Exploration with a Map Occupancy Filter

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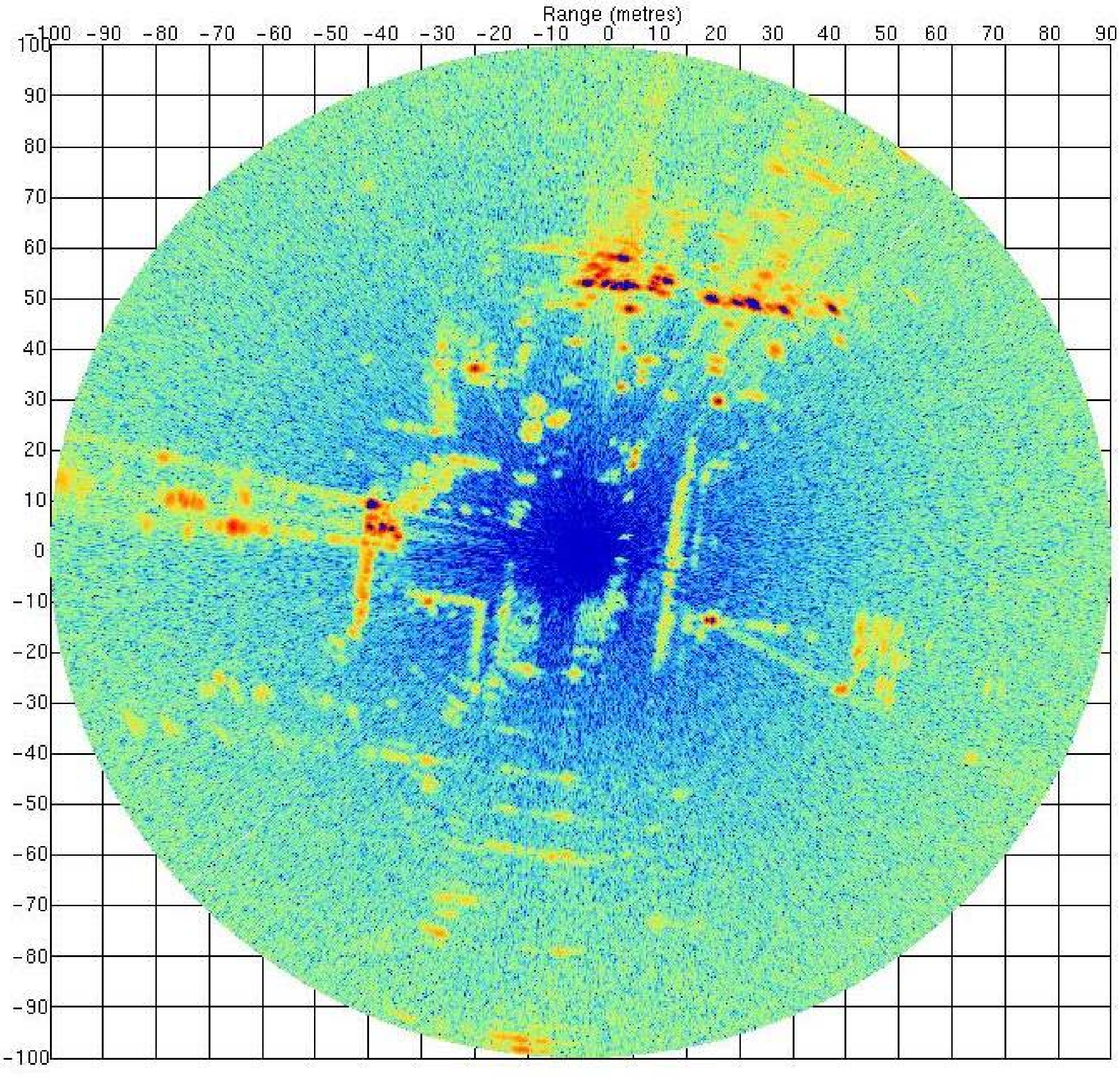
Introduction

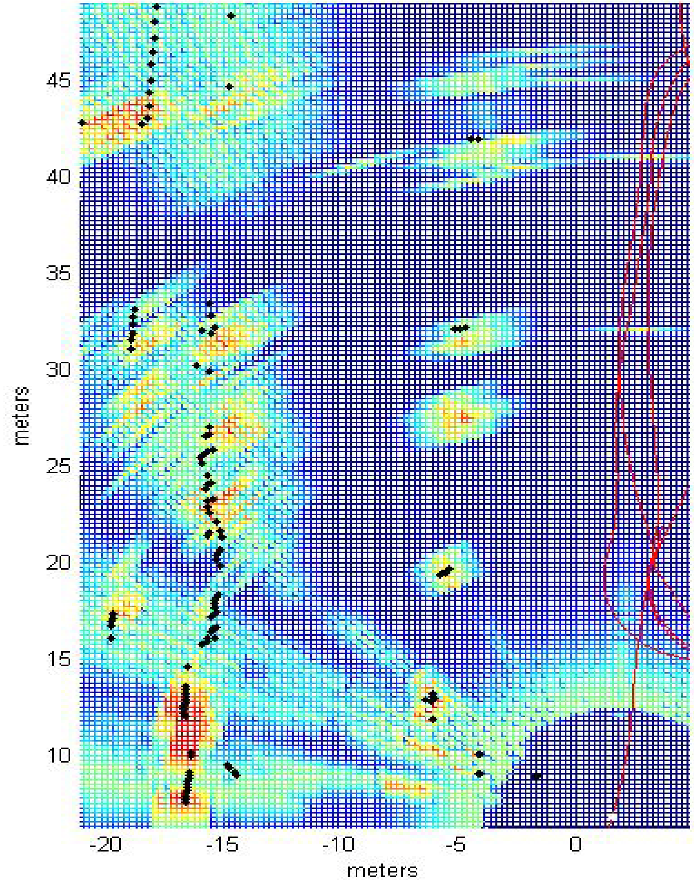
- Data fusion utilising rarely used intensity information for feature existence estimation.
- Probabilistic navigation including both spatial & existence map parameters.
- “Occupancy Filter” using signal intensity information to propagate posterior density of existence RVs.
- Measurement Models for estimating probabilities of detection & false alarm.
- Experiments demonstrating map building and entropy based exploration with millimetre wave RADAR data.

Motivation – Radar/Sonar Scans



Motivation – Utilising Intensity Information

Note: Trees + lamp posts



Note laser misses lamp posts,
But "seen" by RADAR.

Concepts/Related Work

- Outdoors, feature management techniques often necessary to identify unreliable features (false alarms/outliers).

- Literature related to identifying true features:

  - Binary Bayes filter used to propagate feature existence variables from a sensor model [Montemerlo; Thrun 2001].

  - Geometric feature track quality measures, based on feature innovations [Dissanayake et. al; D. Makarsov, H. Durrant-Whyte, 2001].

  - Noise power thresholds/Max SNR for point target identification [Williams, Majumder, Clark 2001, 1999].

Concepts

- With signal detection theory, feature existence RV becomes directly observable.
- Heuristic models for propagating existence probabilities unnecessary.
- Discrete Bayes filter no longer applicable to existence parameter propagation, since measurement likelihood not deterministic.
- Particle filter framework for posterior distribution estimation of existence variables derived.

Probabilistic Navigation

SLAM evaluates:

$$p(\mathbf{x}_t, \mathbf{m}_t, \mathbf{c}_t \mid \mathbf{z}^t, \mathbf{u}^t, \mathbf{x}_0)$$

$\mathbf{x}_t$ = vehicle pose at time t, $\mathbf{m}_t$= estimate of map variables,
$\mathbf{c}_t$ = current measurement $\mathbf{z}_t$ to map association info.
$\mathbf{z}^t, \mathbf{u}^t$ = history of measurement and vehicle input data.
$\mathbf{m}_t$ generally contains Euclidean coordinates only.

Consider here mapping only case – posterior:

$$p(\mathbf{m}_t \mid \mathbf{z}^t, \mathbf{x}^t, \mathbf{c}^t, \mathbf{u}^t, \mathbf{x}_0) = p(\mathbf{m}_t \mid \mathbf{z}^t, \mathbf{x}^t)$$

Probabilistic Navigation

For many sensors, $\mathbf{m}_t$ should contain coords + P (occupancy)

Since $\mathbf{x}^t$ known, coords. of $\mathbf{m}_t$ deterministic through sensor model $\mathbf{H}$.

