

1. Implicit Polynomials

- An implicit polynomial (IP) of degree r :

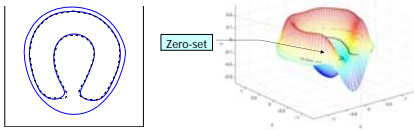
$$P_{\underline{a}}(x, y) = a_{0,0} + a_{1,0}x + a_{0,1}y + a_{2,0}x^2 + a_{1,1}xy + \dots + a_{0,r}y^r = 0$$

- Alternative way to define IP

- Intersection of the 3D polynomial with the zero-plane - zero-sets

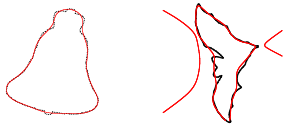
$$z = a_{0,0} + a_{1,0}x + a_{0,1}y + a_{2,0}x^2 + \dots + a_{0,r}y^r$$

$$z = 0$$



- Modeling

- describe curves representing the boundary of 2D objects (data-sets) by Zero-sets of IP.

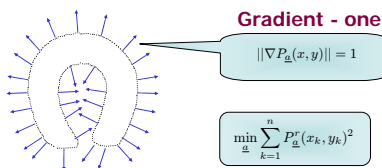


- Classification

- Represent a boundary of an object by a set of invariants based on IP vector of coefficients \underline{g}

2. Gradient-one, MinMax and MinVar – algorithms for object fitting

- Minimize the polynomial values at the data-set points
- Require the gradient to be locally perpendicular to the data boundary avoid zero-set splitting.



Min-Max

$$\|\nabla P_{\underline{a}}(x, y)\| = \sum_{k=0}^r \sum_{i=0}^k |x^i y^{k-i}|$$

Min-Var

$$\|\nabla P_{\underline{a}}(x, y)\| = \sqrt{\sum_{k=0}^r \sum_{i=0}^k x^{2i} y^{2(k-i)}}$$

- Properties

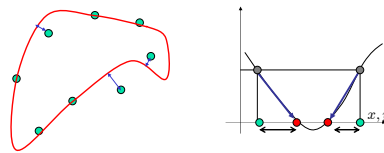
- Min-Max and Min-Var (Helzer et al., 2004) reduce the sensitivity of the zero-set to polynomial coefficients perturbations.
- Gradient-one (T. Tasdizen et al., 2000) is rotation invariant, while Min-Max and Min-Var are not.

3. Min-Max & Min-Var Modifications

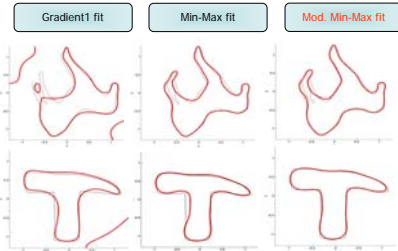
3.1 Improving Fitting Performance

- Minimize approximated geometric distances instead of polynomial values

$$\min_{\underline{a}} \sum_{k=1}^n P_{\underline{a}}^r(x_k, y_k)^2 \iff \min_{\underline{a}} \sum_{k=1}^n \left(\frac{|P_{\underline{a}}(x_k, y_k)|}{|\nabla P_{\underline{a}}(x_k, y_k)|} \right)^2$$



- Examples



3.2 Invariance to rotation

- Require the gradient value to be dependent only on the distance of the data-set points from the origin

- Solution for Min-Max

$$\sum_{l=1}^r \sum_{i=1}^l |x_k^{l-i} y_k^i| \iff \text{mean}_{x^2+y^2=d^2} \sum_{l=1}^r \sum_{i=1}^l |x_k^{l-i} y_k^i|$$

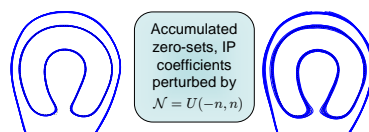
- Solution for Min-Var

$$\text{redefine the polynomial}$$

$$P_{\underline{b}}^r(x, y) = \sum_{l=0}^r \sum_{i=0}^l b_{l-i,i} \sqrt{\binom{l}{i}} x^{l-i} y^i$$

$$\sqrt{\sum_{l=1}^r \sum_{i=1}^l a_k^{2(l-i)} y_k^{2i}} \iff \sqrt{\sum_{l=0}^r (x^2 + y^2)^l}$$

- Dynamic range of \underline{b} is smaller than the dynamic range of \underline{a} and, hence, \underline{b} is less sensitive to coefficient noise



$$\text{Mod. Min-Var: } n = 2^{-10} \cdot \max\{\underline{b}\}$$

$$\text{Min-Var: } n = 2^{-10} \cdot \max\{\underline{a}\}$$

4. Application to 2D Object Recognition

4.1. Data Preprocessing

- Filter out the measurement noise by passing the data-set through a low-pass filter
- Center the data-set and normalize its Scatter Matrix to achieve Affine invariance.
- Scale the data-set so that 75% of it lie inside a circle of radius 1 to avoid large perturbations in the coefficients as a result of data-set noise (T. Tasdizen et al, 2000).

4.2. Multi Order (degree) and Fitting Error Technique (MOFET) for data-set recognition

- Drawbacks of Single-degree recognition (gen. 6 or 8)

- Fails to distinguish contours too complex for selected degree
- Unstable in case of too simple contours

- Recognition based on several polynomials

- Match polynomials of 4 different degrees (2, 4, 6 and 8) to each of the data-sets and extract the invariants.
- Use fitting error measure to improve classification performance.

- Recognition Process

- Assume Gaussian PDF of feature vector
- Learning: estimate the parameters of distribution for each dictionary object.
- Apply the Maximum Likelihood principle for recognition.

- Experimental data-base

- "Multiview Curve Database" (MCD) created by M. Zuliani containing 40 shapes X 7 different points of view
- Each shape perturbed by adding colored noise (20 different perturbations): 40 X 7 X 20 = 5600 objects.



- 6 views X 20 perturbations (per shape) for dictionary, The remaining sets were used for the recognition test.

- Comparative Results (Classification rate)

MOFET	Single Degree				CSS
	2	4	6	8	
96.6%	69.4%	94.8%	94.2%	85.8%	93.8%

5. Conclusion

- Minimizing approximated geometric distances instead of polynomial values of the data-set, results in improved fitting of the data-set.
- Fitting IP of different degrees and utilization of their coefficients and fitting errors benefits from both the stability of low-degree IP and informativeness of high-degree IP, results in a high performance recognizer