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Statistical Inference for Image **Symmetries**

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OUTLINE

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II Image Representation in the Radial Basis Domain

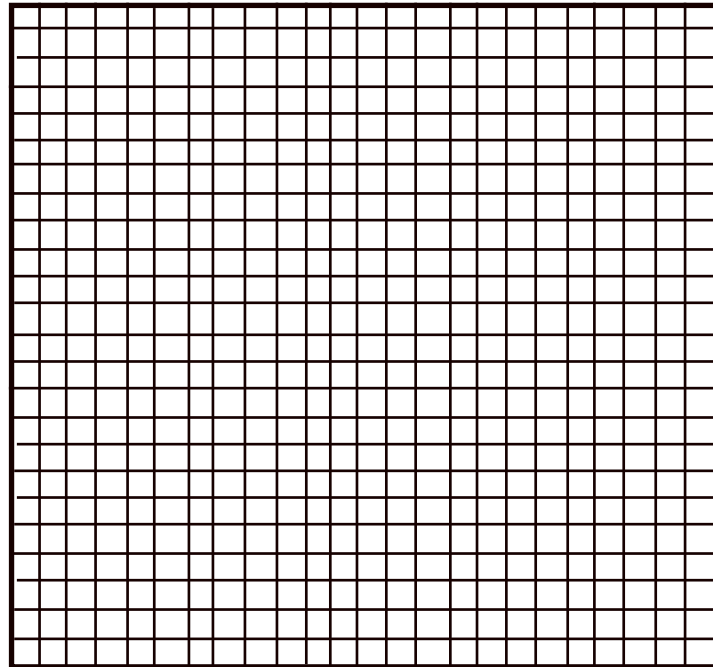
III Semiparametric Inference for Image Symmetry

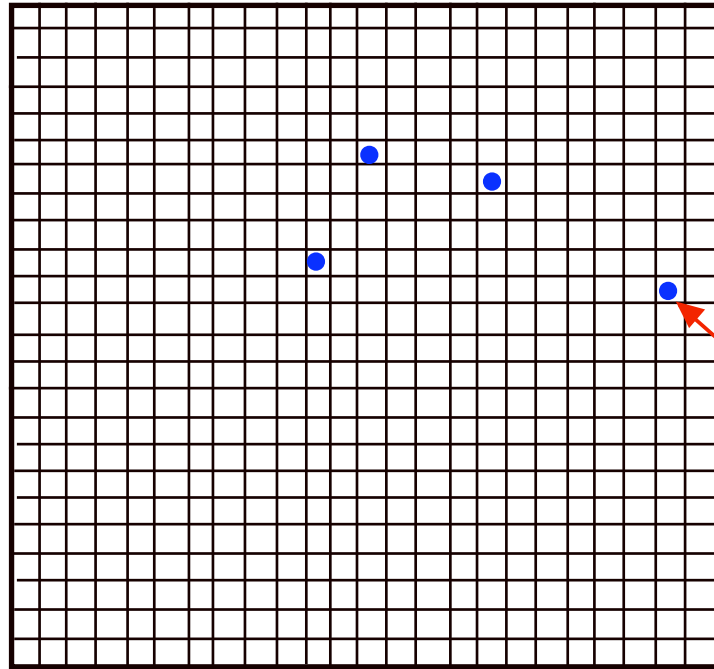
IV Testing for Image Symmetries*

- **Testing Rotational Symmetries***
 - **Testing Radiality**
 - **Testing Reflection and Joint Symmetries**
-

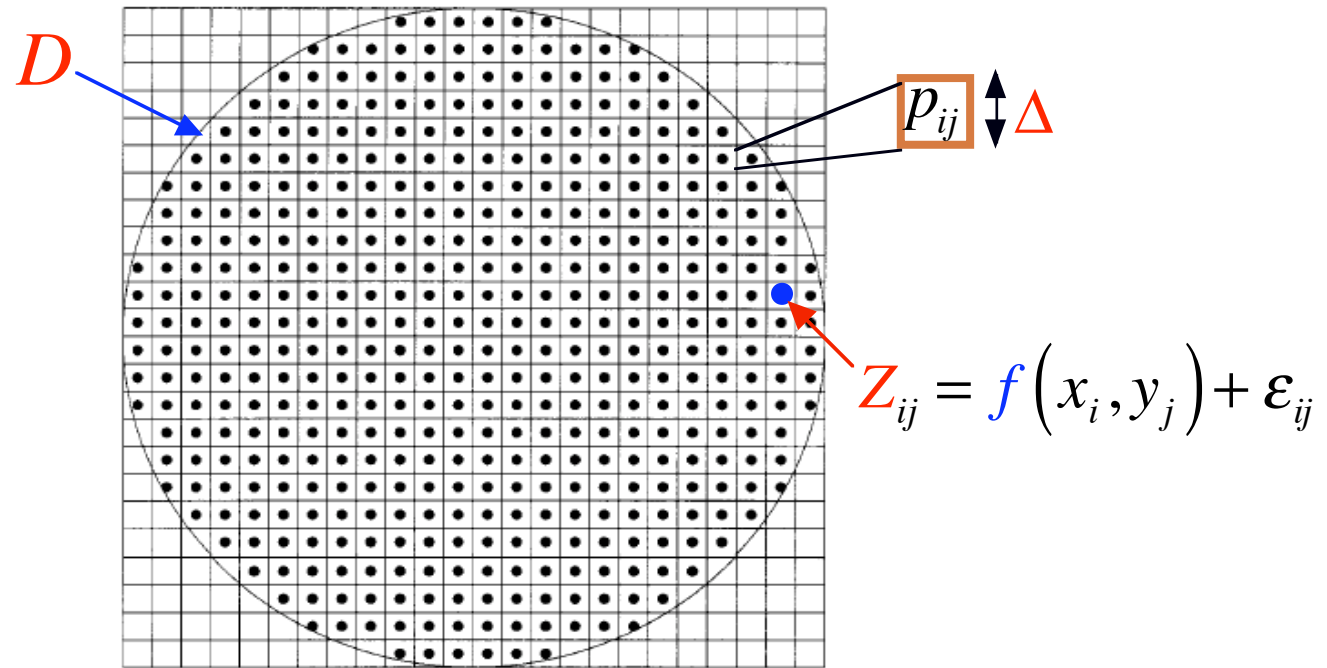
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I Problem Statement





$$Z_{ij} = f(x_i, y_j) + \varepsilon_{ij}$$



of data points $\propto n^2$; $\Delta \propto n^{-1}$

Problem 1: Let $f \in L_2(\mathbf{D})$. Given

$$Z_{ij} = f(x_i, y_j) + \varepsilon_{ij}, \quad 1 \leq i, j \leq n$$

and knowing that

$$f(x, y) = f(x \cos(2\beta^*) + y \sin(2\beta^*), x \sin(2\beta^*) - y \cos(2\beta^*))$$

some $\beta^* \in [0, \pi)$, estimate β^* .

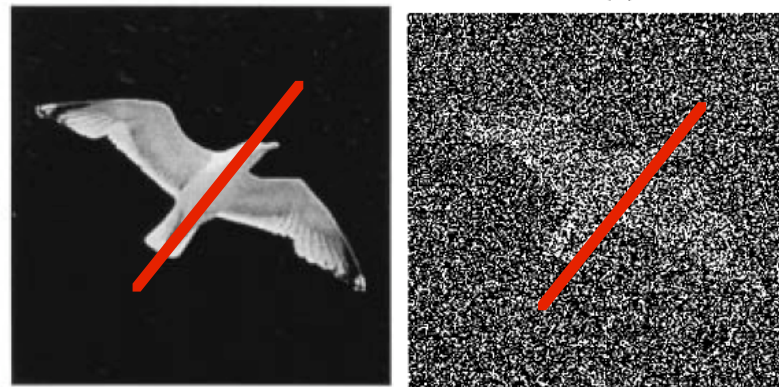
Problem 1: Let $f \in L_2(\mathbf{D})$. Given

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some $\beta^* \in [0, \pi)$, estimate β^* .



