

Dependable Systems
for
Sentient Computing

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Problem

Sentient Computing is **failure sensitive**

Sentient Computing is **failure prone**

Dependability

A dependable system can provide, at any time, a specification of current system performance and status

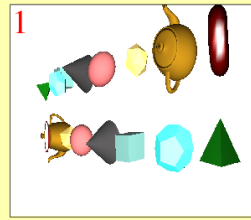
Is it possible to build a dependable location system?

Cantag

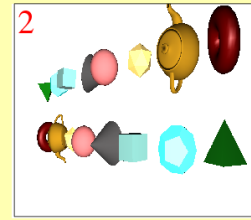
Marker Tracking Framework
for investigating dependability

- Reliable Implementation
- Designed for Instrumentation
- Reconfigurable and flexible

The Projective algorithm (direct linear equations) will exactly fit image noise by distorting the object co-ordinates of the overlay

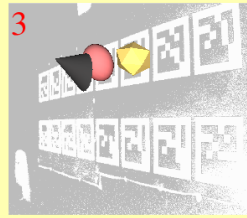


Normal

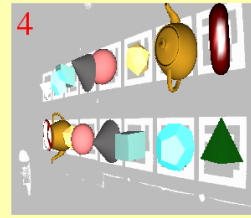


The SpaceSearch algorithm maintains an orthogonal 3D co-ordinate frame

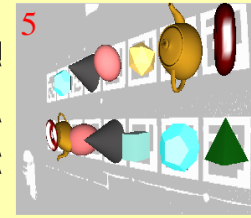
Varying lighting intensity across the image causes false-negatives



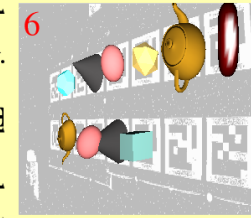
Global Threshold



Threshold

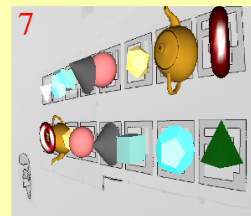


Adaptive Threshold

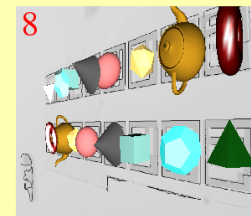


A small window size amplifies noise in the solid regions of the tag

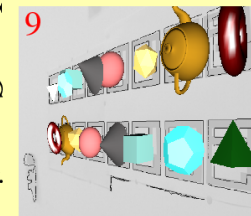
Tags on the edge of the image are most affected by lens distortion



Contour

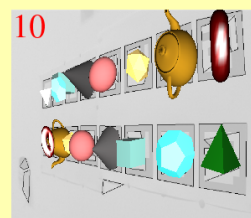


Lens Correction



Simple correction (middle) shows little benefit compared to Full correction (right) for the current lens

Shape fitting quality could be increased by activating the linear regression algorithm to refine the corner estimates



Shape Fit



Accumulated error from previous stages causes inaccuracy in the sample points for the data payload



