Classification of Atomic Density Distributions using Scale Invariant Blob Localization

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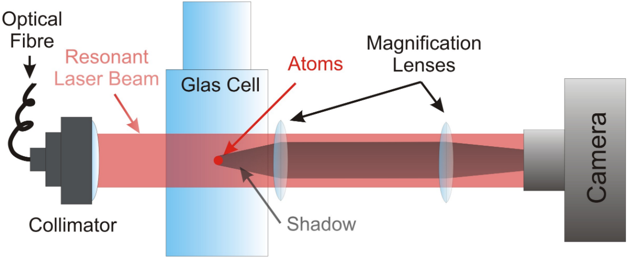
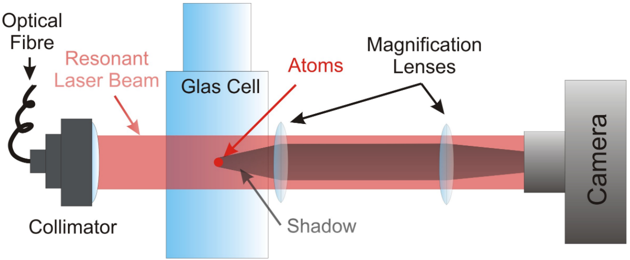
Bose-Einstein Condensate: Imaging System[1]



- At ultra-cold temperatures: capture atoms with a CCD camera

[1] Klempt, Scherer, Topic et al., Phys. Rev. Lett., Vol. 103, 104, 105 (2009/2010)

Bose-Einstein Condensate: Imaging System[1]



- At ultra-cold temperatures: capture atoms with a CCD camera
- Density distributions: Bessel functions J_l with zeros β_{nl}:

$$n_{nl}(\mathbf{r}) \propto J_l^2(\beta_{nl} \frac{|\mathbf{r}|}{r_{\mathrm{tf}}}) \qquad (|\mathbf{r}| < r_{\mathrm{tf}}) \tag{1}$$

- Atoms at different states $\Leftrightarrow$ Types of Bessel and zeros

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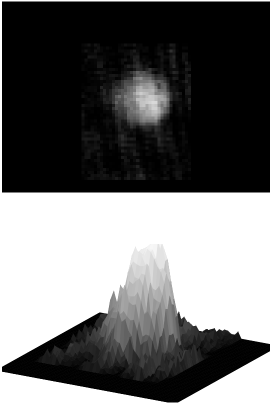
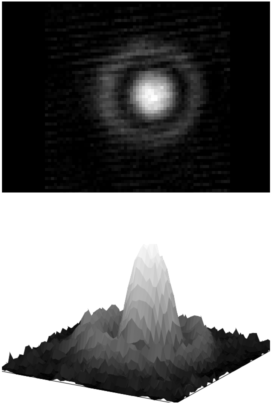
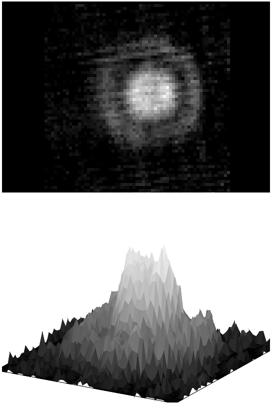
Atomic Density Distributions



$J_0^2, n = 1 \rightarrow I_0$

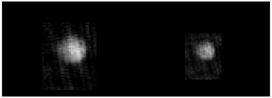


$J_0^2, n = 2 \rightarrow I_1$

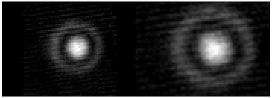


$J_1^2, n = 2 \rightarrow I_2$

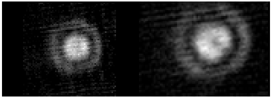
Goal: Automatic Classification



I_0



I_1



I_2

- Different scales, not necessarily circular
- Strong noise
- Known shape of inputs: Bessel functions

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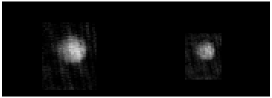
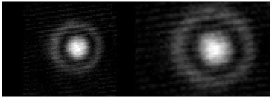
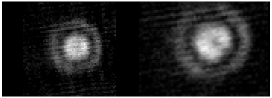


I_0



I_1



I_2

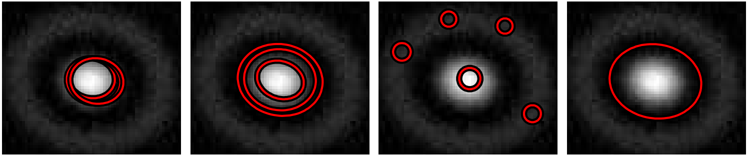
- Different scales, not necessarily circular
- Strong noise
- Known shape of inputs: Bessel functions