Problem 2: Let $f \in L_2(\mathbf{D})$. Given

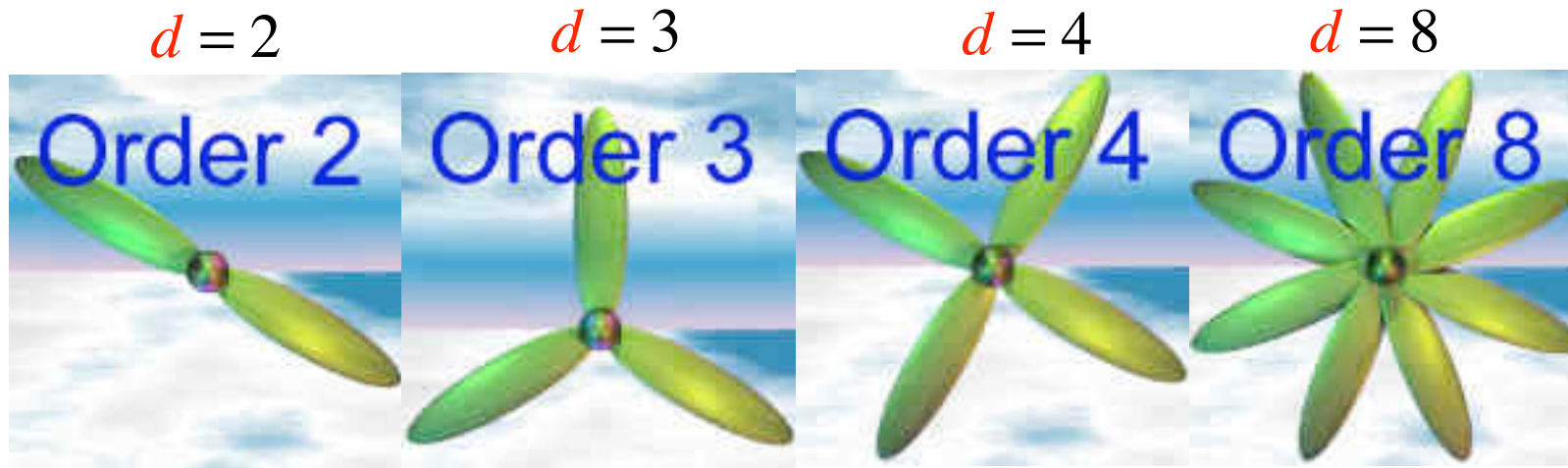
$$Z_{ij} = f(x_i, y_j) + \varepsilon_{ij}, \quad 1 \leq i, j \leq n$$

verify whether the null hypothesis

$$H^S : f(x, y) \equiv (Sf)(x, y)$$

is true or not

$(Sf)(x, y)$: **Reflectional** Symmetry, **Rotational** Symmetry



An image becomes invariant under rotations through an angle $\frac{2\pi}{d}$



$$d = \infty$$

Radially Symmetric Objects

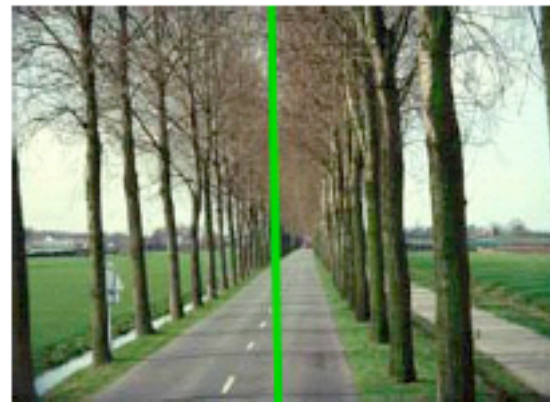
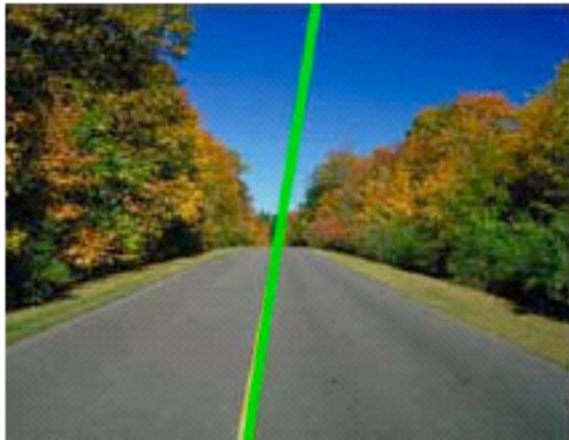
$$f(x, y) = g\left(\sqrt{x^2 + y^2}\right)$$

► **Symmetry**

- Hermann Weyl, *Symmetry*, Princeton Univ. Press, 1952.
 - J. Rosen, *Symmetry in Science: An Introduction to the General Theory*, Springer, 1995.
 - J.H. Conway, H. Burgiel, and C. Goodman-Strauss, *The Symmetry of Things*, A K Peters, 2008.
 - M. Livio, *The Equation That Couldn't Be Solved: How Mathematical Genius Discovered the Language of Symmetry*, Simon & Schuster, 2006.
- “...Livio writes passionately about the role of **symmetry** in human perception, arts,....”



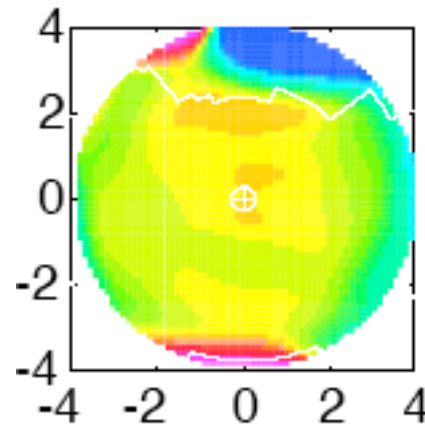
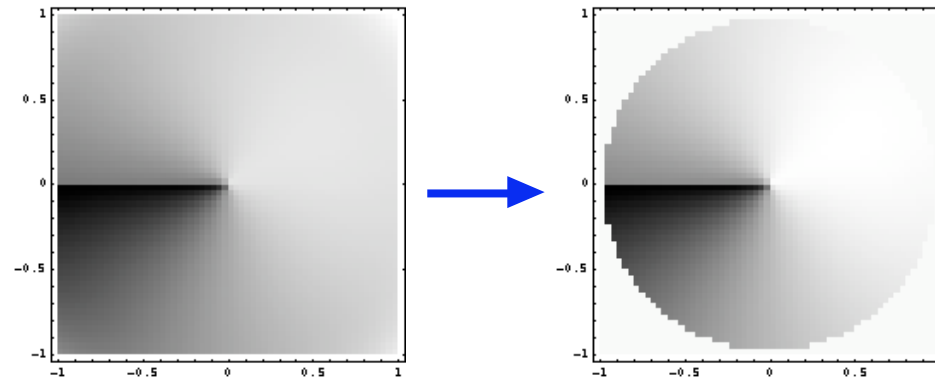
A E







II Image Representation in the Radial Basis Domain



■ Radial **Moments** and **Expansions (Zernike Basis)**

- $A_{pq}(f) = \iint_D f(x,y) V_{pq}^*(x,y) dx dy$

$$= \int_0^{2\pi} \int_0^1 f(\rho, \theta) R_{pq}(\rho) e^{-iq\theta} \rho d\rho d\theta$$

