

Moment Invariants based object Recognition for Different Pose and Appearances in Real Scenes

Authors: Swati Nigam, Kaushik Deb, Ashish Khare

Published in: Informatics, Electronics & Vision (ICIEV), 2013 International Conference

Presented By: Shayhan Ameen Chowdhury



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Goal

- A new approach had been proposed for shape based recognition of object(Human) in real world.



Goal (Cont..)



Introduction

- With the emergence of computer vision application object recognition in real scenes has become an active research area.



Two-Dimensional Geometric Transformations

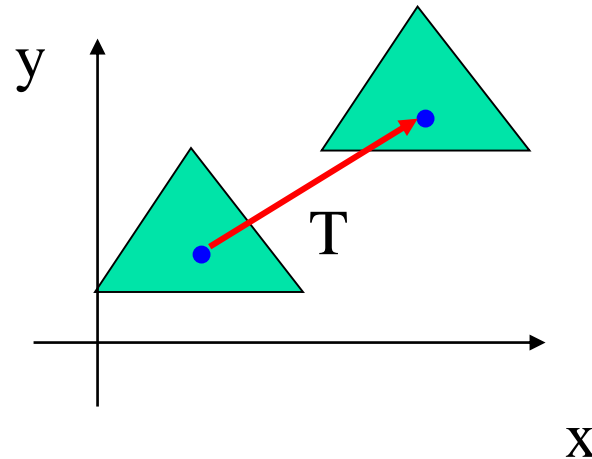
➤ **Basic Transformations**

- Translation
- Rotation
- Scaling



Translation

- Moves objects without deformation

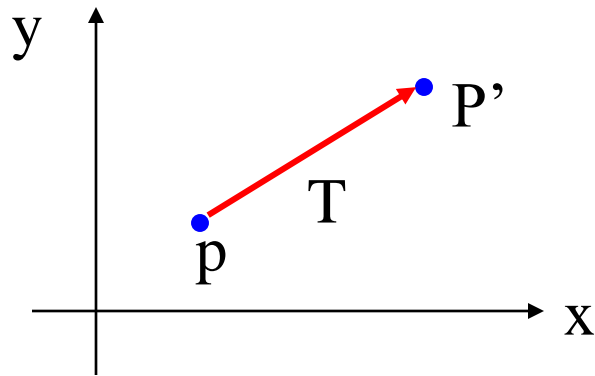


Translation

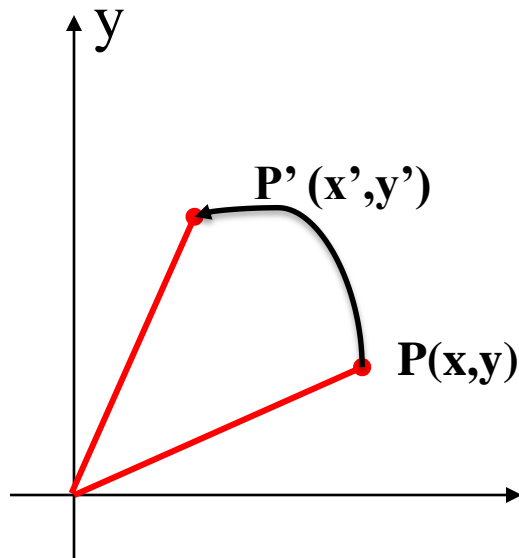
→ Translation transformation

$$x' = x + t_x$$

$$y' = y + t_y$$



Rotation

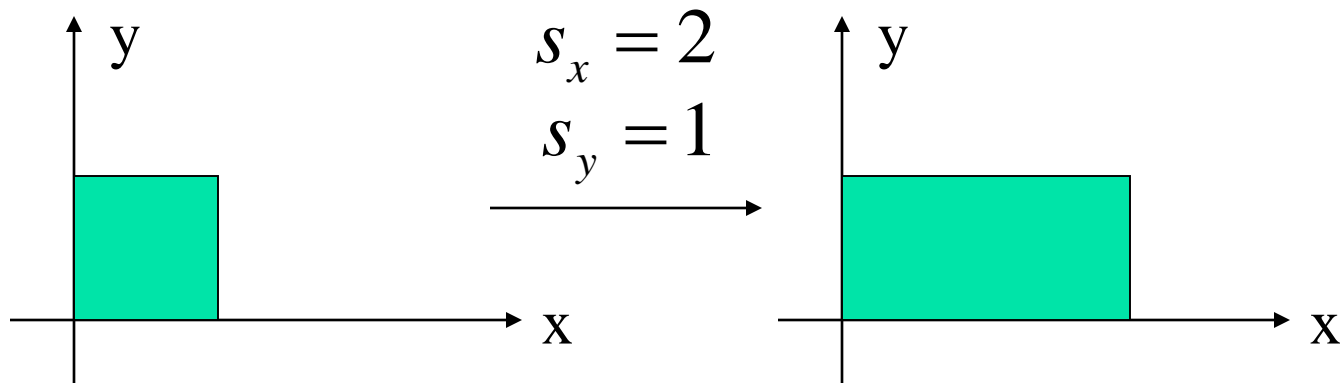


Rotation

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix}$$



Scaling



Scaling

$$x' = x \cdot s_x$$

$$y' = y \cdot s_y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix}$$



Shape based object recognition

- Shape based object recognition
 - Boundary based object recognition