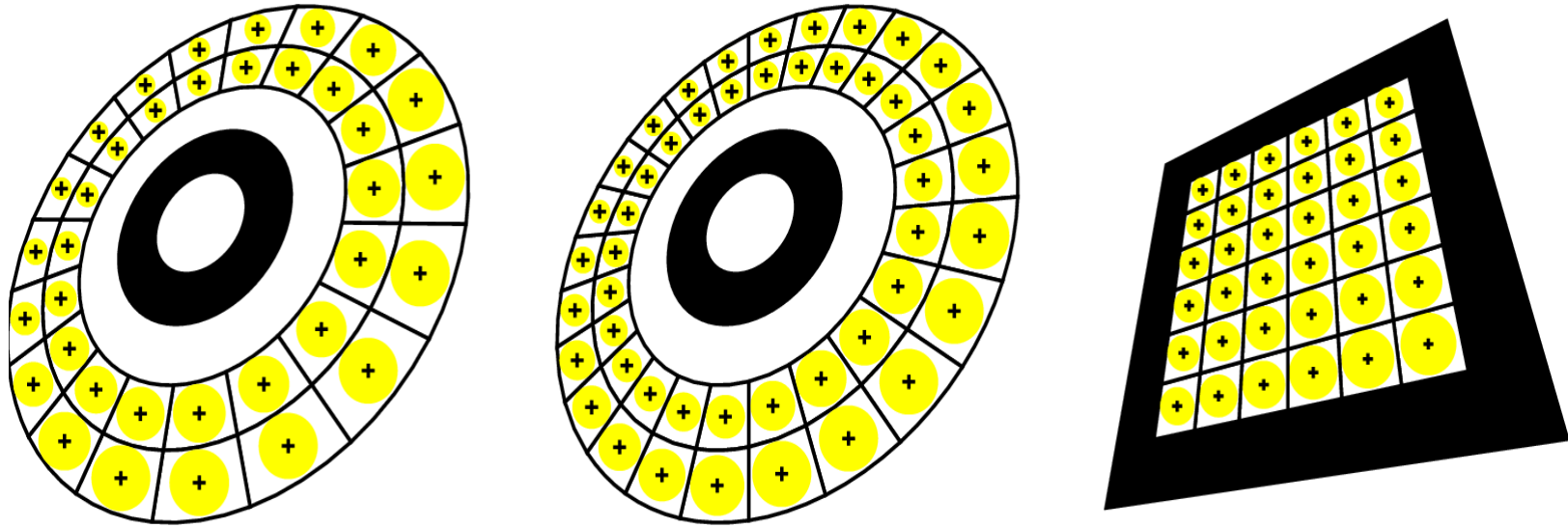
Decode



Algorithmic Dependability

How does my system behave in theory?