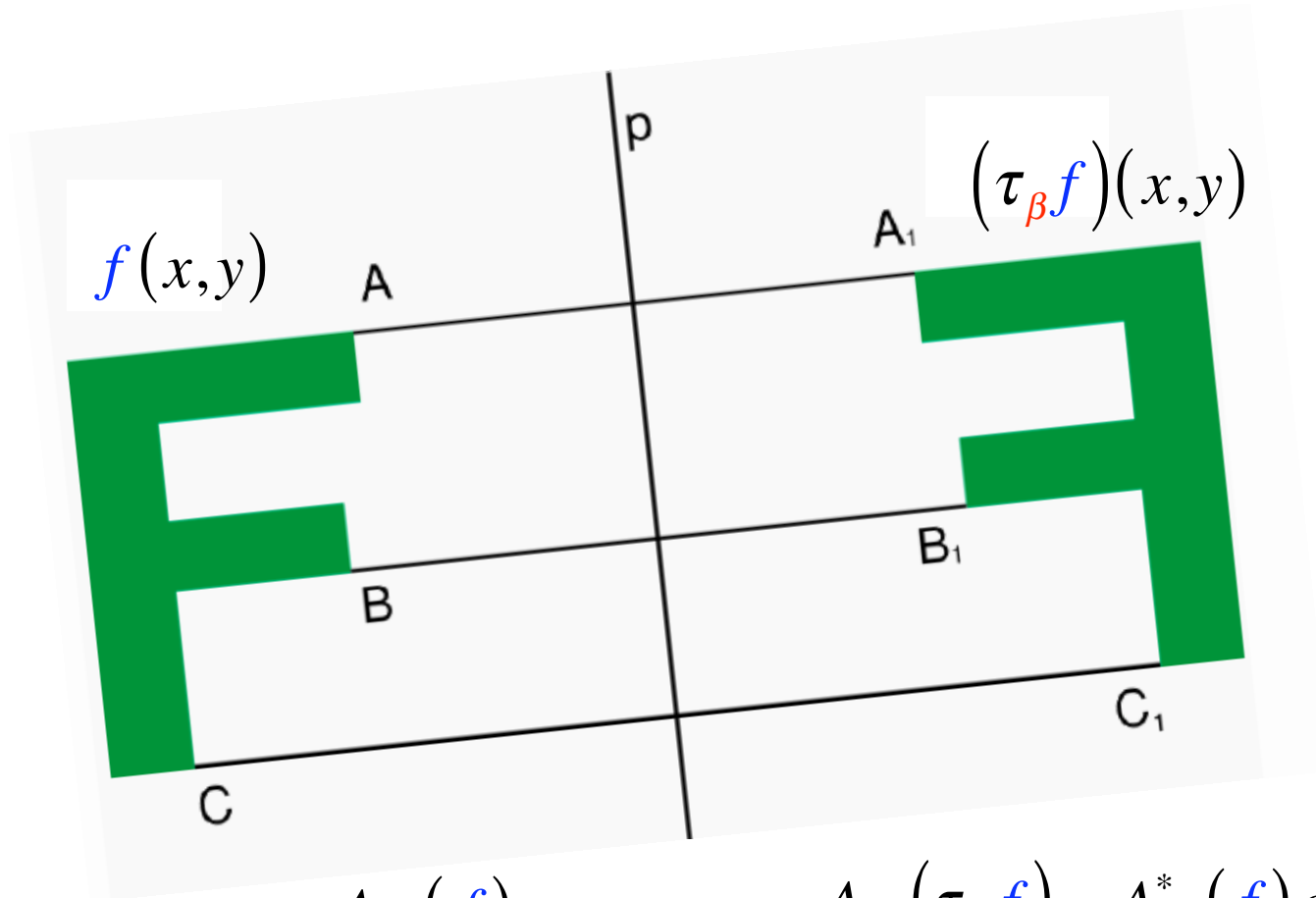
Degree
Angular dependence

Bhatia & Born: "On circle polynomials of Zernike and related orthogonal sets".
Proc. Cambr. Phil. Soc. 1954

- $L_2(D) \ni f(x,y) \approx \sum_{p=0}^{\infty} \sum_{|q| \leq p} \frac{p+1}{\pi} A_{pq}(f) V_{pq}(x,y)$

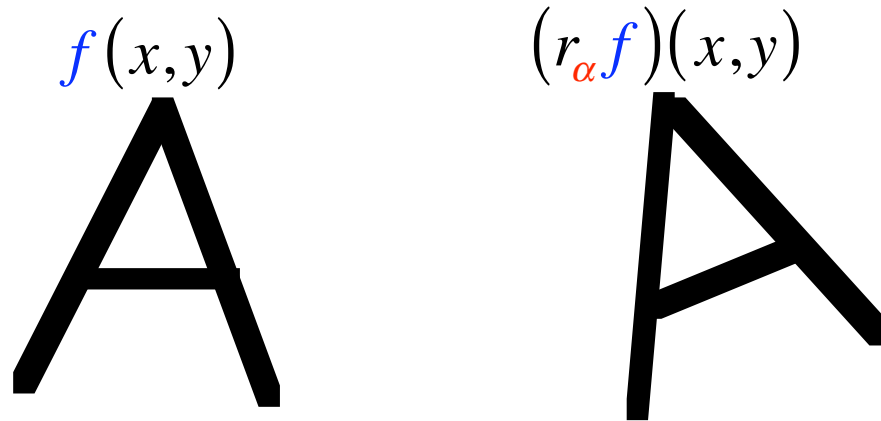
■ **Invariant Properties**

→ **Reflection**



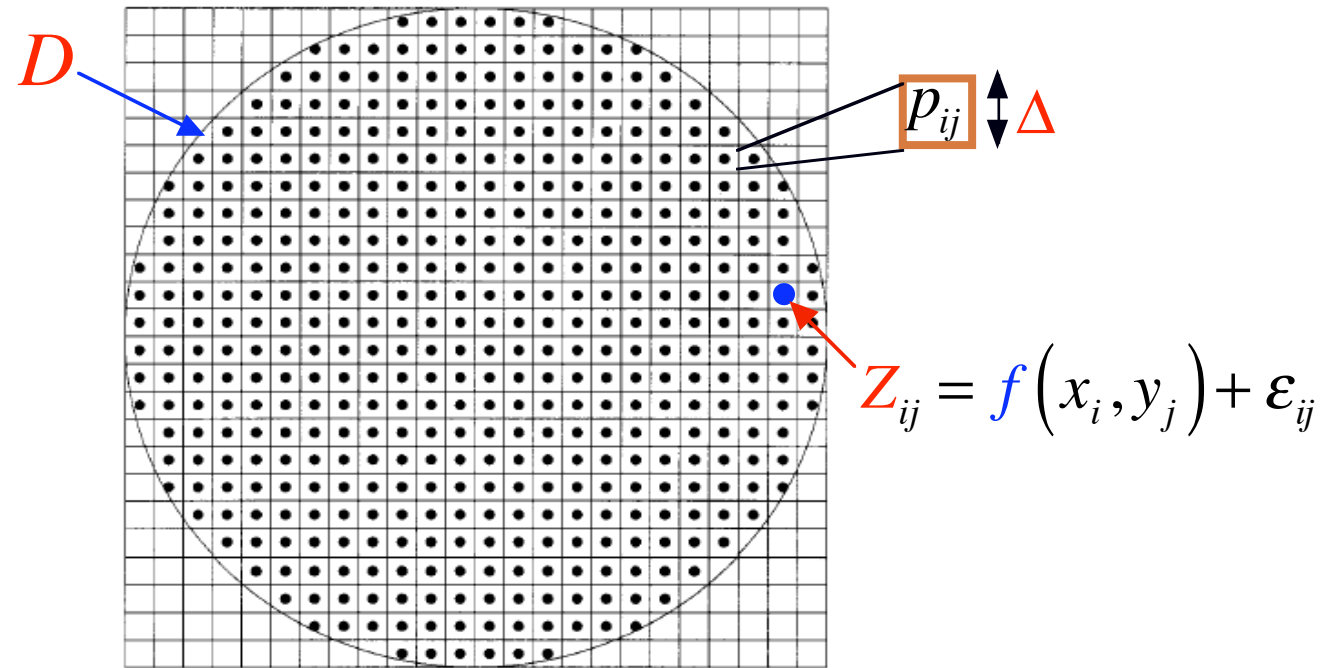
$$A_{pq}(f) \longrightarrow A_{pq}(\tau_\beta f) = A_{pq}^*(f) e^{-i2q\beta}$$