Determine location and shape parameters to perform classification:

- $I_0 \cup I_1$ differ from I_2 by the Curvature in its center
- I_0 and I_1 differ by a Ring Structure

Scale Invariant Feature Detection

- Image pyramid to obtain scale invariance (MSER: watershed based)
- Detect feature at dominant scale (*Scale Space Extremum*)



Hessian-Affine | MSER | SIFT | Proposed

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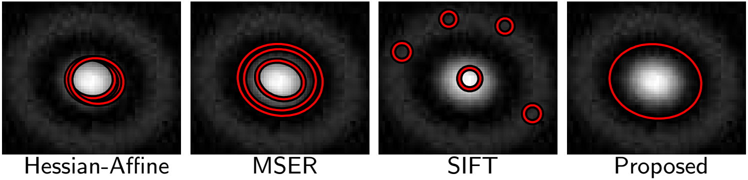

- Ambiguous results
- Shape not considered
- Accuracy ?

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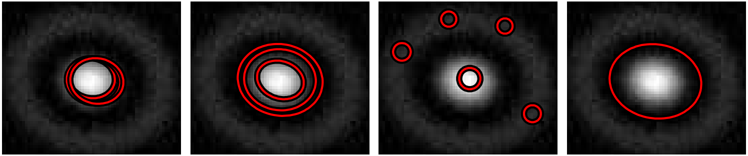


Hessian-Affine MSER SIFT Proposed

- Ambiguous results
- Shape not considered
- Accuracy ?

Proposed:

- Unique feature
- Localization of first zeros

Outline

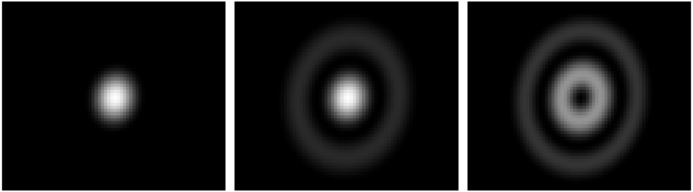
Localization of Atomic Density Distributions

Classification of Atomic Density Distributions

Results

Conclusion

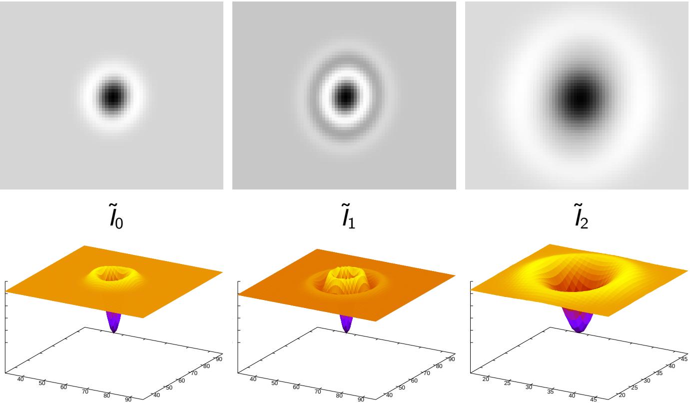
Feature Shape in the Scale Space



$\tilde{I}_0$ $\tilde{I}_1$ $\tilde{I}_2$

- Experimental analysis
- Synthetic test images of the three classes I_0, I_1, and I_2

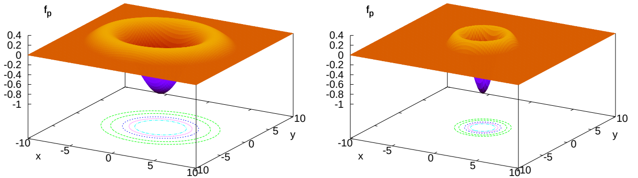
Feature Shape in the Scale Space



$\tilde{I}_0$ $\tilde{I}_1$ $\tilde{I}_2$

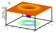
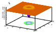
$DoG_{(0,3)}$ $DoG_{(0,2)}$ $DoG_{(1,3)}$

SINC Function Model



Function Model $f_{\mathbf{p}}$:

$$f_{\mathbf{p}}(\mathbf{x}) = \begin{cases} v \cdot \dfrac{\sin\sqrt{R_{\mathbf{x}_0,\Sigma}(\mathbf{x})}}{\sqrt{R_{\mathbf{x}_0,\Sigma}(\mathbf{x})}} & \text{, for } R_{\mathbf{x}_0,\Sigma}(\mathbf{x}) \leq t_0 \\ 0 & \text{, otherwise} \end{cases}$$