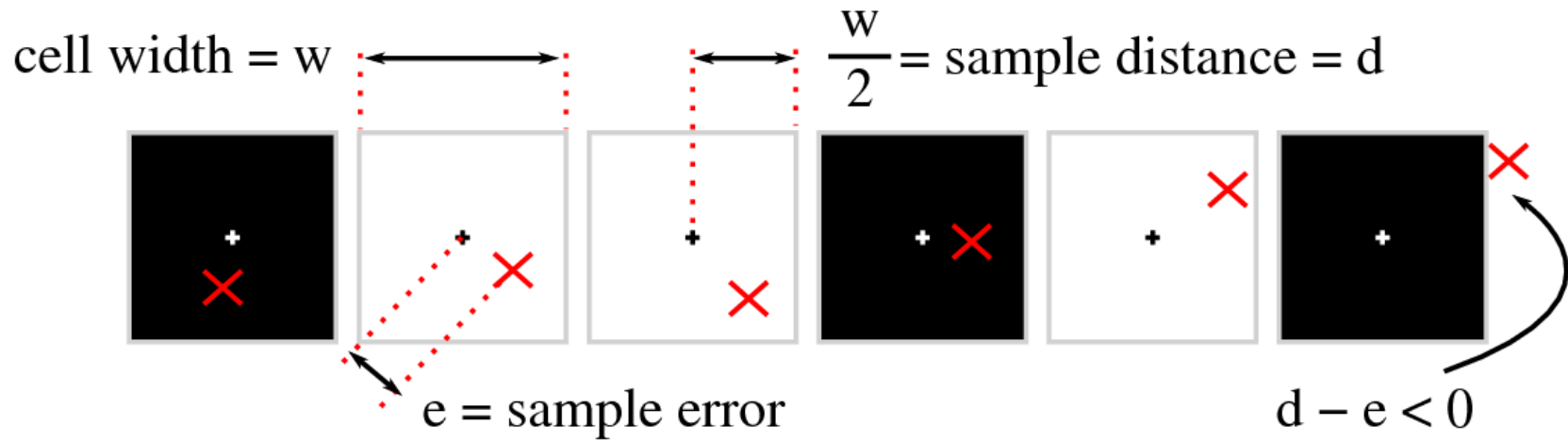
Sample Distance



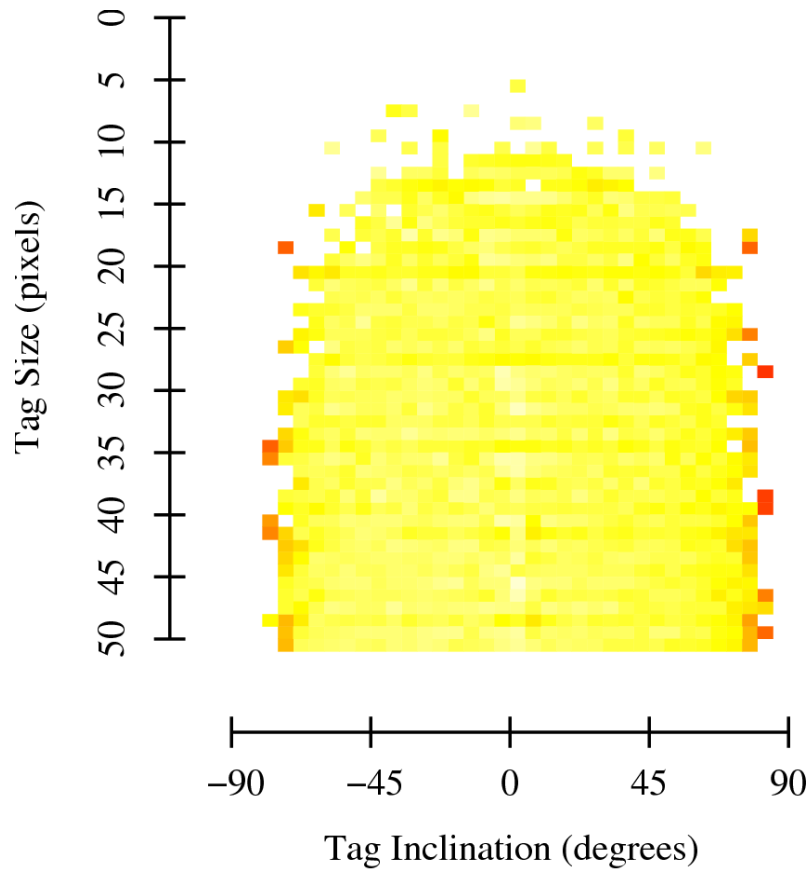
Abstract, information-theoretic limit

Optimising tag design requires
