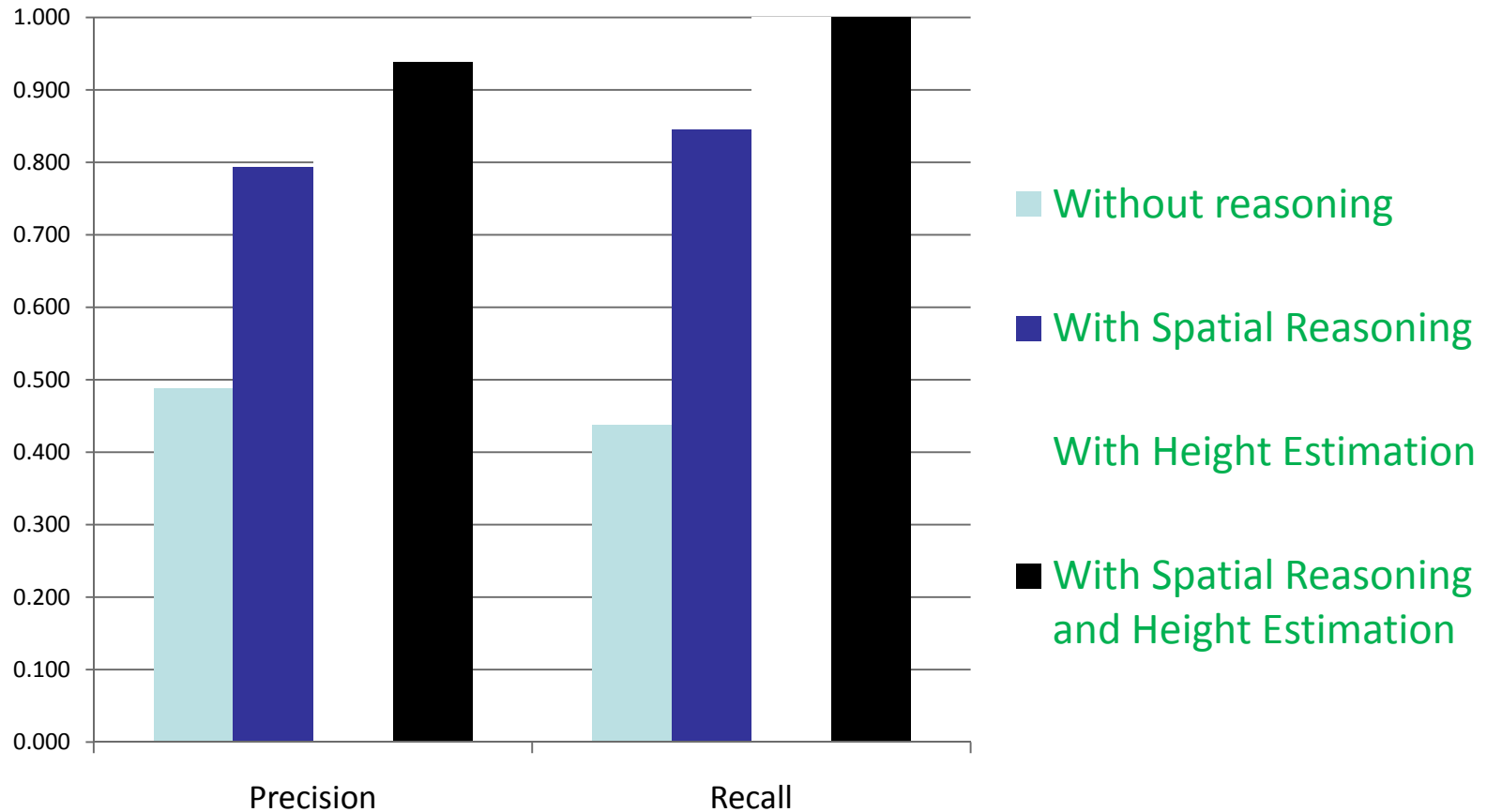
# Recall - 18 events





# Overall Improvements

## 18 events





## Summary

- A novel framework using state transitions for non-obtrusive biometric-based indoor smart environments.
- A characterization of the performance of the smart environment using concepts of precision and recall.
- Improvements in the performance metrics by integrating reasoning and recognition.
  
- Events → Recognition
- Transition Function → Reasoning
- State → Retrieval



**3 R's of  
Smart Environments**



## Future work

- Evolutionary learning
- Back-propagation of information
- Error propagation
- Fuse biometric recognizers, such as gait, voice, etc.
- Test on larger environments and different layouts
- Support speech-based information retrieval queries