Need only to estimate existence variables – independent of location!

Posterior of interest $p(\mathbf{m}_{E_t} \mid \mathbf{z}_E^t)$, $\mathbf{m}_{E_t} \subseteq \mathbf{m}_t$,

$\mathbf{z}_E \subseteq \mathbf{z}$ gives measurements of RV via $\mathbf{H}_E = p(\mathbf{z}_E \mid \mathbf{m})$

Probabilistic Navigation

Posterior can be estimated (updated) by:

1. Bayes filter (assume conditional measurement independence)

$$p(\mathbf{m}_{E_t} \mid \mathbf{z}_E^t) = \gamma \; p(\mathbf{z}_{E_t} \mid \mathbf{m}_{E_t}) \, p(\mathbf{m}_{E_{t-1}} \mid \mathbf{z}_E^{t-1}) \qquad (1)$$

Note: Sensor Model $p(\mathbf{z}_{E_t} \mid \mathbf{m}_{E_t})$ is *not deterministic* and should take account of measurement intensity.

2. *Dempster-Shafer Theory of Evidence*

generates mass distributions (beliefs)

$$\{M_\varnothing, M_f, M_e, M_{f \cup e}\} = \{\varnothing, \text{full}, \text{emptiness}, \text{ignorance}\}$$

1. Bayes Filter

Consider prob. existence, given measurement $= P(\mathbf{m}_{E_t} \mid \mathbf{z}_E^t)$

$\mathbf{z}_E^t$ considered as hypothesis decision on target presence or absence:

$$P(\mathbf{m}_{E_t=e} \mid D) = \gamma_1 P(D \mid \mathbf{m}_{E_t=e}) P(\mathbf{m}_{E_{t|t-1}=e})$$

$$\gamma_1^{-1} = P(D \mid \mathbf{m}_{E_t=e}) P(\mathbf{m}_{E_{t|t-1}=e}) + P(D \mid \mathbf{m}_{E_t=\bar{e}}) P(\mathbf{m}_{E_{t|t-1}=\bar{e}}) \qquad (2)$$

$$P(\mathbf{m}_{E_t=e} \mid \overline{D}) = \gamma_2 P(\overline{D} \mid \mathbf{m}_{E_t=e}) P(\mathbf{m}_{E_{t|t-1}=e})$$

$$\gamma_1^{-1} = P(\overline{D} \mid \mathbf{m}_{E_t=e}) P(\mathbf{m}_{E_{t|t-1}=e}) + P(\overline{D} \mid \mathbf{m}_{E_t=\bar{e}}) P(\mathbf{m}_{E_{t|t-1}=\bar{e}})$$

where $E_t \in \{e, \bar{e}\}$, e denotes existence, $\bar{e}$ non-existence.

Statistically correct posterior of existence random variable.

1. Bayes Filter

$P(D \mid \mathbf{m}_{E_t = e})$ - Probability of Target Detection

$P(D \mid \mathbf{m}_{E_t = \bar{e}})$ - Probability of False Alarm

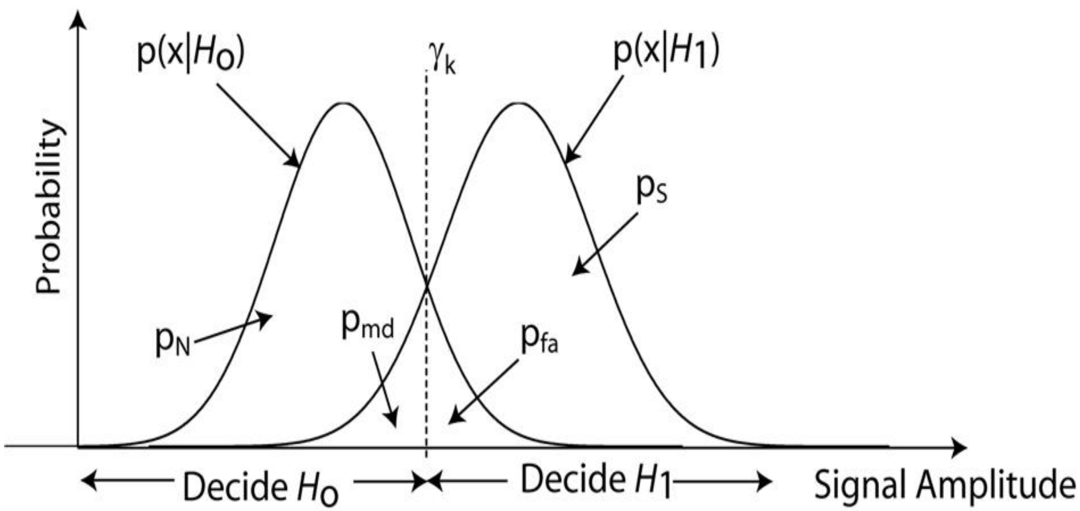
$P(\bar{D} \mid \mathbf{m}_{E_t = e})$ - Probability of Missed Detection

$P(\bar{D} \mid \mathbf{m}_{E_t = \bar{e}})$ - Probability of “Noise”

Probabilities can be calculated exactly under known Sensor SNR conditions, and assumed known noise statistics.

Else, they must be estimated through propagation of existence random variable (eqn. (1)) – stochastic filtering.

2: Dempster-Shafer



$$P(H_1 \mid D) = \int_{\gamma_k}^{\infty} p(x \mid H_1)dx$$

$$P(H_0 \mid \overline{D}) = \int_{-\infty}^{\gamma_k} p(x \mid H_0)dx$$

$$P(H_0 \mid D) = \int_{-\infty}^{\gamma_k} p(x \mid H_1)dx$$

$$P(H_1 \mid \overline{D}) = \int_{\gamma_k}^{\infty} p(x \mid H_0)dx$$

For any given hypothesis, finite probability exists of alternative hypothesis being true. Model remaining ambiguity as "unknown term"

Dempster-Shafer theory allows for "unknown states".

2: Dempster-Shafer

After observation $\mathbf{z}_t$, beliefs are assigned as:

$$\left.\begin{aligned} m(M_f \mid \mathbf{z}_t) &= P(H_1 \mid D) \\ m(M_e \mid \mathbf{z}_t) &= P(H_1 \mid \overline{D}) \\ m(M_u \mid \mathbf{z}_t) &= 1 - P(H_1 \mid D) - P(H_1 \mid \overline{D}) \end{aligned}\right\} \text{for } x = H_1$$

$$\left.\begin{aligned} m(M_f \mid \mathbf{z}_t) &= P(H_0 \mid D) \\ m(M_e \mid \mathbf{z}_t) &= P(H_0 \mid \overline{D}) \\ m(M_u \mid \mathbf{z}_t) &= 1 - P(H_0 \mid \overline{D}) - P(H_0 \mid D) \end{aligned}\right\} \text{for } x = H_0$$

Map *P* (full, empty and unknown) updates carried out according to Dempster's rule of combination.

Occupancy Filter

1: Bayes Filter:

Propagate pdf $p(\mathbf{m}_{E_t} \mid \mathbf{z}_E^t) = \gamma \; p(\mathbf{z}_E^t \mid \mathbf{m}_{E_t})\, p(\mathbf{m}_{E_{t|t-1}} \mid \mathbf{z}_E^{t-1})$

assuming static map $p(\mathbf{m}_{E_{t|t-1}} \mid \mathbf{z}_E^{t-1}) = p(\mathbf{m}_{E_{t-1|t-1}} \mid \mathbf{z}_E^{t-1})$

and constraint $\int p(\mathbf{m}_{E_t = e} \mid \mathbf{z}_E^t) + \int p(\mathbf{m}_{E_t = \bar{e}} \mid \mathbf{z}_E^t) = 1$

2: Dempster-Shafer:

Dempster's fusion of uncertain beliefs

Note, that under DS: P (Occupancy) $\neq$ 1- P (Emptiness)

Bayes Occupancy Filter

Start with two sensor model distributions:

$$p(\mathbf{z}_{E_t=e} \mid \mathbf{m}_{E_t=e}) = P\,\text{(detection)}, \quad p(\mathbf{z}_{E_t=e} \mid \mathbf{m}_{E_t=\bar{e}}) = P\,\text{(false alarm)}$$

And 2 priors: $p(\mathbf{m}_{E_{t|t-1}=e} \mid \mathbf{z}_E^{t-1}) \quad p(\mathbf{m}_{E_{t|t-1}=\bar{e}} \mid \mathbf{z}_E^{t-1})$