maximising the sample distance

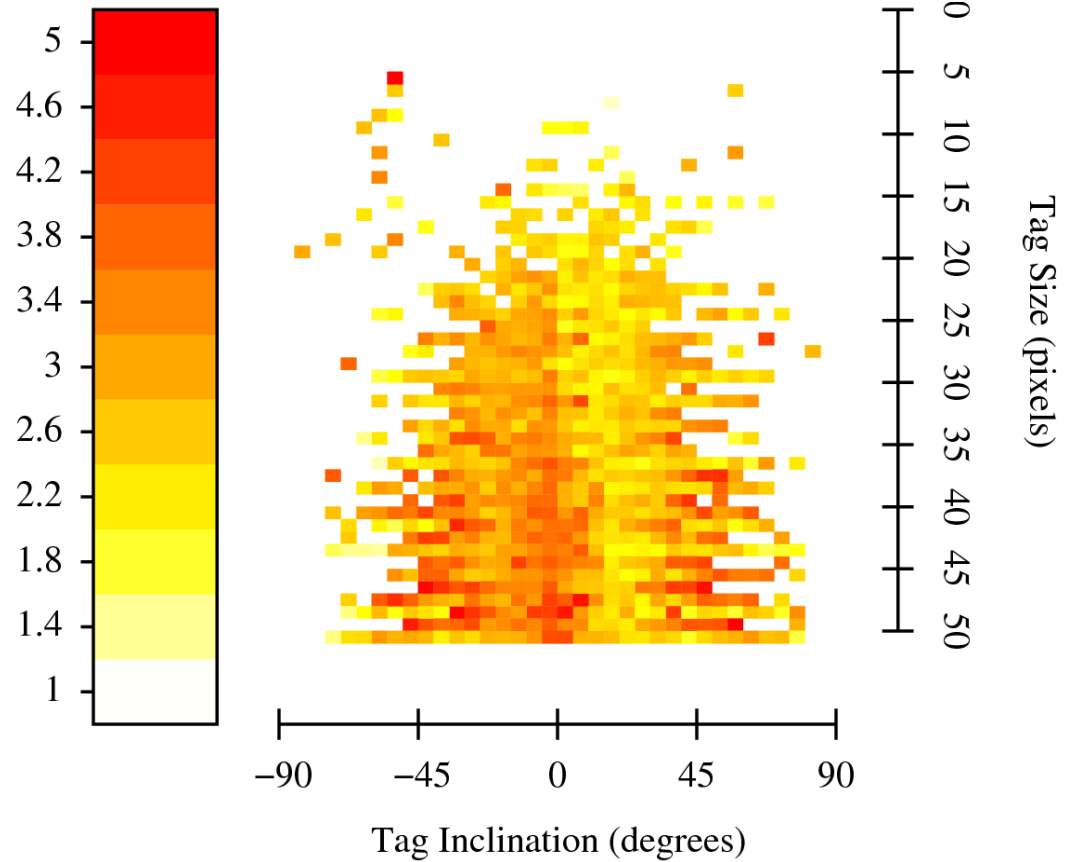
Sample Error



Sample Error

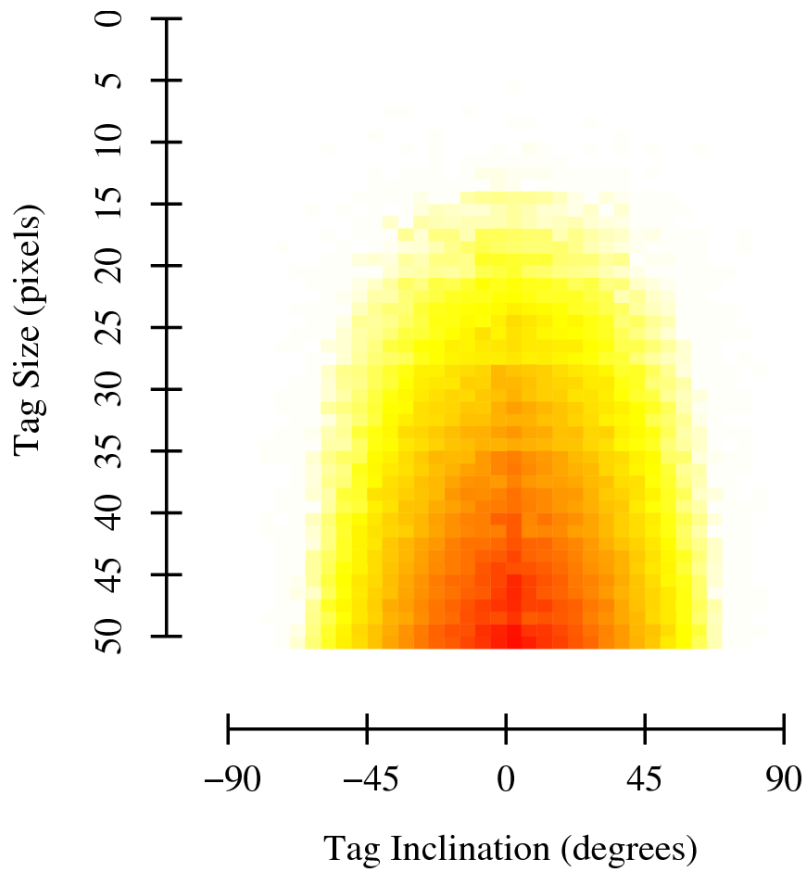


FitEllipseLS