SINC Function Model  

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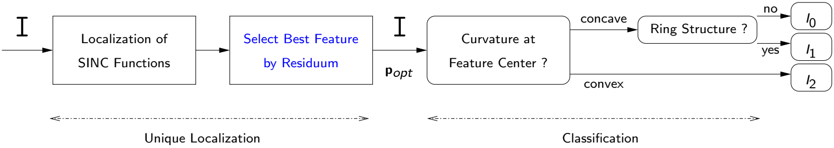
$$R_{\mathbf{x}_0,\Sigma}(\mathbf{x}) := (\mathbf{x} - \mathbf{x}_0)^\top \Sigma^{-1} (\mathbf{x} - \mathbf{x}_0), \qquad \Sigma = \begin{pmatrix} a^2 & b \\ b & c^2 \end{pmatrix}$$

Minimize Residuum $e_{\mathbf{p}}$ using LM

$$e_{\mathbf{p}} = \sum_{\mathbf{x} \in \mathcal{N}} \left(f_{\mathbf{p}}(\mathbf{x}) - DoG_{(o,i)}(\mathbf{x}) \right)^2 \qquad (3)$$

$$\mathbf{p} = (x_0, y_0, a, b, c, v)$$

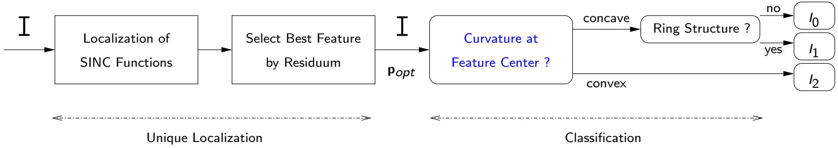
Workflow Diagram



Select best feature:

- Choose feature with minimal Residuum $e_{\mathbf{p}_{opt}}$
- Brute force search
- Computational expense increases, but acceptable (10 sec / image)

Workflow Diagram

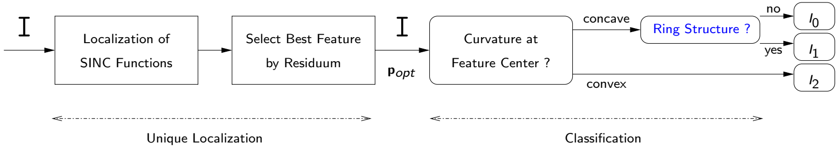


Curvature at Feature Center:

Evaluate gradients (DoG) in neighborhood $\mathcal{N}$:

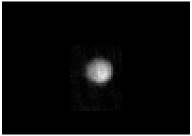
$$\mathcal{N} concave \Rightarrow \quad I_0 \cup I_1$$
$$\mathcal{N} convex \Rightarrow \quad I_2$$

Workflow Diagram

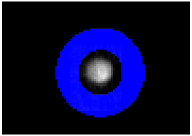


Ring Structure Localization:

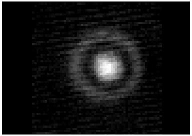
- Use function parameters $\mathbf{p}_{opt}$ to determine ring area $\mathcal{S}$



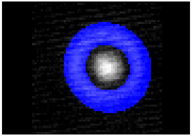
Input I_0



$\mathcal{S}$ of I_0

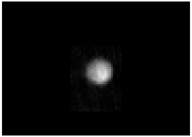


Input I_1

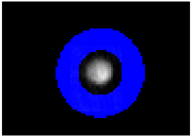


$\mathcal{S}$ of I_1

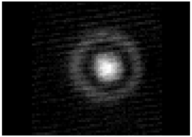
Normalized Energy Function



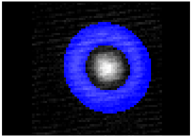
Input I_0



$\mathcal{S}$ of I_0



Input I_1



$\mathcal{S}$ of I_1

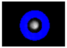
Normalized Energy $E_{\mathcal{S}}$:

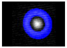
$$E_{\mathcal{S}} = \frac{1}{A_{\mathcal{S}}} \int_{S} |\mathtt{I}(\mathbf{x})|^2 d\mathbf{x}$$