→ **Rotation**



$$A_{pq}(f) \longrightarrow A_{pq}(r_\alpha f) = A_{pq}(f) e^{-iq\alpha}$$

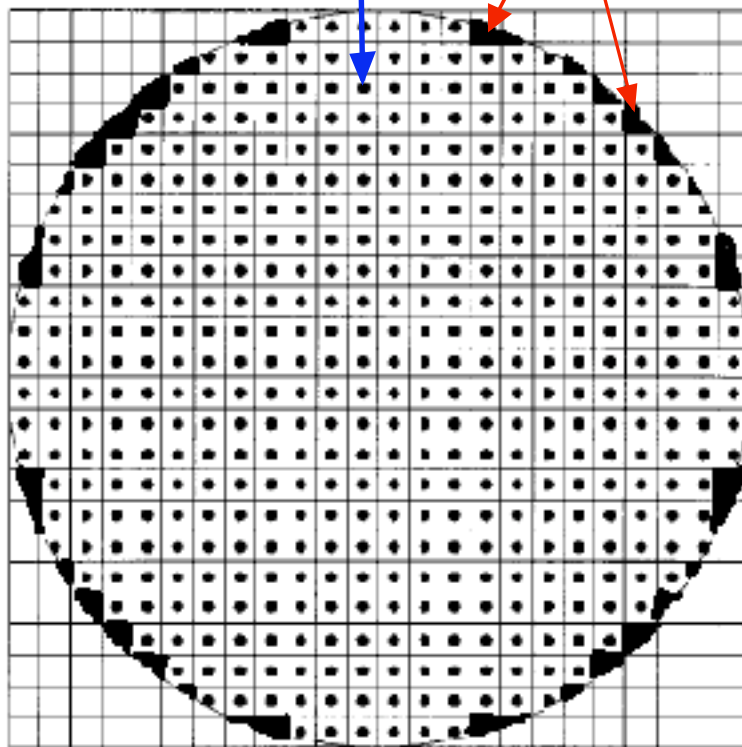
■ $A_{pq}(f)$ from noisy data



$$\hat{A}_{pq}(f) = \sum_{(x_i, y_j) \in D} w_{pq}(x_i, y_j) z_{ij}$$

$$w_{pq}(x_i, y_j) = \iint_{p_{ij}} V_{pq}^*(x, y) dx dy \approx \Delta^2 V_{pq}^*(x_i, y_j)$$

$$E\hat{A}_{pq} = A_{pq}(f) + D_{pq}(\Delta) + G_{pq}(\Delta)$$



$$D_{pq}(\Delta) = O(\Delta)$$

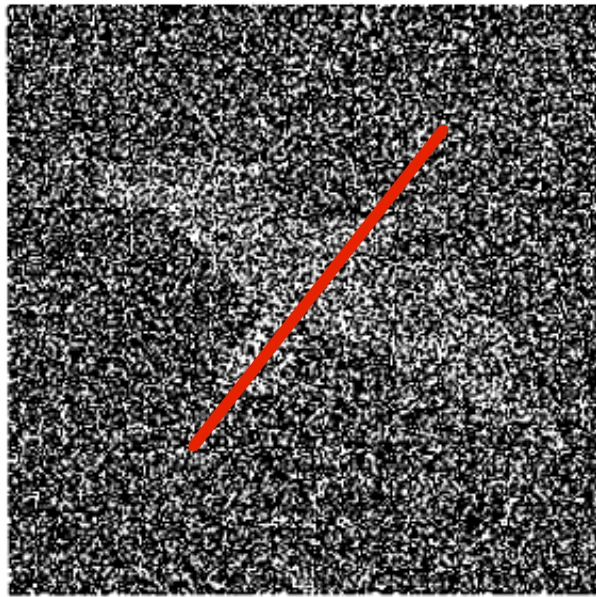
$$G_{pq}(\Delta) = O(\Delta^\gamma)$$

$$1 < \gamma = \frac{285}{208}$$

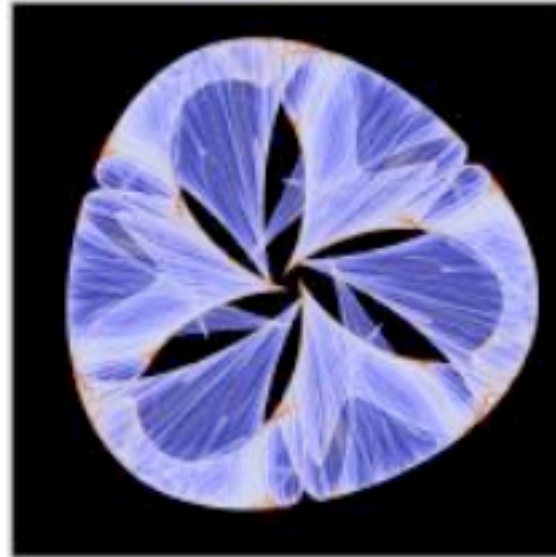
*Gauss lattice points problem of a circle *

III Semiparametric Inference for Image Symmetry

Estimation of symmetry parameters: the **axis of symmetry** (β), the **degree** of rotational symmetry (d) of **nonparametric** image function: $\theta = \theta(f)$, $f \in L_2(D)$.



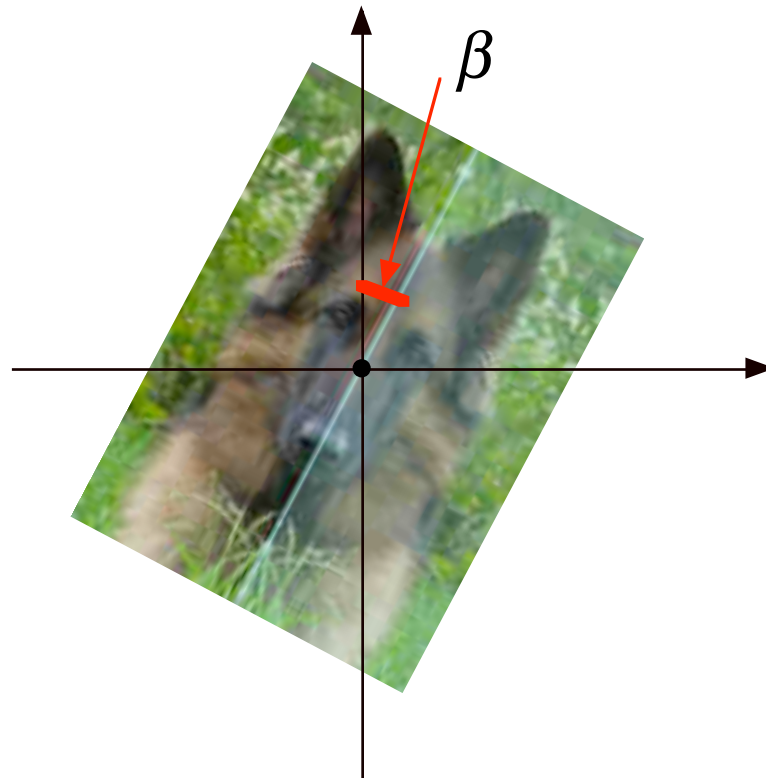
β^*



d^*

Semiparametric Inference on the Axis of Reflectional Symmetry

$$A_{pq}(\tau_{\beta} f) = e^{-2iq\beta} A_{p,-q}(f)$$



- **Contrast Function**

$$M_N(\beta, f) = \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p \left| A_{pq}(f) - e^{-2iq\beta} A_{p,-q}(f) \right|^2$$



$$\begin{aligned}
 M(\beta, f) &= \sum_{p=0}^{\infty} \frac{p+1}{\pi} \sum_{q=-p}^p \left| A_{pq}(f) - e^{-2iq\beta} A_{p,-q}(f) \right|^2 \\
 &= \left\| f - \tau_{\beta} f \right\|^2
 \end{aligned}$$

- **Assumption**

Suppose that $f \in L_2(D)$ is **invariant** under some unique reflection τ_{β^*}