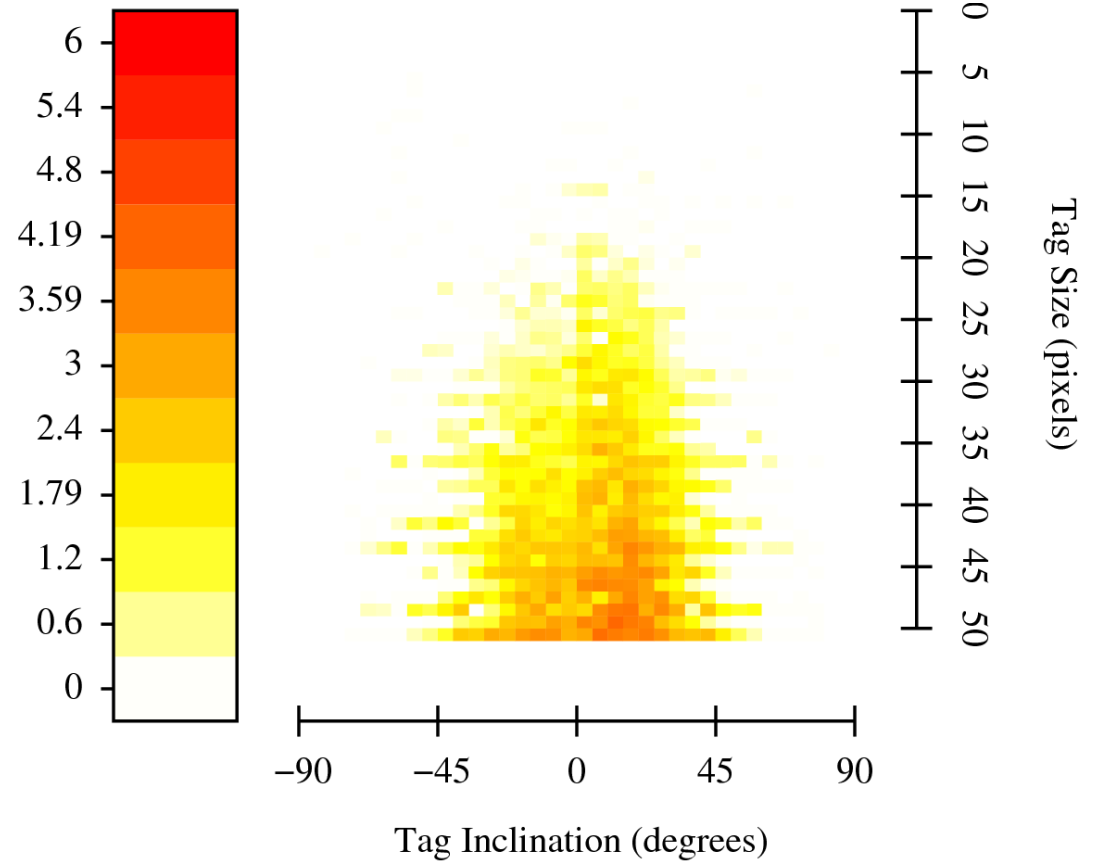


FitEllipseSimple

Sample Strength



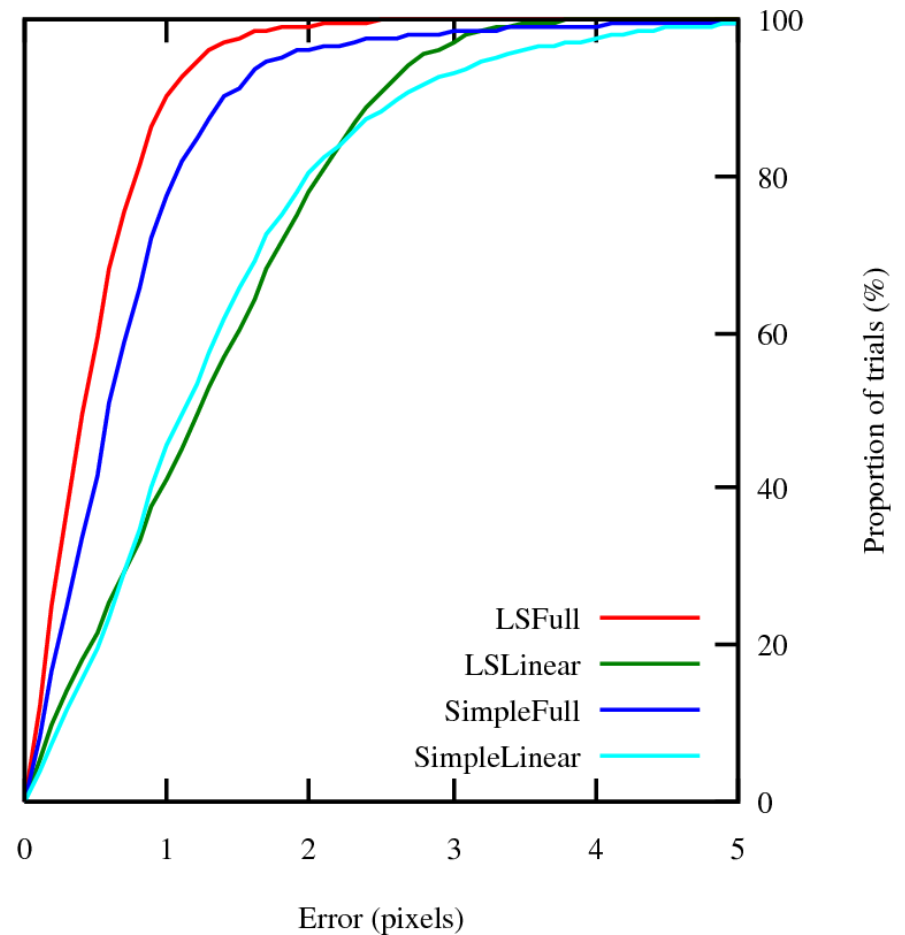
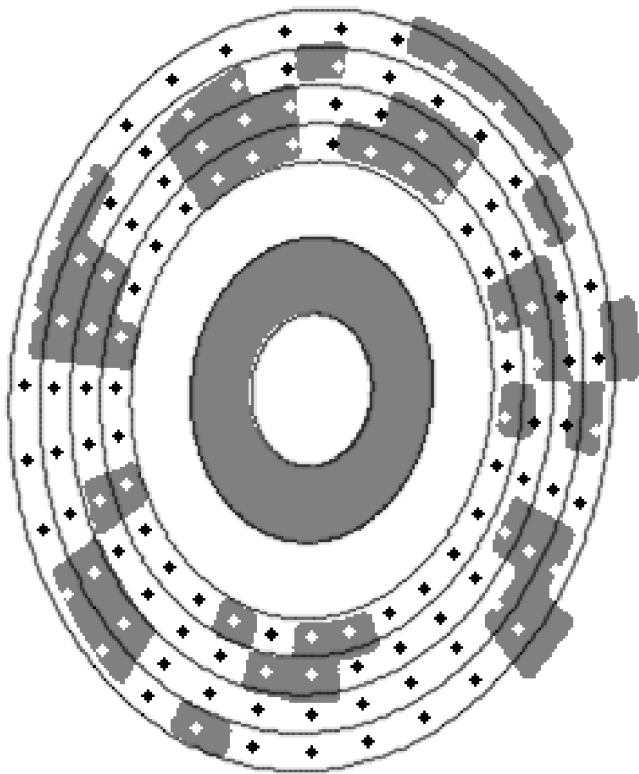
FitEllipseLS