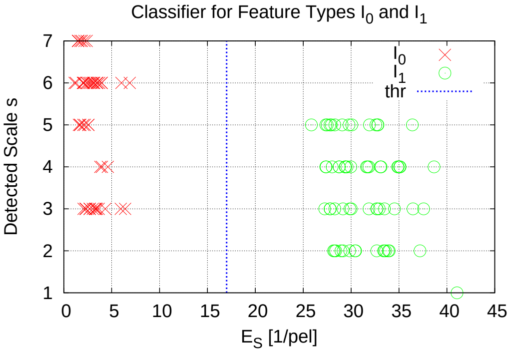
Classification:

$$E_{\mathcal{S}} < thr \Rightarrow I_0$$
$$E_{\mathcal{S}} > thr \Rightarrow I_1$$

Energy E_S







- Simple threshold value *thr* sufficient
- Scale invariant classification

Classification rate

	I_0	I_1	I_2	Σ
TP_{Curv}	96.2%		75.0%	85.6%
TP_{Ring}	100%	100%	–	100%
TP_{Σ}	96.2%	100%	75.0%	90.4%

True Positives (TP)

- *Curvature* stage: TP_{Curv} : 85.6%
- *Ring Structure* stage TP_{Ring} : 100%

Summary:

- New robust and accurate blob detector
- Incorporate known shape of targets
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- Incorporate known shape of targets
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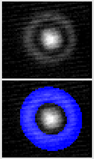
- Application: classification of atomic densities

→ Perfect Ring Structure detection

→ Overall classification rate : 90.4%



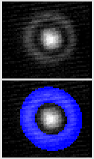
Conclusion

Summary:

- New robust and accurate blob detector
- Incorporate known shape of targets
- Extract shape parameters from blobs
- Application: classification of atomic densities

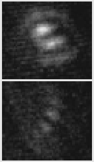
→ Perfect Ring Structure detection

→ Overall classification rate : 90.4%

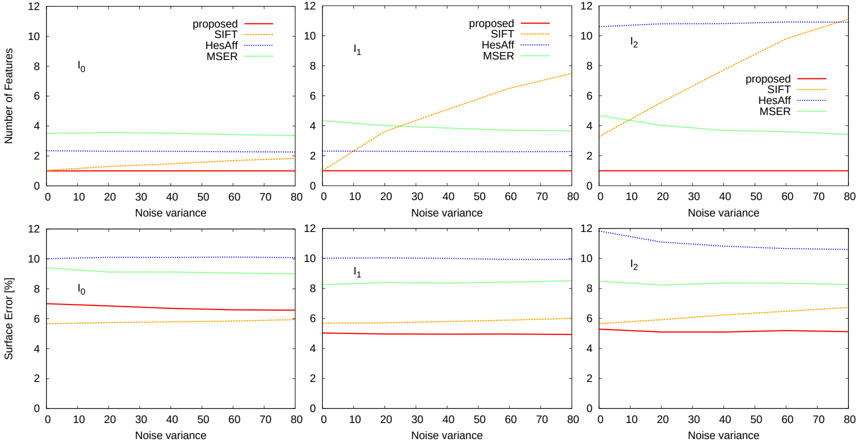


Future Work:

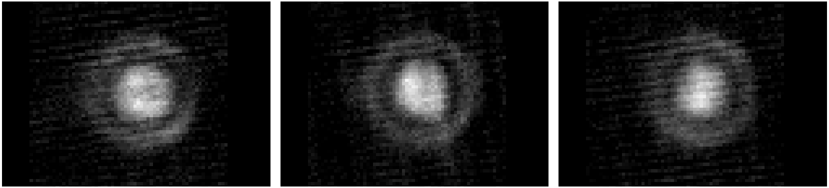
- Estimate noise structure and compensate
- Classify more Atom Distribution Types



Top: number of detected features, Bottom: the mean *Surface Error*

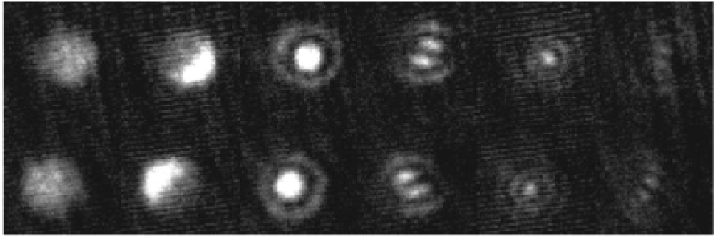


Classification failure examples for features I_2



- Misclassification caused by strong noise covering the convex shape in the feature center
- $\Rightarrow$ Blobs of type I_2 very similar to I_1.

More Atom Distribution Types[2]



[2] Scherer et al., Phys. Rev. Lett., Vol. 105 (2010)