 - Region based object recognition



Boundary based object recognition

- At which point the image brightness / intensity changes sharply



Boundary based object recognition

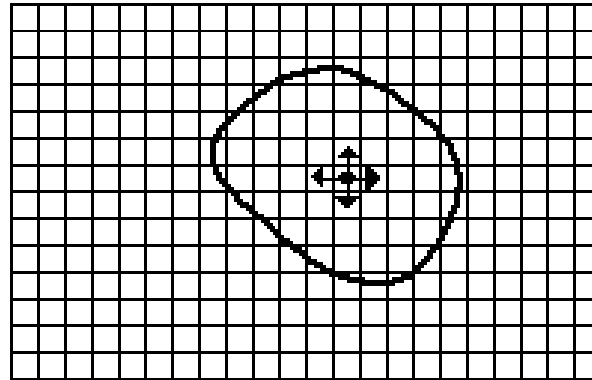


Region based object recognition

- This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented.

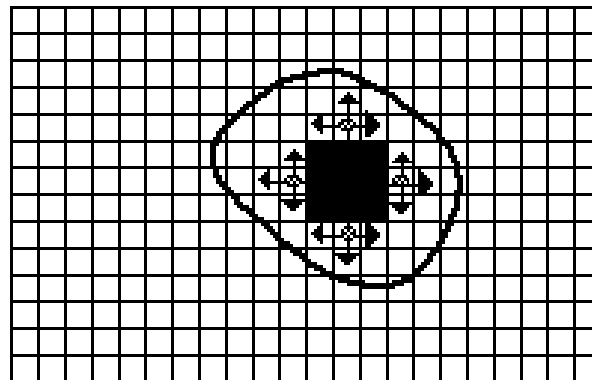


Region based object recognition



- Seed Pixel
- ↑ Direction of Growth

(a) Start of Growing a Region



- Grown Pixels
- Pixels Being Considered

(b) Growing Process After a Few Iterations

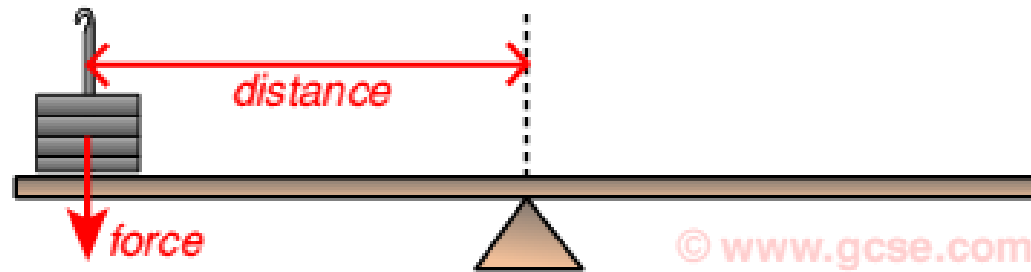
Boundary / Region

- The boundary base approach depend of information achieved from boundary pixel only. But region base approach retrieve information from both boundary and internal pixel.



Moment(cont.)

- A moment is defined as a force multiplied by the perpendicular distance from the line of action of the force to the pivot



Moment

$$\text{Moment} = \text{Force} \times \text{Distance}$$



The math of moments

- In pure math, the n^{th} order moment about the point c is defined as:

- $$\mu_n = \int_{-\infty}^{+\infty} (x - c)^n f(x) dx$$



- We're interested in images – they have two dimensions. So we need two independent variables. So the formula becomes:

- $$\mu_{mn} = \iint (x - c_x)^m (y - c_y)^n f(x, y) dx dy$$



→ The Moment of an $M \times N$ image $f(x,y)$ can be defined as

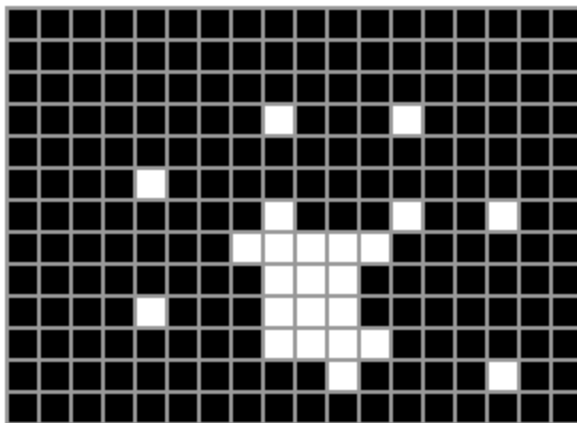
$$\rightarrow m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x)^p (y)^q f(x, y)$$



Calculating area

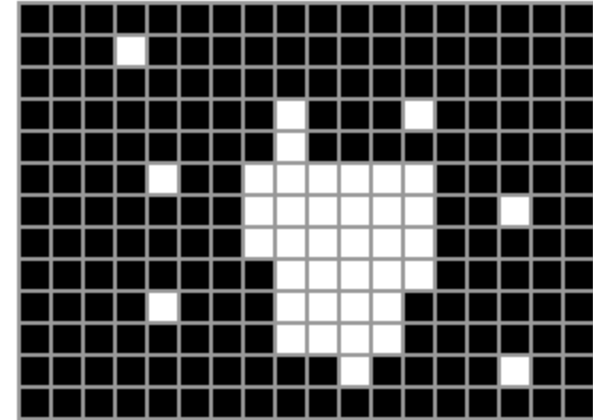
$$\rightarrow m_{00} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x)^0 (y)^0 f(x, y)$$

$$\rightarrow m_{00} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)$$



Centroid

- Centroid = $(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}})$
- Consider the m_{10} first moment:
- $\text{Sum}_x = \sum \sum x f(x, y)$
- Centroid = $(\frac{\text{sum}_x}{m_{00}}, \frac{\text{sum}_y}{m_{00}})$



Translation invariance

→ $\mu_{pq} = \iint (x - \bar{x})^p (y - \bar{y})^q f(x, y) dx dy$

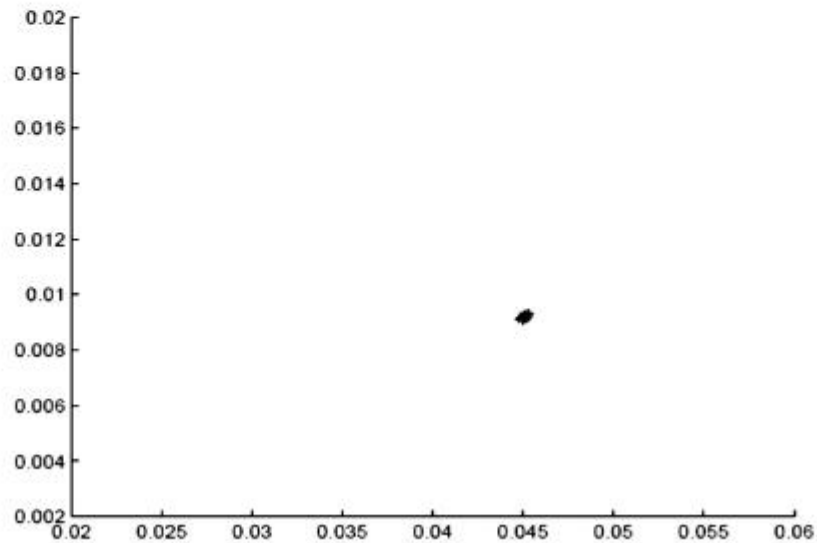
→ Where

→ $\bar{x} = \frac{m_{10}}{m_{00}}$

→ $\bar{y} = \frac{m_{01}}{m_{00}}$



Translation invariance(Cont.)



Scale invariance

→ $f'(x,y)$: new image scaled by λ

→ $f'(x,y) = f(\frac{x}{\lambda}, \frac{y}{\lambda})$

→ Variable Transformation

→ $x' = \frac{x}{\lambda}$ $y' = \frac{y}{\lambda}$ $dx = \lambda dx'$ $dy = \lambda dy'$



Scale invariance(Cont..)

$$\begin{aligned}\Rightarrow \mu'_{pq} &= \iint (x)^p (y)^q f\left(\frac{x}{\lambda}, \frac{y}{\lambda}\right) dx dy \\ &= \iint (\lambda x')^p (\lambda y')^q f(x', y') \lambda^2 dx' dy' \\ &= \lambda^p \lambda^q \lambda^2 \iint (x')^p (y')^q f(x', y') dx' dy' \\ &= \lambda^{(p+q+2)} \mu_{pq}\end{aligned}$$



Scale invariance(Cont..)