FitEllipseSimple

Predictive Metrics

Estimate sample strength from image

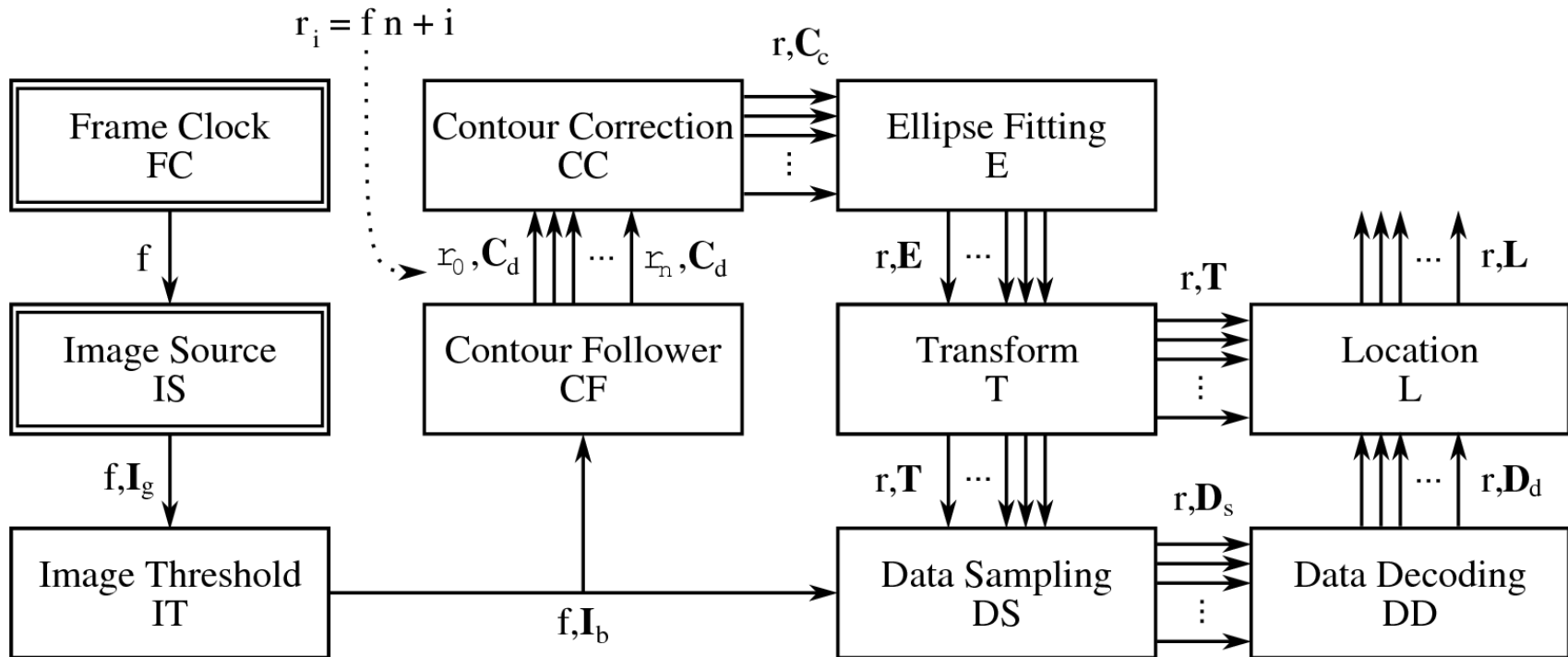


Runtime Dependability

Need to integrate our predictive metrics
with the runtime system

Also need runtime checks of our algorithms,
an asymmetric cost in many cases

The Cantag Pipeline



Inference Rules

$$\begin{array}{c}
 \text{(IT)} \frac{\mathcal{V}_{IS}^+(f) \quad \mathcal{C}_{IT}^+(f)}{\mathcal{V}_{IT}^+(f)} \\
 \\
 \text{(CF}^+\text{)} \frac{\mathcal{V}_{IT}^+(f) \quad \mathcal{C}_{CF}^+(r)}{\mathcal{V}_{CF}^+(r)} f = \lfloor r/n \rfloor \qquad \text{(CF}^-\text{)} \frac{\mathcal{V}_{IT}^+(t) \quad \mathcal{C}_{CF}^-(r)}{\mathcal{V}_{CF}^-(r)} t = \lfloor r/n \rfloor \\
 \\
 \text{(CC)} \frac{\mathcal{V}_{CF}^+(r) \quad \mathcal{C}_{CC}^+(r)}{\mathcal{V}_{CC}^+(r)} \\
 \\
 \text{(E}^+\text{)} \frac{\mathcal{V}_{CC}^+(r) \quad \mathcal{C}_E^+(r)}{\mathcal{V}_E^+(r)} \qquad \text{(E}^-\text{)} \frac{\mathcal{V}_{CC}^+(r) \quad \mathcal{C}_E^-(r)}{\mathcal{V}_E^-(r)} \\
 \\
 \text{(T)} \frac{\mathcal{V}_E^+(r) \quad \mathcal{C}_T^+(r)}{\mathcal{V}_T^+(r)} \\
 \\
 \text{(DS)} \frac{\mathcal{V}_T^+(r) \quad \mathcal{V}_{IT}^+(t) \quad \mathcal{C}_{DS}^+(r)}{\mathcal{V}_{DS}^+(r)} \\
 \\