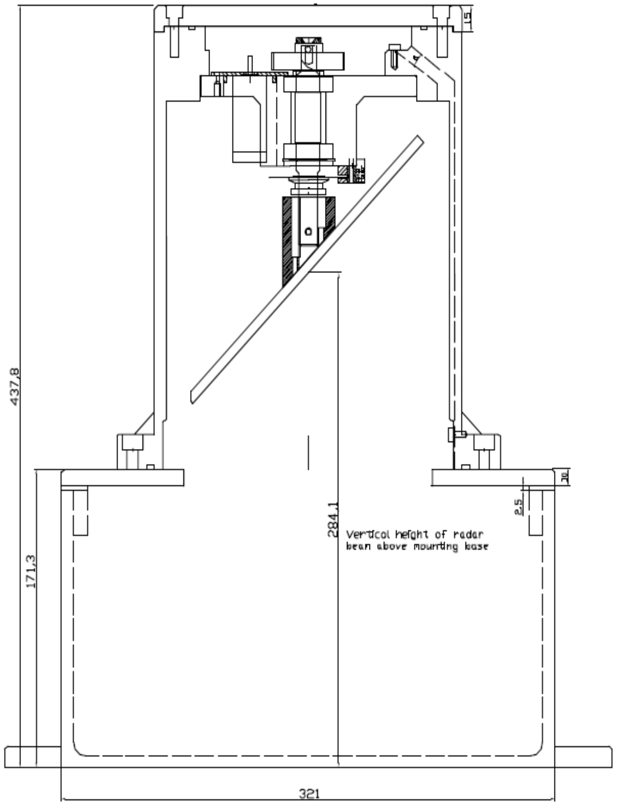
Estimate posterior: $p(\mathbf{m}_{E_t} \mid \mathbf{z}_E^t)$

Particle filter:

1) Draw samples from priors and measurement likelihoods
2) weight samples,
3) Convolve according to Bayes rule (eqns. (2))
4) Resample to give particle approximation.