Hence, if $\tau_{\beta^*} f = f$ then we have

$$M(\beta^*, f) = 0$$

or

$$M_N(\beta^*, f) = 0 \text{ for all } N$$

- **Uniqueness** of β^*

Lemma U: Under **Assumption** the solution of

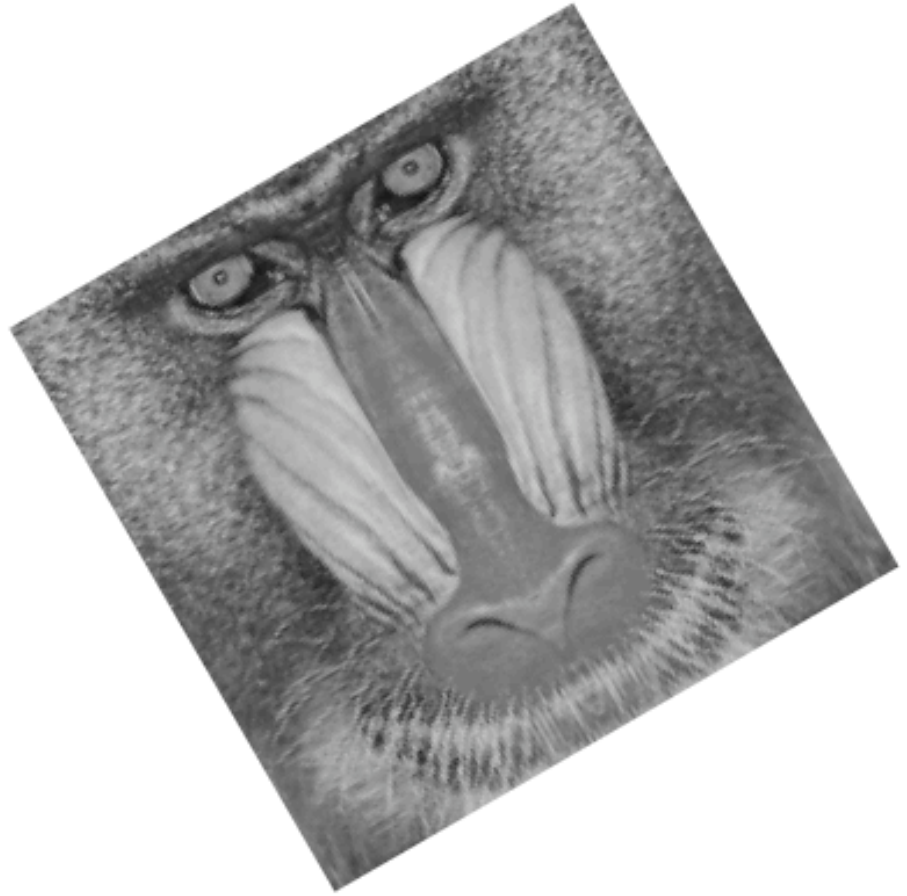
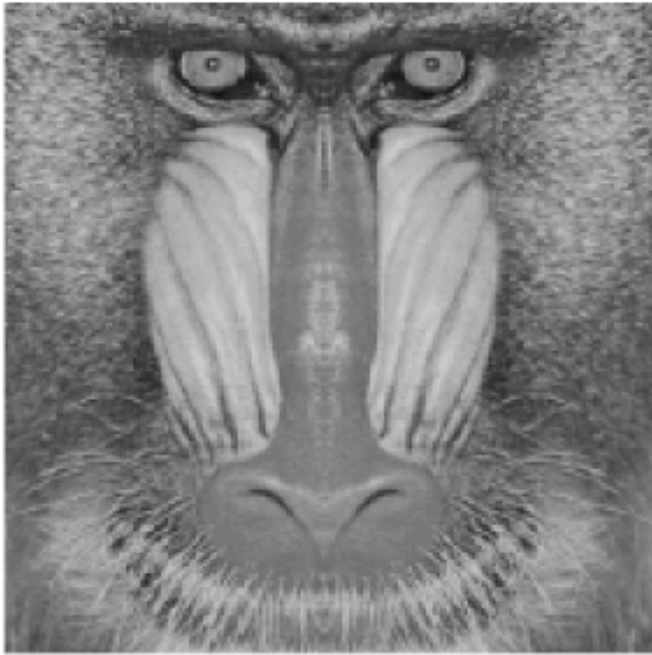
$$M_N(\beta, f) = 0$$

is uniquely determined and must equal β^* if we choose N so large that $M_N(\beta, f)$ contains $\{A_{pq}(f) \neq 0\}$ for which the **gcd** of q 's is 1.

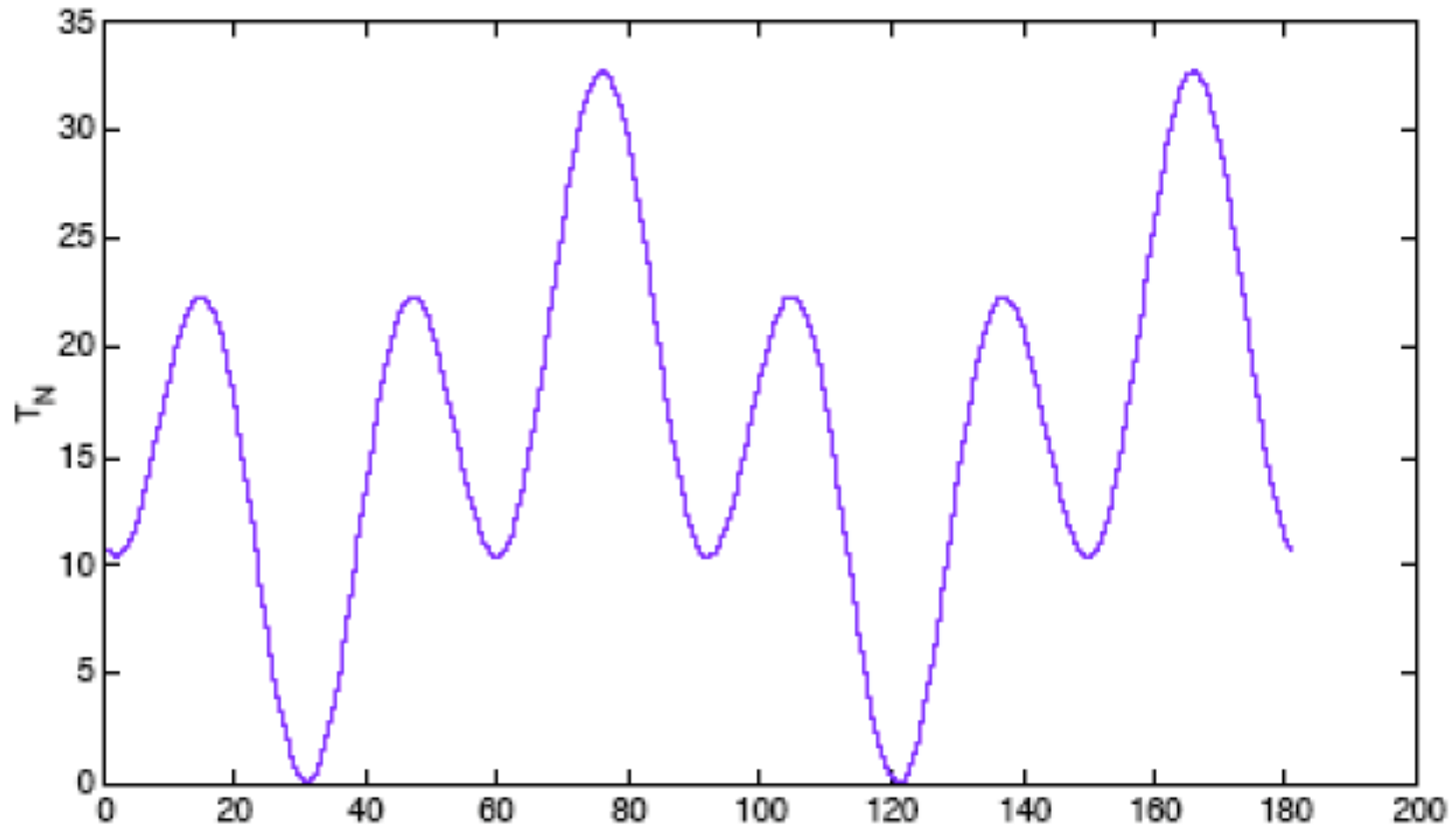
$$\{A_{p_1q_1}(f) \neq 0, \dots, A_{p_rq_r}(f) \neq 0\}, p_i \leq N, i = 1, \dots, r$$