 \text{(DD}^+\text{)} \frac{\mathcal{V}_{DS}^+(r) \quad \mathcal{C}_{DD}^+(r)}{\mathcal{V}_{DD}^+(r)} \qquad \text{(DD}^-\text{)} \frac{\mathcal{V}_{DS}^+(r) \quad \mathcal{C}_{DD}^-(r)}{\mathcal{V}_{DD}^-(r)} \\
 \\
 \text{(L}^+\text{)} \frac{\mathcal{V}_{DD}^+(r) \quad \mathcal{V}_T^+(r) \quad \mathcal{C}_L^+(r)}{\mathcal{V}_L^+(r)} \qquad \text{(L}_1^-\text{)} \frac{\mathcal{V}_{CF}^-(r)}{\mathcal{V}_L^-(r)} \qquad \text{(L}_2^-\text{)} \frac{\mathcal{V}_{DD}^-(r)}{\mathcal{V}_L^-(r)}
 \end{array}$$

```

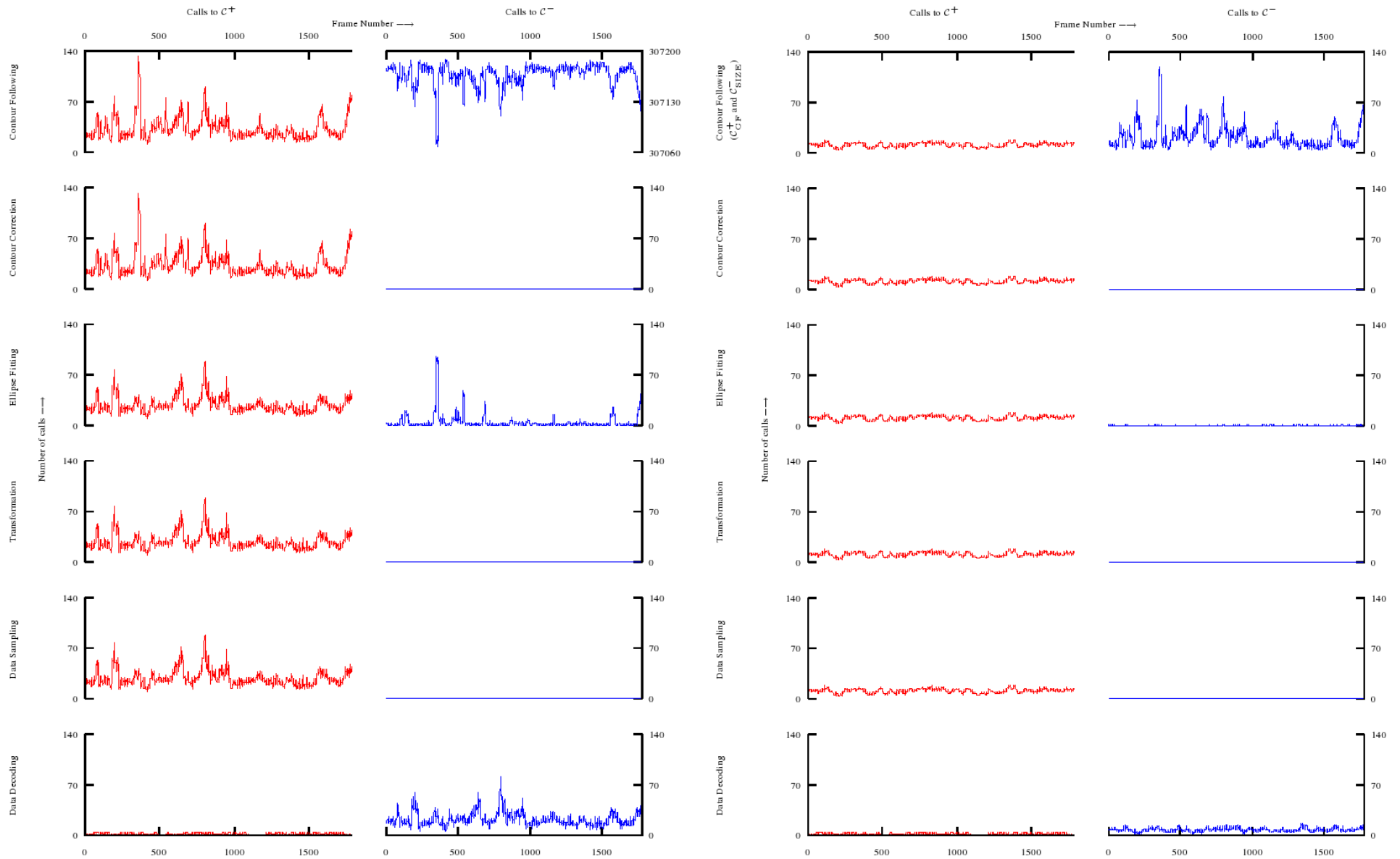
vFCp(_) . % Trusted Component
vISp(_) . % Trusted Component
n(307200) . % 640x480 image

vITp(T) :- vISp(T), cITp(T) . % Rule IT
vCFp(S) :- n(R), T is S // R, % Rule CF+
           vITp(T), cCFp(S) .
vCFn(S) :- n(R), T is S // R, % Rule CF-
           vITp(T), cCFn(S) .
vCCp(S) :- vCFp(S), cCCp(S) . % Rule CC
vEp(S) :- vCCp(S), cEp(S) . % Rule E+
vEn(S) :- vCCp(S), cEn(S) . % Rule E-
vTp(S) :- vEp(S), cTp(S) . % Rule T
vDsp(S) :- vTp(S), vITp(S), % Rule DS
           cDsp(S) .
vDDp(S) :- vDsp(S), cDDp(S) . % Rule DD+
vDDn(S) :- vDsp(S), cDDn(S) . % Rule DD-
vLp(S) :- vDDp(S), vTp(S), % Rule L+
          cLp(S) .
vLn1(S) :- vCFn(S) . % Rule L1-
vLn2(S) :- vDDn(S) . % Rule L2-
vLn(S) :- vLn1(S) ; vLn2(S) .