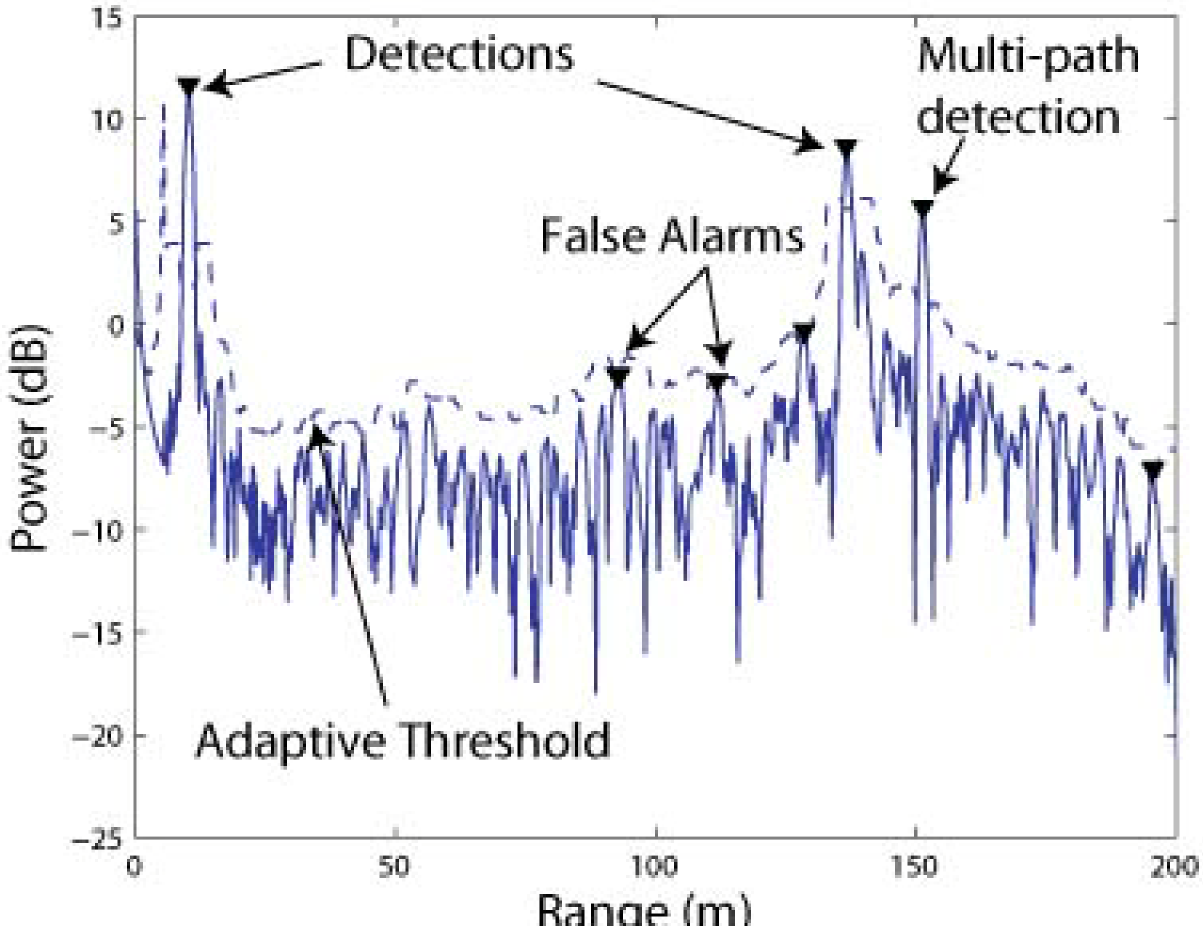
Measurement Model

FMCW Scanned MMW Radar

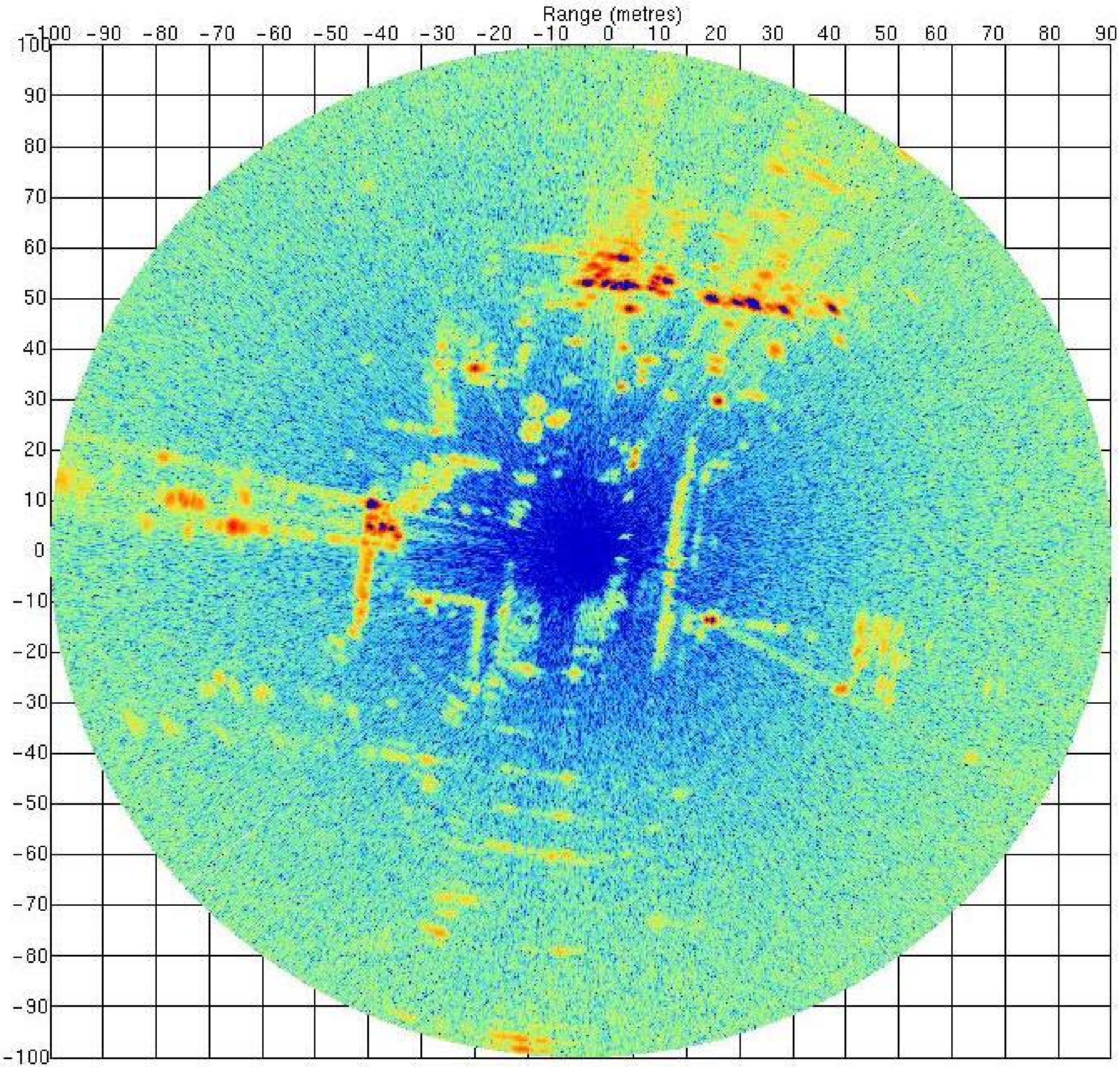


Measurement Model

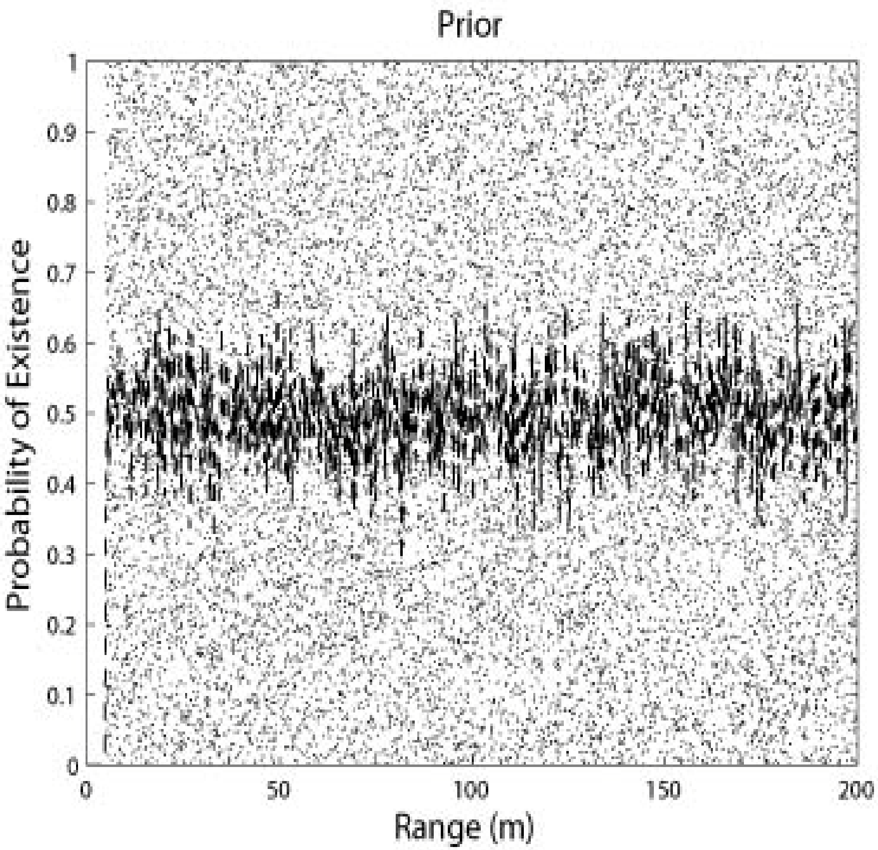
Model uses signal detection theory to generate adaptive intensity threshold (CFAR) based on SNR estimates.