$$\text{gcd}(q_1, \dots, q_r) = 1.$$

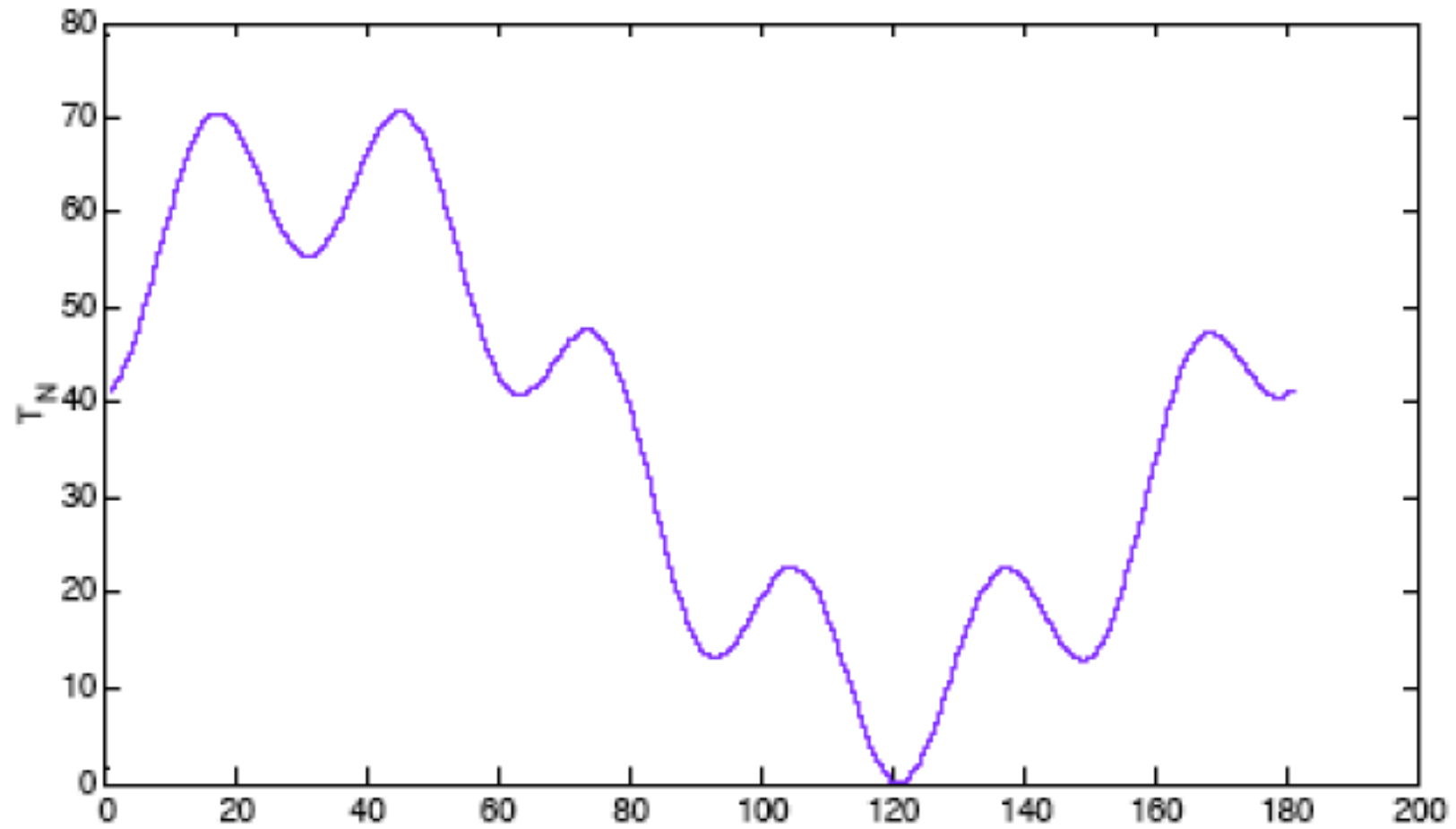
$$\beta^* = 120^\circ$$



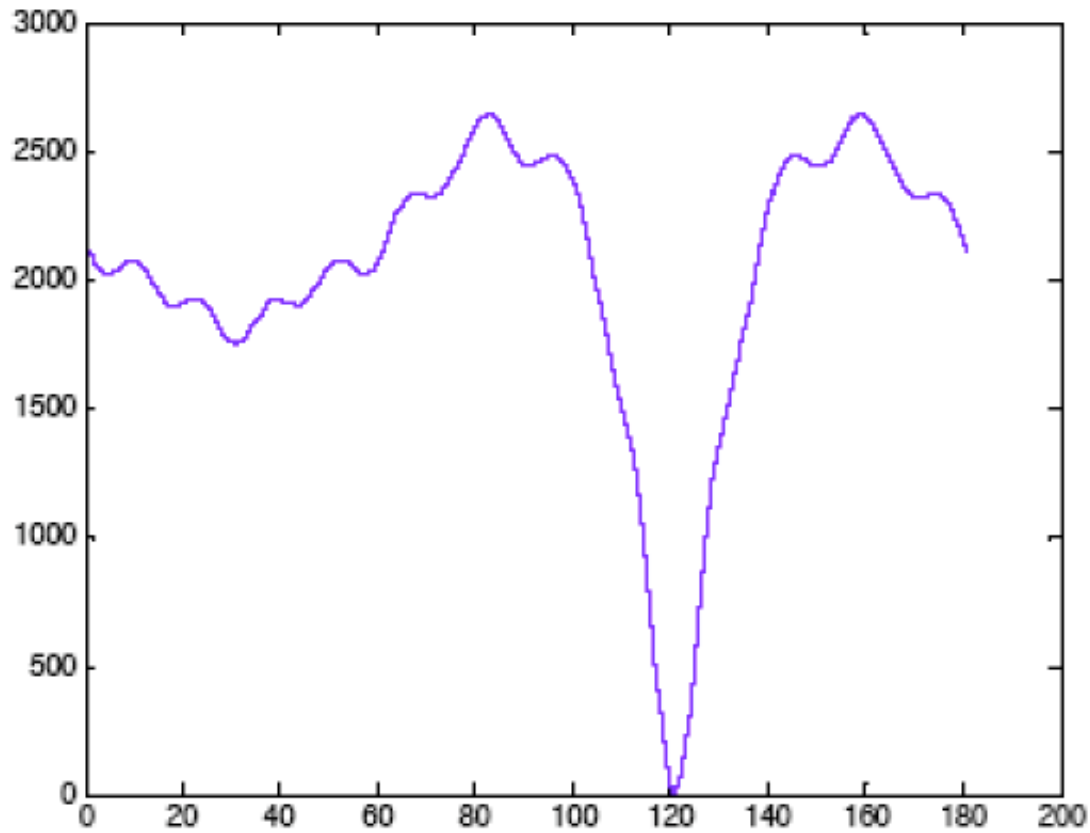
$M_N(\beta, f)$ based only on $A_{42}(f), A_{86}(f)$



$M_N(\beta, f)$ based only on $A_{51}(f), A_{86}(f)$



$$M_{14}(\beta, f) = \sum_{p=0}^{14} \frac{p+1}{\pi} \sum_{q=-p}^p \left| A_{pq}(f) - e^{-2iq\beta} A_{p,-q}(f) \right|^2$$



$$A_{pq}(f) = |A_{pq}(f)| e^{ir_{pq}(f)}$$

$$\Rightarrow M_N(\beta, f) = \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p 4 |A_{pq}(f)|^2 \left(1 - \cos(2r_{pq}(f) + 2q\beta)\right)$$

\Rightarrow

β^* :

$$r_{pq}(f) + q\beta^* = l\pi$$

for all (p, q) with $|A_{pq}(f)| \neq 0$.