```

Use prolog as
automated checker

Costs of Validation



Improving Performance

Reorganise original system to ease the inference burden

Runtime costs are reduced but rule complexity increases

```
theory Bat
imports Main
begin

theorem laststar:
|  $\forall l. VPP\ l \longrightarrow LASTP(l,l)$  ;
 $\forall i\ tp. LASTP(i,tp) \wedge VPM\ (Suc\ i) \longrightarrow LASTP(Suc\ i,tp)$  ;
 $\forall t\ te\ n. SP(n,0) \wedge SP(Suc\ n,te) \wedge 0 < t \wedge t < te \longrightarrow VPM\ t$  ]
 $\longrightarrow$ 
 $(\forall i\ tc\ n. SP(n,0) \wedge SP(Suc\ n,tc) \wedge 0 < i \wedge i < tc \wedge VPP\ 0 \longrightarrow LASTP(i,0))$ 
 $\wedge$ 
 $(\forall i\ n\ te\ tp. SP(n,0) \wedge SP(Suc\ n,te) \wedge 0 \leq i \wedge i < te \wedge VPM\ 0 \wedge LASTP(0,tp)$ 
 $\longrightarrow LASTP(i,tp))$ 
apply(subgoal_tac
 $\forall n\ te.$ 
 $(\forall t. SP(n,0) \wedge SP(Suc\ n,te) \wedge 0 \leq t \wedge t < te \wedge VPP\ 0 \longrightarrow LASTP(t,0))$ 
 $\wedge$ 
 $(\forall t\ tp. SP(n,0) \wedge SP(Suc\ n,te) \wedge 0 < t \wedge t < te \wedge VPM\ 0 \wedge LASTP(0,tp)$ 
 $\longrightarrow LASTP(t,tp))$ 
)
apply(blast)
apply(rule allI, rule allI)
apply(subgoal_tac
 $[\forall l. SP(n,0) \wedge SP(Suc\ n,te) \wedge 0 < l \wedge l < te \longrightarrow VPM\ l]$ 
 $\implies$ 
 $(\forall t. SP(n,0) \wedge SP(Suc\ n,te) \wedge 0 \leq t \wedge t < te \wedge VPP\ 0 \longrightarrow LASTP(t,0))$ 
 $\wedge$ 
 $(\forall t\ tp. SP(n,0) \wedge SP(Suc\ n,te) \wedge 0 < t \wedge t < te \wedge VPM\ 0 \wedge LASTP(0,tp)$ 
 $\longrightarrow LASTP(t,tp))$ 
)
)
apply(blast)
apply(rule congI, rule allI)
apply(induct_tac t)
apply(simp all)
apply(rule allI, rule allI)
apply(induct_tac t)
apply(simp all)
done
end
```


Conclusion

- Recipe for dependability
 - 1) Provide as reliable an implementation as feasible
 - 2) Develop predictive metrics
 - 3) Identify observable metrics and validate them
 - 4) Integrate into the real system using a Prolog reasoning engine
 - 5) Add additional inferences for performance improvements---prove these correct in HOL

The End

Andrew Rice, Christopher Cain and John Fawcett. Dependable Coding for Fiducial Tags. In *Proceedings of the 2nd Ubiquitous Computing Symposium*, pages 155--163, 2004.

Andrew Rice, Christopher Cain and John Fawcett. Dependable Coding for Fiducial Tags (Extended Version). In *Ubiquitous Computing Systems*, LNCS 3598, pages 259--274, 2004.

Andrew Rice and Robert Harle. Evaluating Lateration-Based Positioning Algorithms for Fine-Grained Tracking. In *Joint Workshop on Foundations of Mobile Computing (DIAL-M-POMC)*, pages 54--61, 2005.

Andrew C Rice, Alastair R Beresford and Robert K Harle. Cantag: an open source software toolkit for designing and deploying marker-based vision systems. In *Fourth Annual IEEE International Conference on Pervasive Computer and Communications*, pages 12--21, 2006.

Andrew C Rice and Alastair R Beresford. Dependability and Accountability for Context-aware Middleware Systems. In *Workshop on Middleware Support for Pervasive Computing (PerWare)*, pages 378--382, 2006.

Andrew C Rice, Robert K Harle and Alastair R Beresford. Analysing fundamental properties of marker-based vision system designs. *Pervasive and Mobile Computing*, November 2006.