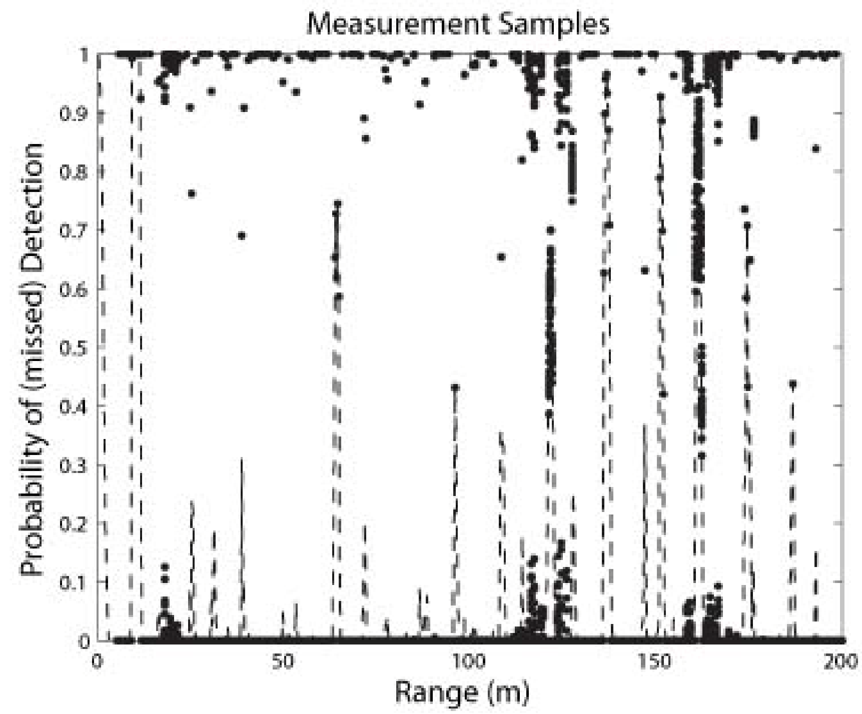
2D Radar Scan



Bayes Filter Results



Uniform a-priori samples at each range bin

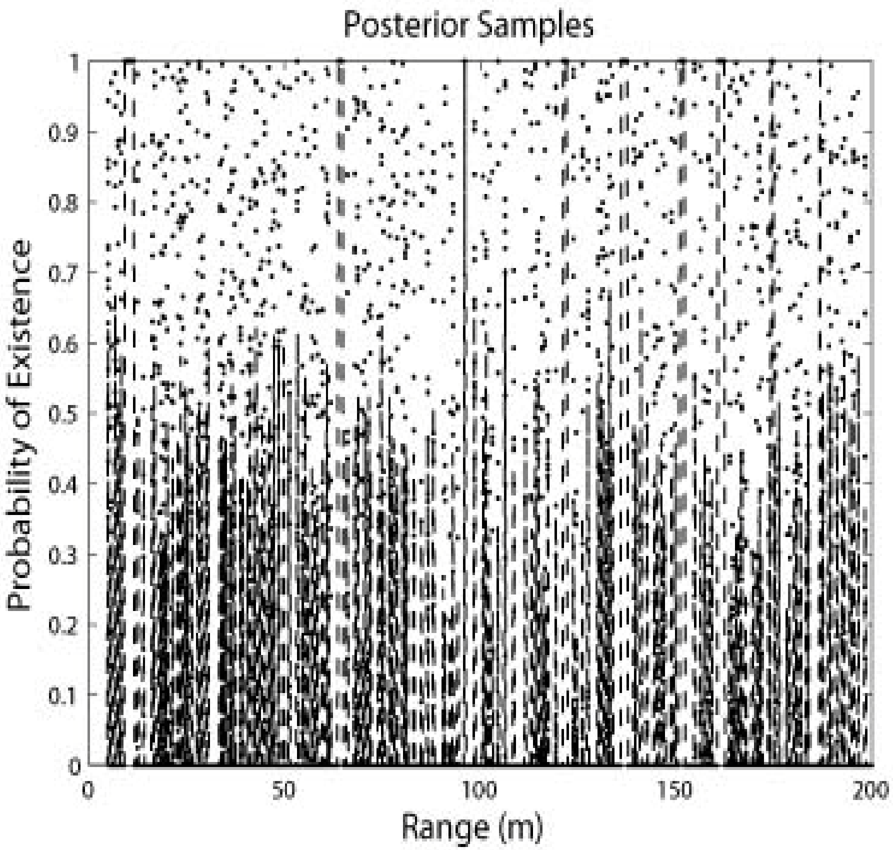


Particle approximations of

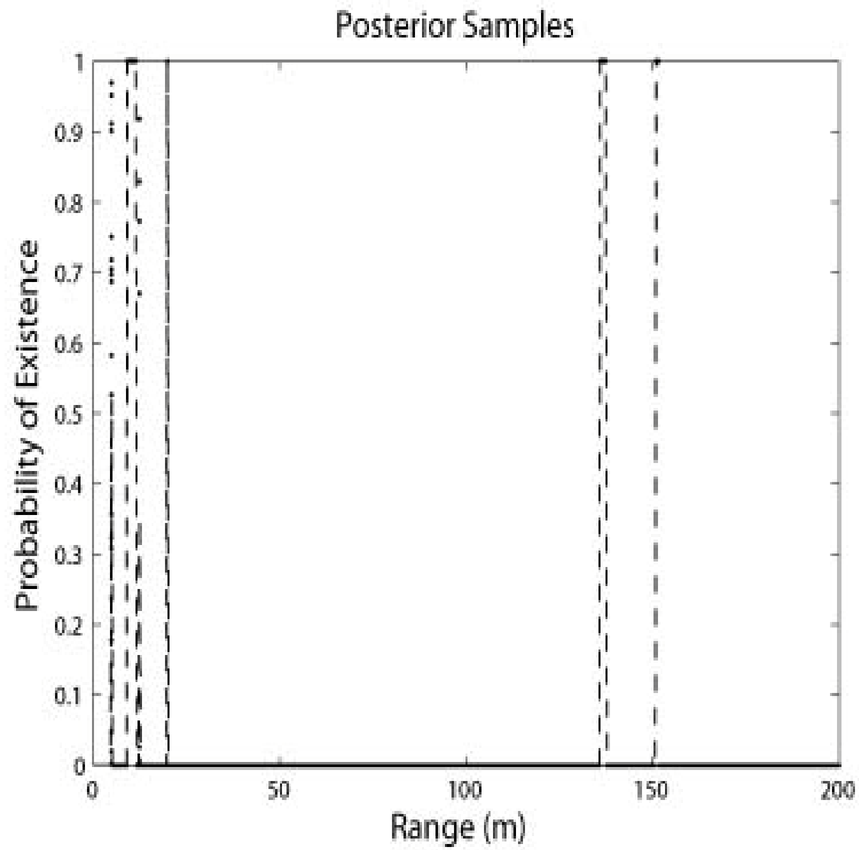
$$p(\mathbf{z}_{E_t=e} \mid \mathbf{m}_{E_t=e}) \text{ or } p(\mathbf{z}_{E_t=e} \mid \mathbf{m}_{E_t=\overline{e}})$$

Dashed line = mean prob. detection

Bayes Filter Results



Posterior existence samples after 1 filter iteration.