- **Estimated Contrast Function**

$$\begin{aligned}\hat{M}_N(\beta) &= \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p \left| \hat{A}_{pq} - e^{-2iq\beta} \hat{A}_{p,-q} \right|^2 \\ &= \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p 4 \left| \hat{A}_{pq} \right|^2 \left(1 - \cos(2\hat{r}_{pq} + 2q\beta) \right)\end{aligned}$$

$$\hat{\beta}_{\Delta,N} = \arg \min_{\beta \in [0, \pi)} \hat{M}_N(\beta)$$

→ van der Vaart: **Asymptotic Statistics**, 1998.

- Accuracy of $\hat{\beta}_{\Delta,N}$

Theorem 3.1

Let $f \in BV(D)$ and be reflection invariant w.r.t. a unique axis $\beta^* \in [0, \pi)$. Let N be so large that β^* is determined as the unique zero of $M_N(\beta, f)$. Then

$$\hat{\beta}_{\Delta,N} \rightarrow \beta^* \text{ (P) as } \Delta \rightarrow 0$$

Proof: $\sup_{\beta \in [0, \pi)} \left| \hat{M}_N(\beta) - M_N(\beta, f) \right| \rightarrow 0 \text{ (P)}$

Theorem 3.2

$$\hat{\beta}_{\Delta,N} = \beta^* + O_P(\Delta) \quad \left(\rightarrow \sqrt{n^2} \text{ rate} \leftarrow \right)$$

Proof:

- $0 = \hat{M}_N^{(1)}(\hat{\beta}_{\Delta,N}) = \hat{M}_N^{(1)}(\beta^*) + \hat{M}_N^{(2)}(\tilde{\beta})(\hat{\beta}_{\Delta,N} - \beta^*)$
- $\hat{\beta}_{\Delta,N} - \beta^* = -\frac{\hat{M}_N^{(1)}(\beta^*)}{\hat{M}_N^{(2)}(\tilde{\beta})}$

- From **Theorem 3.1**:

$$\sup_{\beta \in [0, \pi)} \left| \hat{M}_N^{(2)}(\beta) - M_N^{(2)}(\beta, f) \right| \rightarrow 0 \quad (\text{P})$$

$$\tilde{\beta} \rightarrow \beta^* \quad (\text{P})$$

$$\hat{M}_N^{(2)}(\tilde{\beta}) \rightarrow M_N^{(2)}(\beta^*, f)$$

$$= \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p 16q^2 |A_{pq}(f)|^2 \neq 0$$

- $\Delta^{-1} \left(\hat{\beta}_{\Delta, N} - \beta^* \right) \approx - \frac{\Delta^{-1} \hat{M}_N^{(1)} \left(\beta^* \right)}{M_N^{(2)} \left(\beta^*, f \right)}$

- $\hat{M}_N^{(1)} \left(\beta^* \right) = \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p 8q \left| \hat{A}_{pq} \right|^2 \sin \left(2\hat{r}_{pq} + 2q\beta^* \right)$

$$\left(\rightarrow r_{pq}(f) + q\beta^* = l\pi \leftarrow \right)$$

$$= \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p 8q \left| \hat{A}_{pq} \right|^2 \sin \left(2 \left(\hat{r}_{pq} - r_{pq}(f) \right) \right)$$

$$\approx \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p 8q |A_{pq}(f)|^2 \sin\left(2(\hat{r}_{pq} - r_{pq}(f))\right)$$

- $\hat{A}_{pq} = A_{pq}(f) + O_P(\Delta)$

- $\hat{r}_{pq} - r_{pq}(f) = O_P(\Delta)$



Theorem 3.3 Let f be $\text{Lip}(1)$. $E\varepsilon^4 < \infty$.

$$\Delta^{-1}\left(\hat{\beta}_{\Delta,N} - \beta^*\right) \Rightarrow N\left(0, \frac{8\sigma^2}{M_N^{(2)}(\beta^*, f)}\right)$$

$$M_N^{(2)}(\beta^*, f) = \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p 16q^2 |A_{pq}(f)|^2$$

⇒ **Confidence Interval** for β^*

$$\left[\hat{\beta}_{\Delta,N} - \Phi^{-1}(1-\alpha) \frac{2\sqrt{2}\Delta\hat{\sigma}}{\sqrt{\hat{M}_N^{(2)}}}, \hat{\beta}_{\Delta,N} + \Phi^{-1}(1-\alpha) \frac{2\sqrt{2}\Delta\hat{\sigma}}{\sqrt{\hat{M}_N^{(2)}}} \right]$$

- $\hat{M}_N^{(2)} = \sum_{p=0}^N \frac{p+1}{\pi} \sum_{q=-p}^p 16q^2 |\hat{A}_{pq}|^2$
- $\hat{\sigma}^2 = \frac{1}{4C(\Delta)} \sum_{(x_i, y_j), (x_{i+1}, y_j), (x_i, y_{j+1}) \in D} \left\{ (Z_{i,j} - Z_{i+1,j})^2 + (Z_{i,j} - Z_{i,j+1})^2 \right\}$

Remark 1: f is not reflection symmetric

$$\hat{\beta}_{\Delta, N} \rightarrow \beta^\circ = \arg \min_{\beta} \|f - \tau_{\beta} f\|^2$$

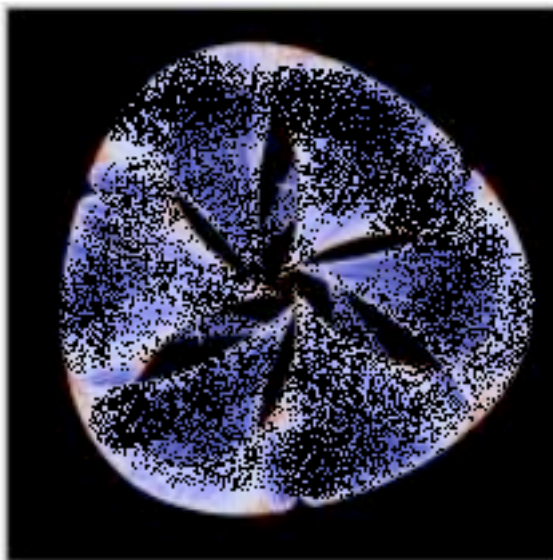
Original



“symmetrized”



Remark 2: Estimation d ($\in \{2, 3, 4, \dots\}$) for images invariant under rotations through an angle $\frac{2\pi}{d}$?



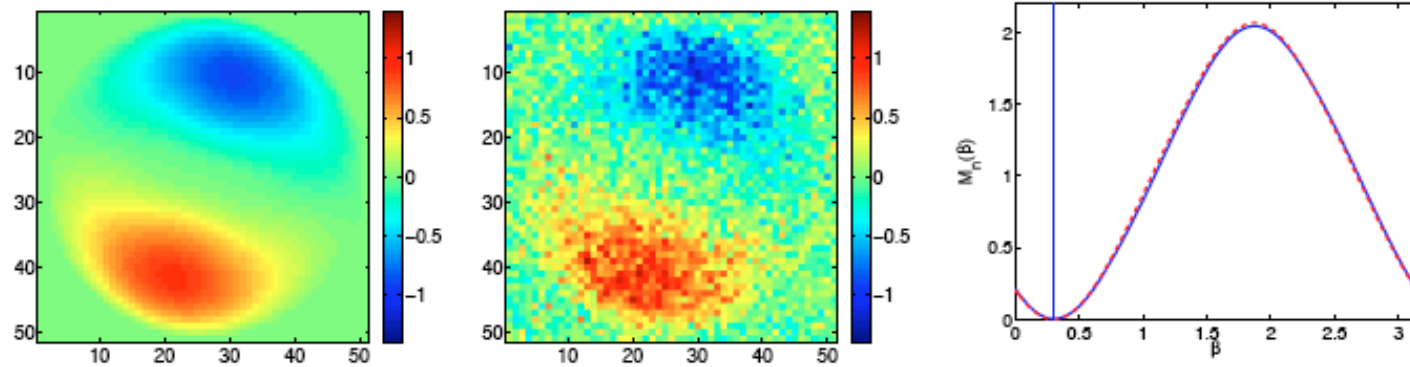


Figure 1: Reflection symmetric function f_1 without noise, with noise, and $M_7(\beta)$ (full curve) and $\hat{M}_7(\beta)$ (dashed curve). Parameters are $n = 25$ and signal-to-noise-ratio= 5.

The vertical line indicates the direction of reflection symmetry in the true image.

$$f_1(\rho, \theta) = c_1 \cdot x \cdot (1 - \rho) \cdot \left(\sin(y + \sqrt{x^2 + y^4}) + \sin(-y + \sqrt{x^2 + y^4}) \right)$$

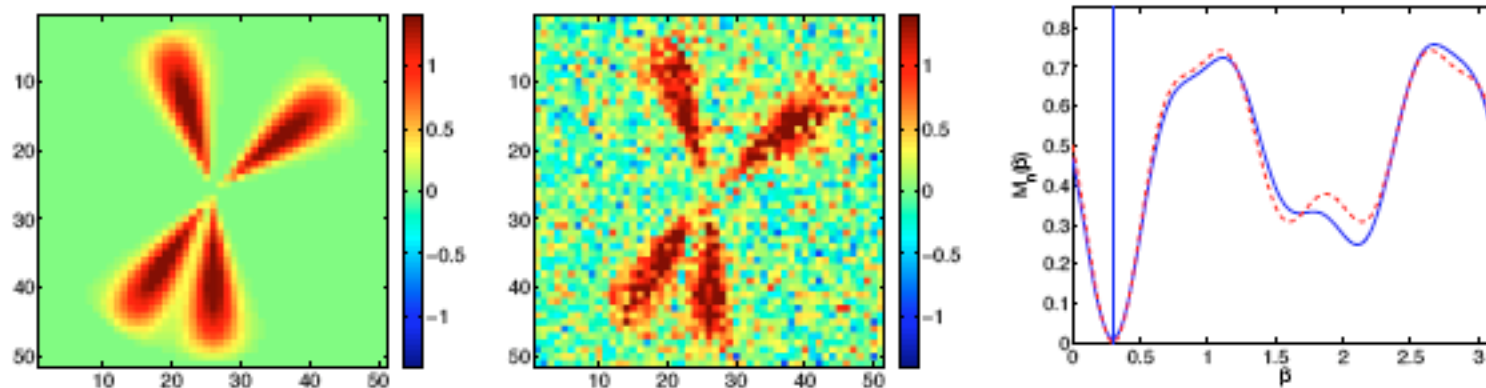


Figure 2: Reflection symmetric function f_2 without noise, with noise, and $M_7(\beta)$ (full curve) and $\hat{M}_7(\beta)$ (dashed curve). Parameters are $n = 25$ and signal-to-noise-ratio= 5. The vertical line indicates the direction of reflection symmetry in the true image.

$$f_2(\rho, \theta) = c_2 \cdot \rho \cdot (1 - \rho) \cdot \left(e^{\cos(\theta)/0.02} + e^{\cos(\theta+0.6)/0.02} + e^{\cos(\theta-0.3+\pi)/0.02} + e^{\cos(\theta+0.9+\pi)/0.02} \right),$$

IV Testing for Image Symmetries

Testing Rotational Symmetries

$d = 2$ - testing image symmetry w.r.t. rotation through π

$$A_{pq}(f) \rightarrow A_{pq}(r_d f) = e^{2\pi i q / d} A_{pq}(f) = e^{\pi i q} A_{pq}(f)$$

The **orthogonal projection**

$$\|f - r_d f\|^2 = \sum_{p=0}^{\infty} \sum_{|q| \leq p} \frac{p+1}{\pi} |1 - e^{2\pi i q/d}|^2 |A_{pq}(f)|^2$$

The **test statistic (d=2)**

$$T_N^{r_2} = \sum_{\substack{p=0 \\ p=\text{odd}}}^N \sum_{|q| \leq p} \frac{p+1}{\pi} |\hat{A}_{pq}|^2$$

Theorem 4.1:

A: Under $H^{r_2} : r_2 f = f$ let

$$N \rightarrow \infty, N^7 \Delta \rightarrow 0, \text{ as } \Delta \rightarrow 0$$

Then for

$$T_N^{r_2} = \sum_{\substack{p=0 \\ p=\text{odd}}}^N \sum_{|q| \leq p} \frac{p+1}{\pi} |\hat{A}_{pq}|^2$$

we have

$$\frac{T_N^{r_2} - \sigma^2 \Delta^2 a(N)}{\Delta^2 \sqrt{a(N)}} \Rightarrow N(0, 2\sigma^4) \quad a(N) = \begin{cases} N(N+2)/4 - N & \text{even} \\ (N+1)(N+3)/4 - N & \text{odd} \end{cases}$$

B: Under $\bar{H}^{r_2} : r_2 f \neq f$ let $f \in C^s(D), s \geq 2$ and let

$$N \rightarrow \infty, N^{3/2} \Delta^{\gamma-1} \rightarrow 0, N^{2s+1} \Delta \rightarrow \infty \text{ as } \Delta \rightarrow 0$$

Then we have

$$\frac{T_N^{r_2} - \|f - r_2 f\|^2 / 4}{\Delta} \Rightarrow N \left(0, \sigma^2 \|f - r_2 f\|^2 \right)$$

Proof:

- Under H^{r_2} : $T_N^{r_2}$ is a **quadratic form** of iid random variables

(*de Jong: A CLT for generalized quadratic forms, *Pr.Th.Related Fields*, 1987*)

- Under \bar{H}^{r_2} : $T_N^{r_2}$ is dominated by a **linear term**

Similar results exist for

- $d = 4$ - testing image symmetry w.r.t. rotation by $\pi / 2$
- $d = \infty$ - testing image radially, i.e., $f(x, y) = g(\rho)$
- Testing image **mirror symmetry**
- Joint hypothesis

$$H^{\tau_y, r_2} : r_2 f = f \text{ AND } \tau_y f = f$$

$$\bar{H}^{\tau_y, r_2} : r_2 f \neq f \text{ OR } \tau_y f \neq f$$

V References

Symmetry

- Hermann Weyl, *Symmetry*, Princeton Univ. Press, 1952.
 - J. Rosen, *Symmetry in Science: An Introduction to the General Theory*, Springer, 1995.
 - J.H. Conway, H. Burgiel, and C. Goodman-Strauss, *The Symmetry of Things*, A K Peters, 2008.
 - M. Livio, *The Equation That Couldn't Be Solved: How Mathematical Genius Discovered the Language of Symmetry*, Simon & Schuster, 2006.
- “...Livio writes passionately about the role of **symmetry** in human perception, arts,....”

Symmetry & Statistics

- Given iid (p) sequence Z_1, \dots, Z_n verify whether

$$H_0 : p(z) = p(-z)$$

- $Y_{i,n} = m(x_{i,n}) + Z_{i,n}$

$$H_0 : p(z) = p(-z)$$

→ Fan & Gencay(95), Ahmad & Li (97): $m(\bullet)$ - linear regression

→ Dette et al. (02) : $m(\bullet)$ - nonparametric regression

- Bissantz, Holzmann, and Pawlak, Testing for image symmetries -
- with application to confocal microscopy, **IEEE Trans. Inform. Theory**, 2009.
- Bissantz, Holzmann, and Pawlak, Estimating the axis of
reflectional symmetry of an image, **Annals of Applied
Statistics**, to appear.
-