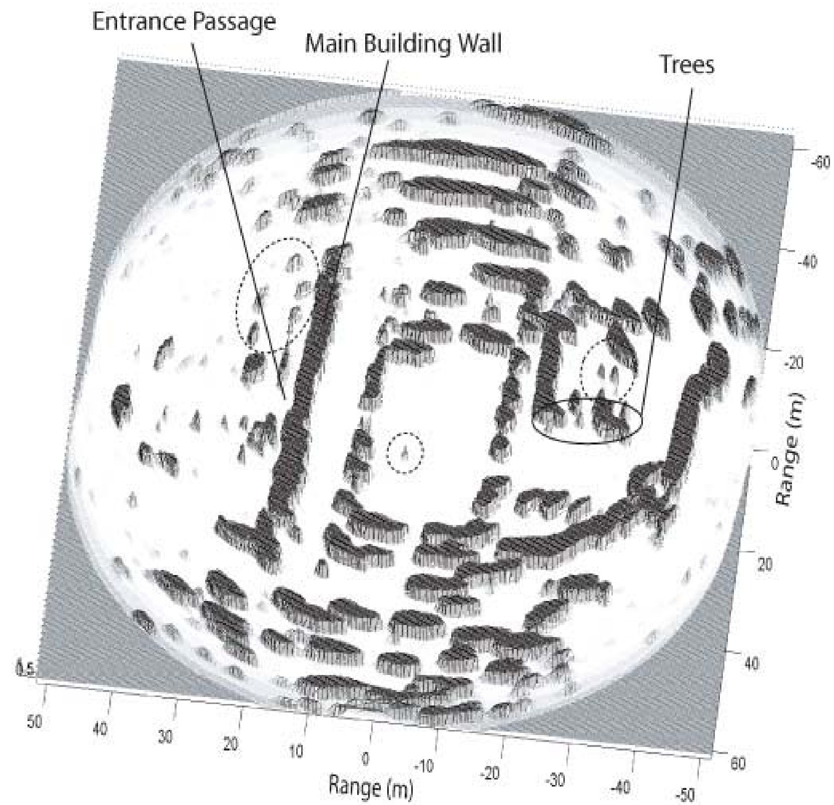


Posterior existence samples after 5 filter iterations

Bayes Filter Results

Bayes Filter Results

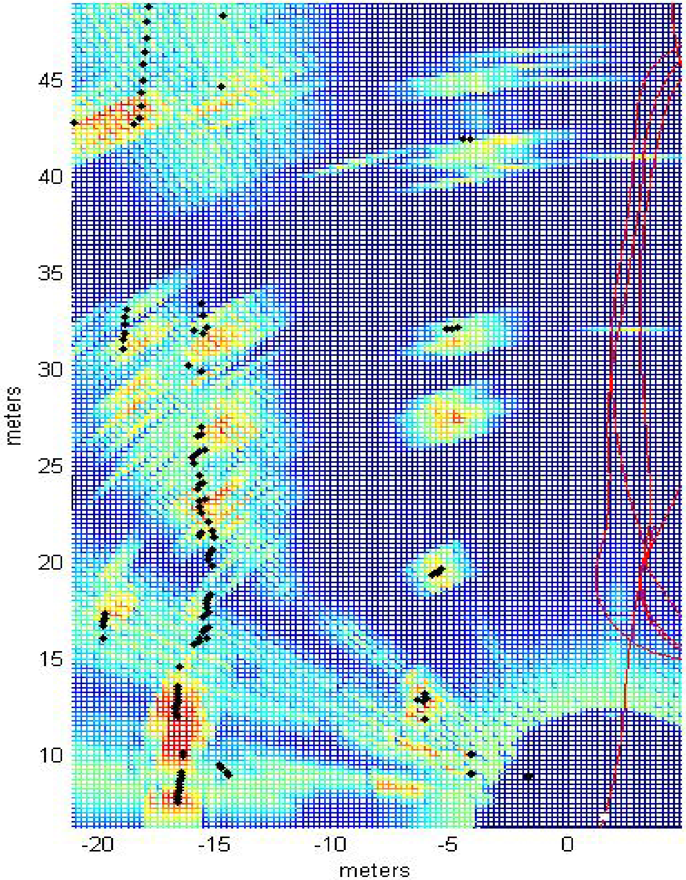
Photo of car park environment



5 Bayes filter fusion updates of P (existence)

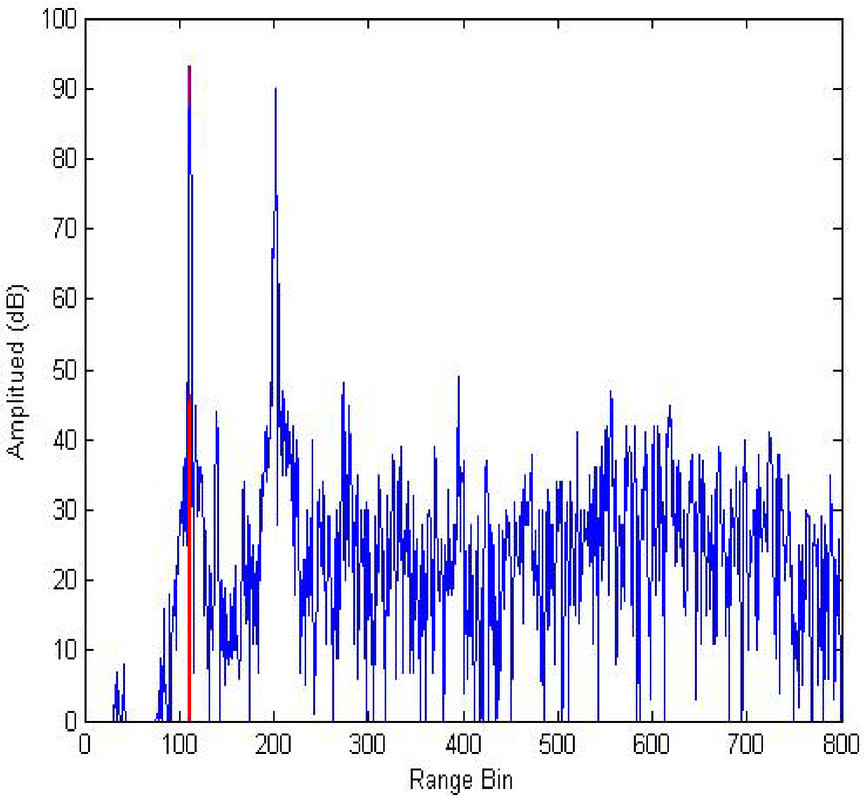
Bayes Filter Results

Note: Trees + lamp posts

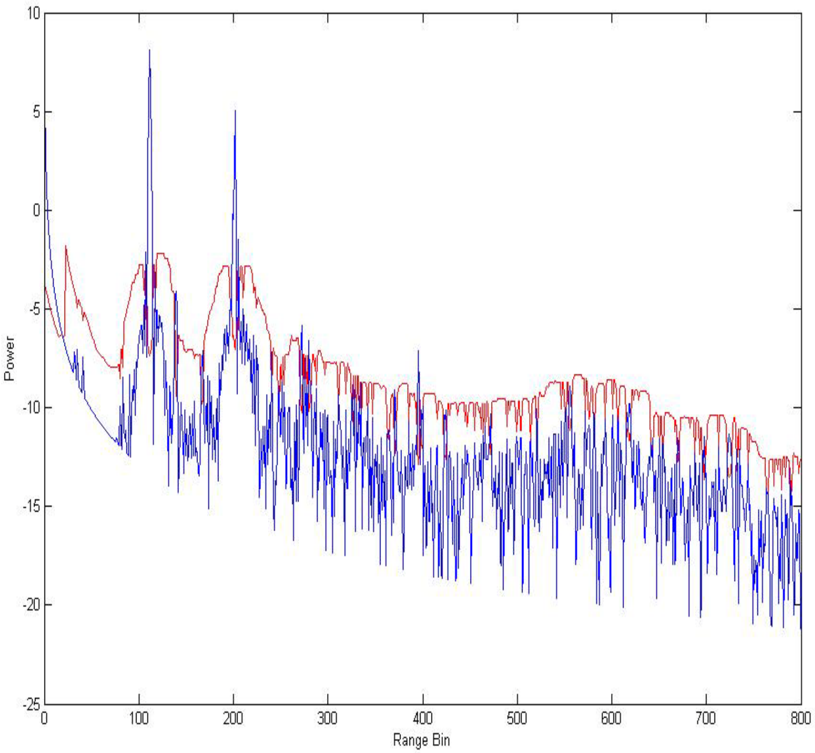


Note laser misses lamp posts,
But “seen” by RADAR.

Dempster Shafer Results

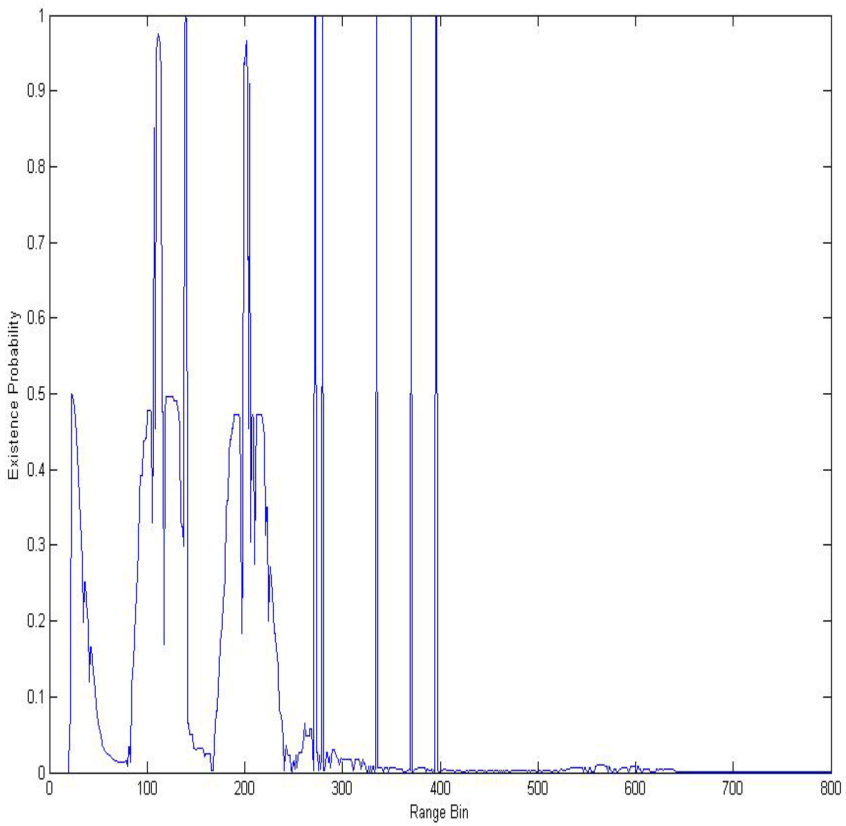


Single bearing, RADAR spectrum (blue) + laser range value (red).

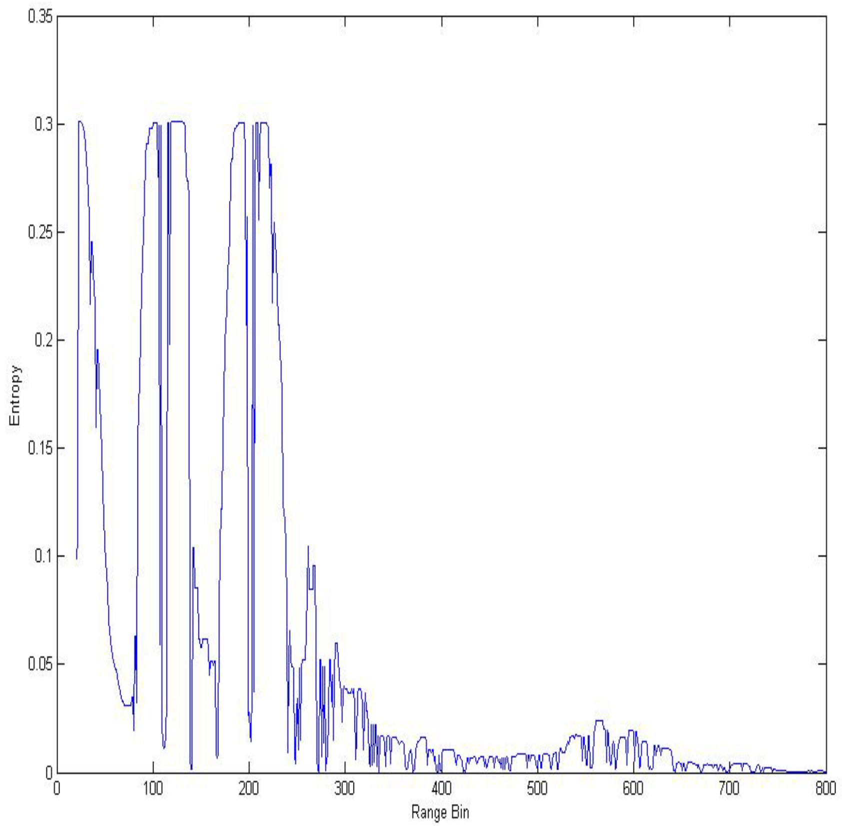


RADAR spectrum after range Compensation removal + CFAR threshold.

Dempster Shafer Results

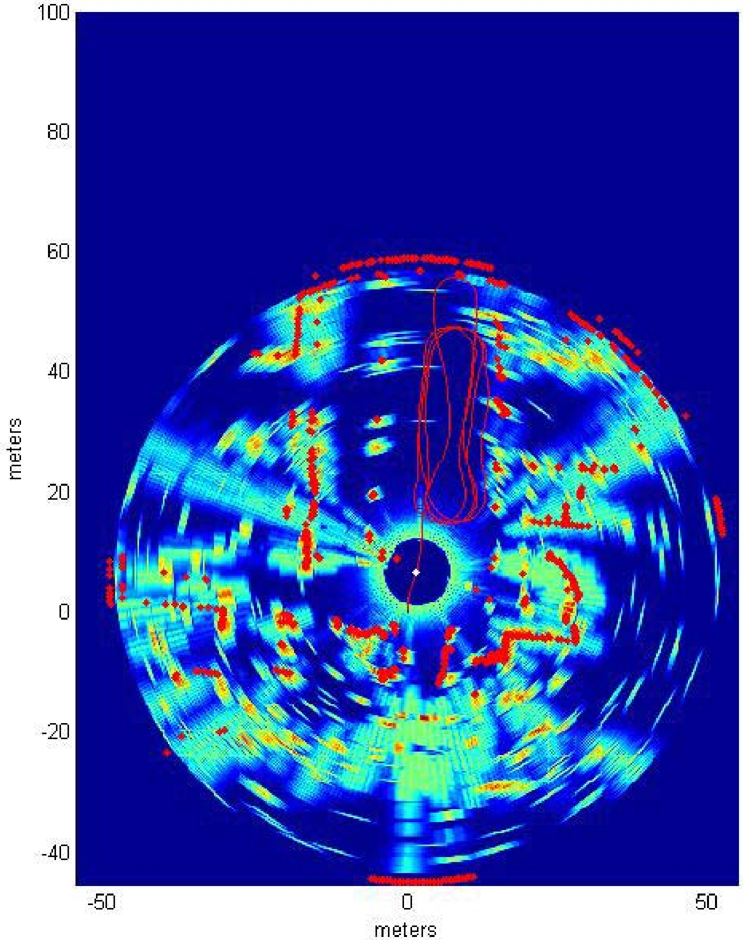


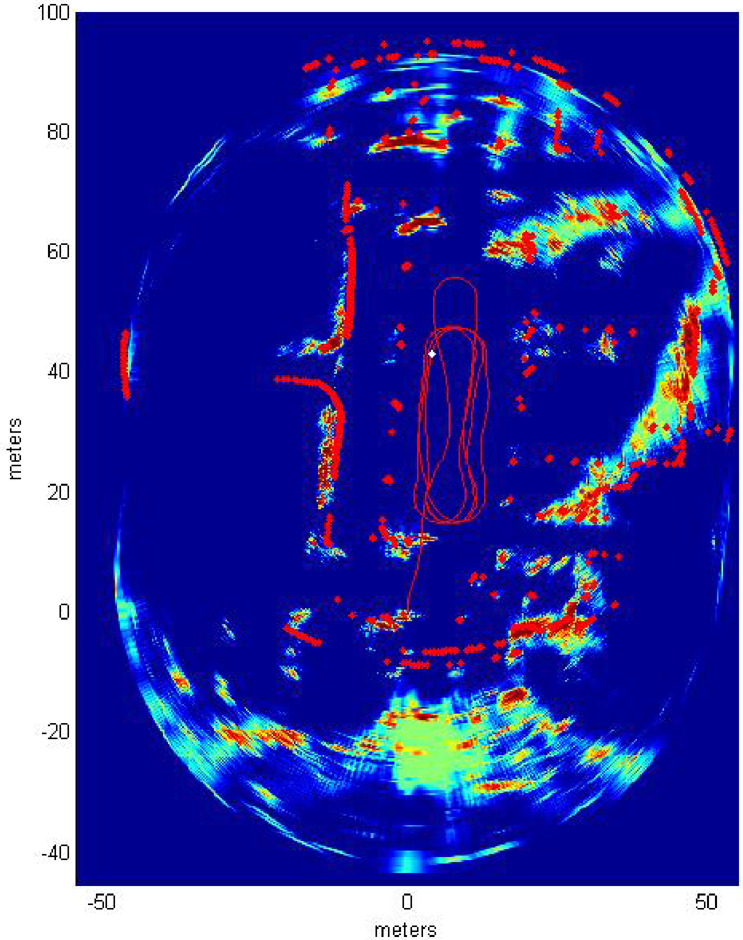
Single bearing, *P* (existence)



Single bearing entropy

Dempster-Shafer Results





P (existence) + laser scan (1 scan)

P (existence) + laser 9 scans.

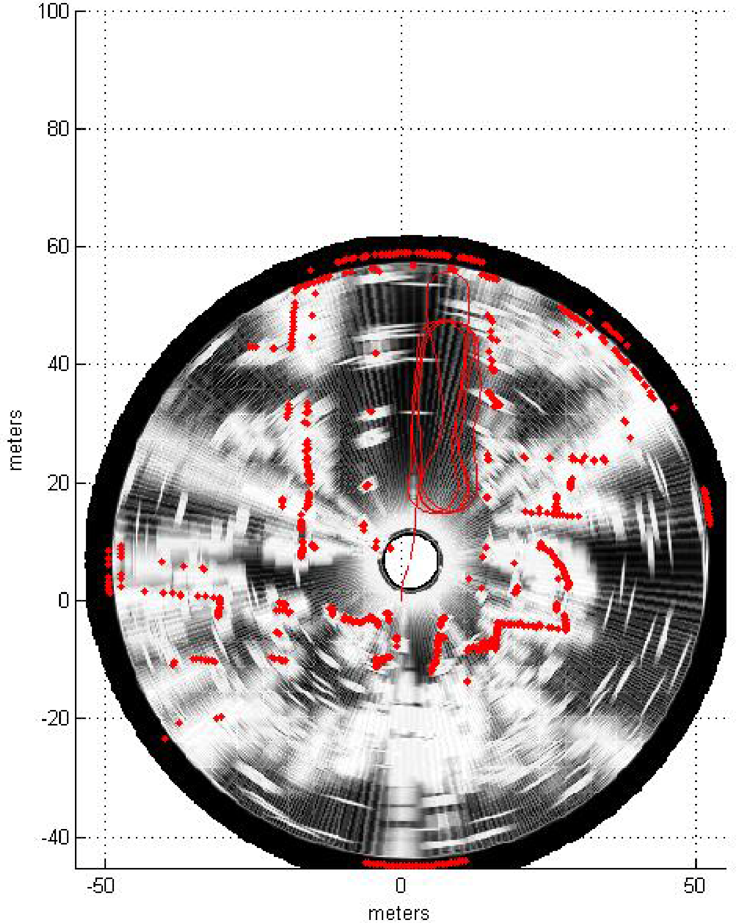
Exploration - Entropy

Entropy = measure of "unexplored" areas of scan – likely to provide maximum information.

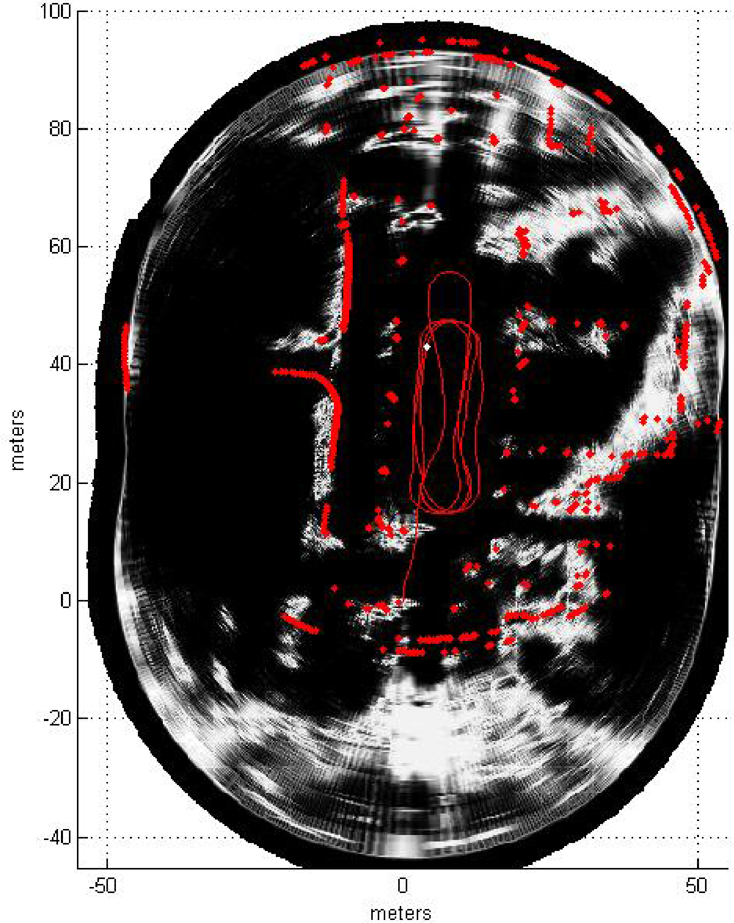
Simple to obtain from grid *P* (occupancy) values:

$$H(m_i) = -P_i \log P_i - (1 - P_i) \log (1 - P_i)$$

Dempster-Shafer Results

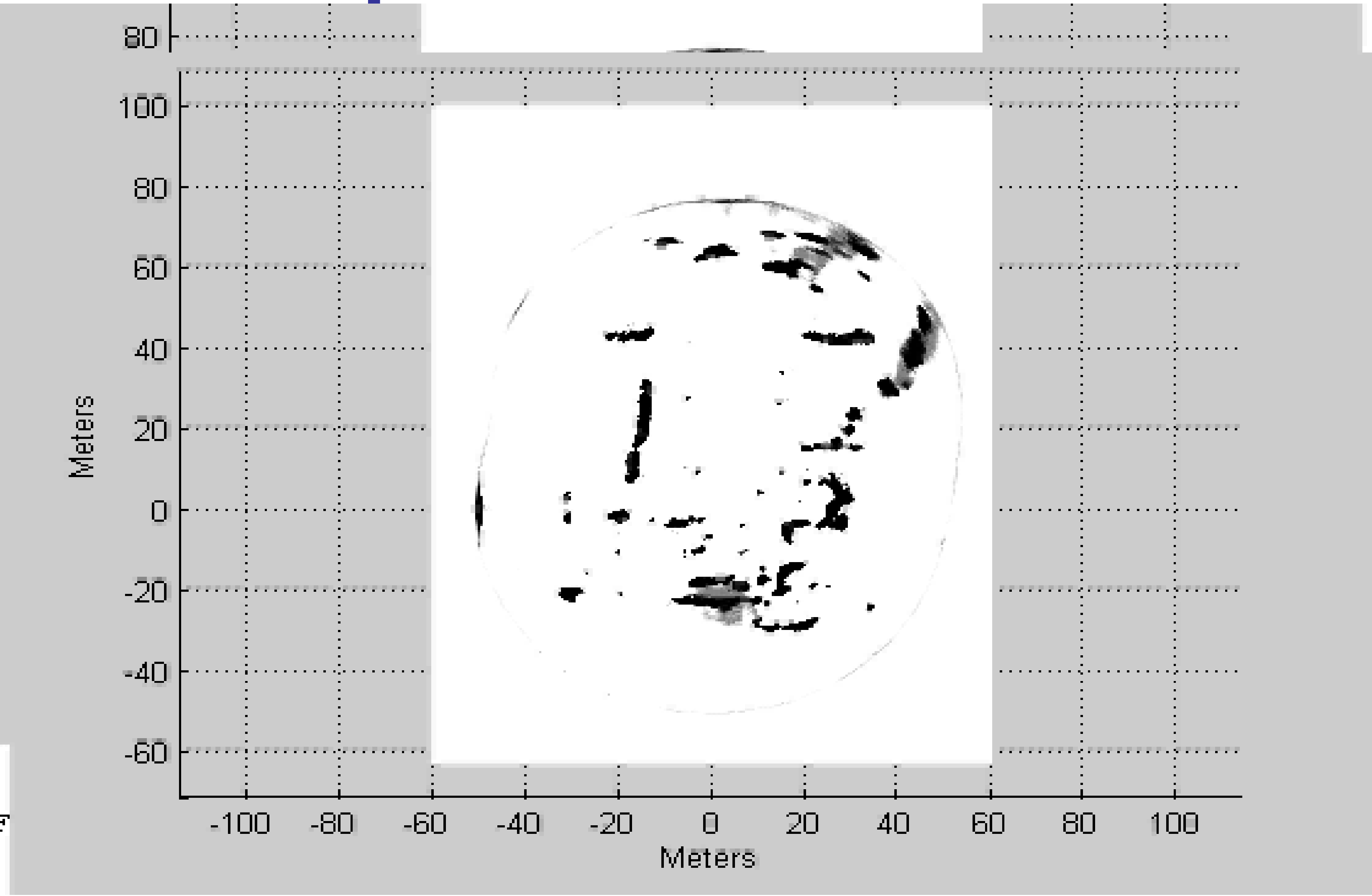


Entropy + laser scan (1 scan)

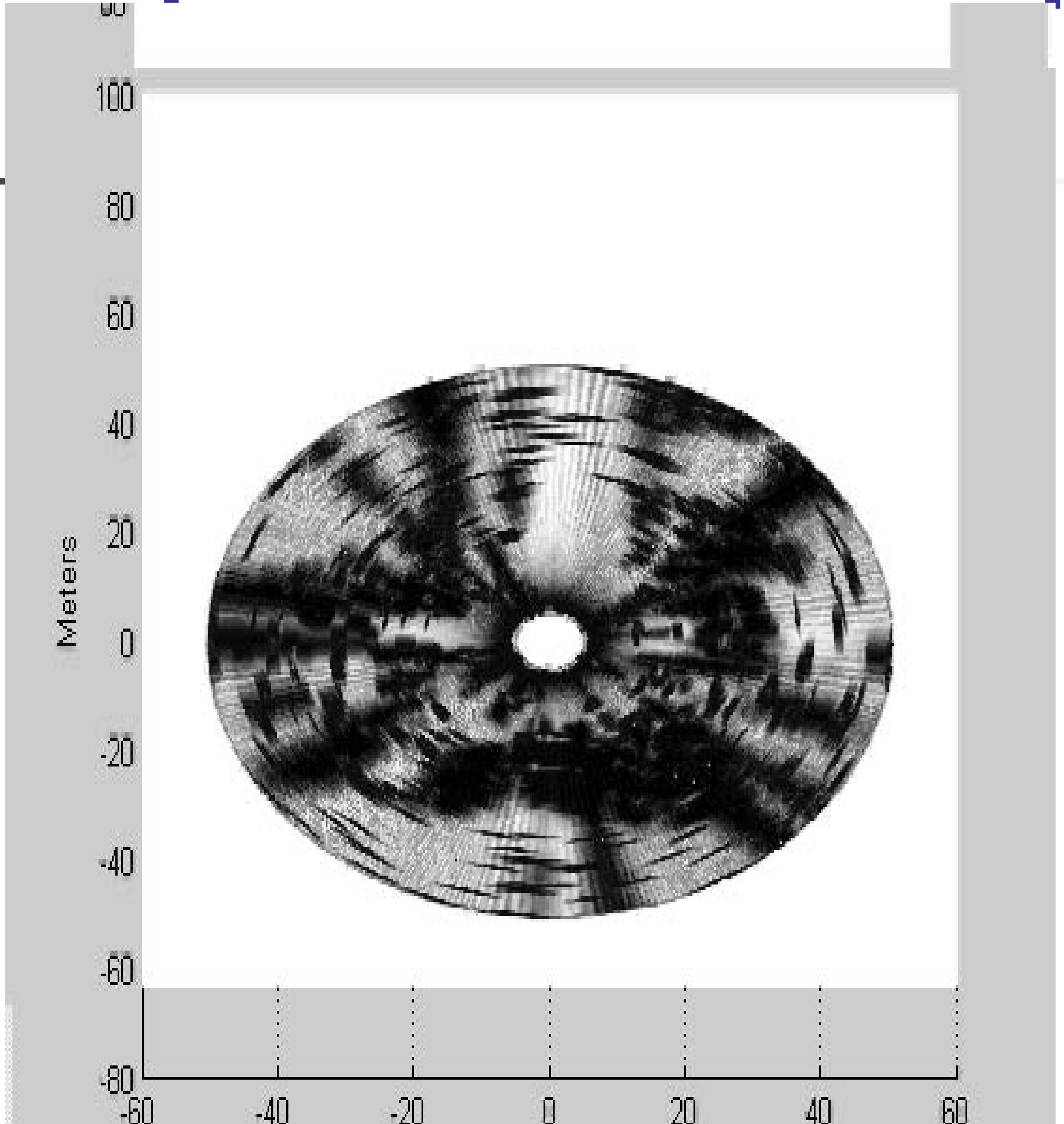


Entropy + laser 9 scans.

Dempster-Shafer Existence



Dempster-Shafer Entropy



Conclusions

- Probabilistic navigation including both spatial & existence map parameters.

- Bayes/Dempster-Shafer "Occupancy Filter" using measurement signal intensity information to propagate posterior density of existence random variables.

- Measurement Models for estimating probabilities of detection & false alarm.

- Experiments demonstrating map building and entropy based exploration with millimetre wave RADAR data.