- Concept: Set total area to 1
- $\mu'_{00} = \lambda^2 \mu_{00} = 1$
- $\lambda = \frac{1}{\sqrt{\mu_{00}}} = \mu_{00}^{-\frac{1}{2}}$
- Scaling invariant modes:
- $\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^\gamma}, \text{ where } \gamma = \frac{p+q+2}{2}$



Moment Invariants

➤ The seven moment invariants are defined in terms of normalized central moment of order 3.

➤ $M1 = (\eta_{20} + \eta_{02})$

➤ $M2 = (\eta_{20} - \eta_{02})^2 + (4 \eta_{11})^2$

➤ $M3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$

➤ $M4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$

➤ $M5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] +$

➤ $3(\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2](6)$

➤ $M6 = (\eta_{20} + \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4 \eta_{11} (\eta_{30} + \eta_{12})^2 (\eta_{21} + \eta_{03})^2$

➤ $M7 = 3(\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$



The Proposed Approach

- Representation of objects in real scenes
Representation is 2D gray function
- Preprocessing of Images
Image normalized to 256 X 256 pixel
- Feature Vector Calculation
We use the set of moment invariants for computing feature vectors
- Classification
 - Calculated feature vectors are supplied into linear support vector machine (SVM).



Result



Comparison with other methods

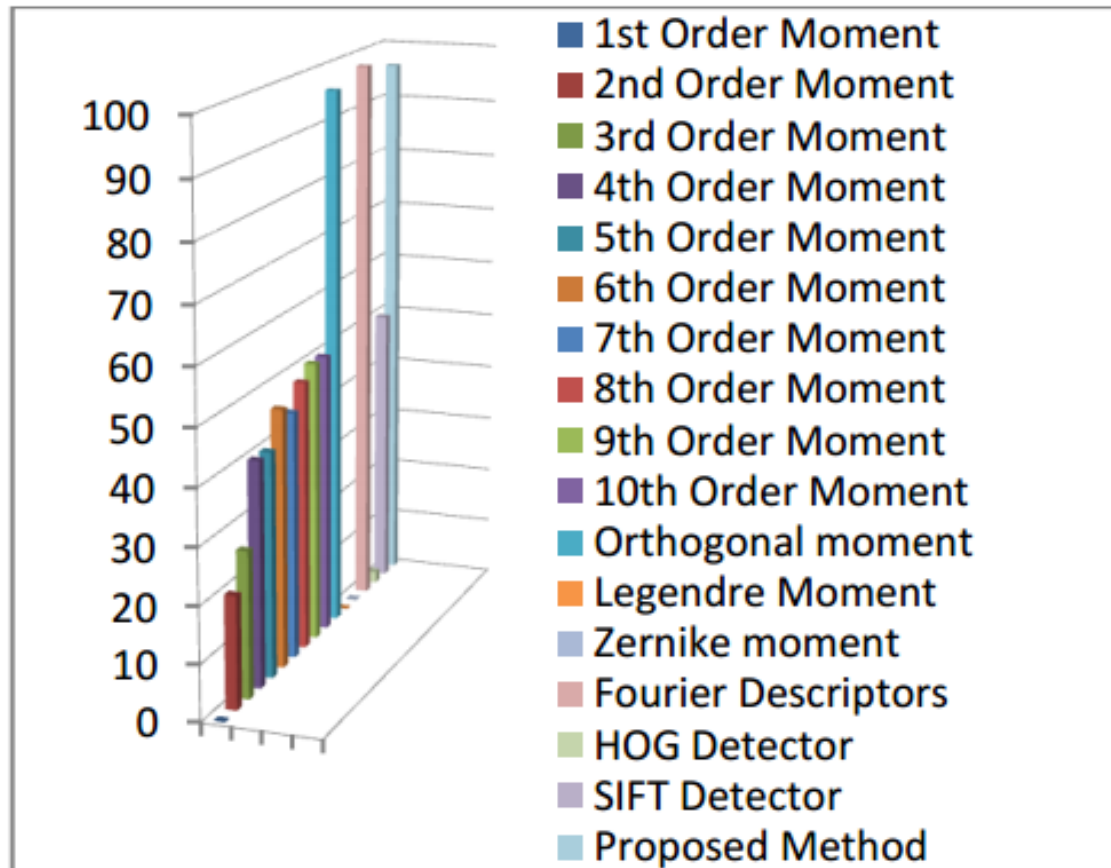


Figure 3. Accuracy of positive images for different methods (in %)

Comparison with other methods

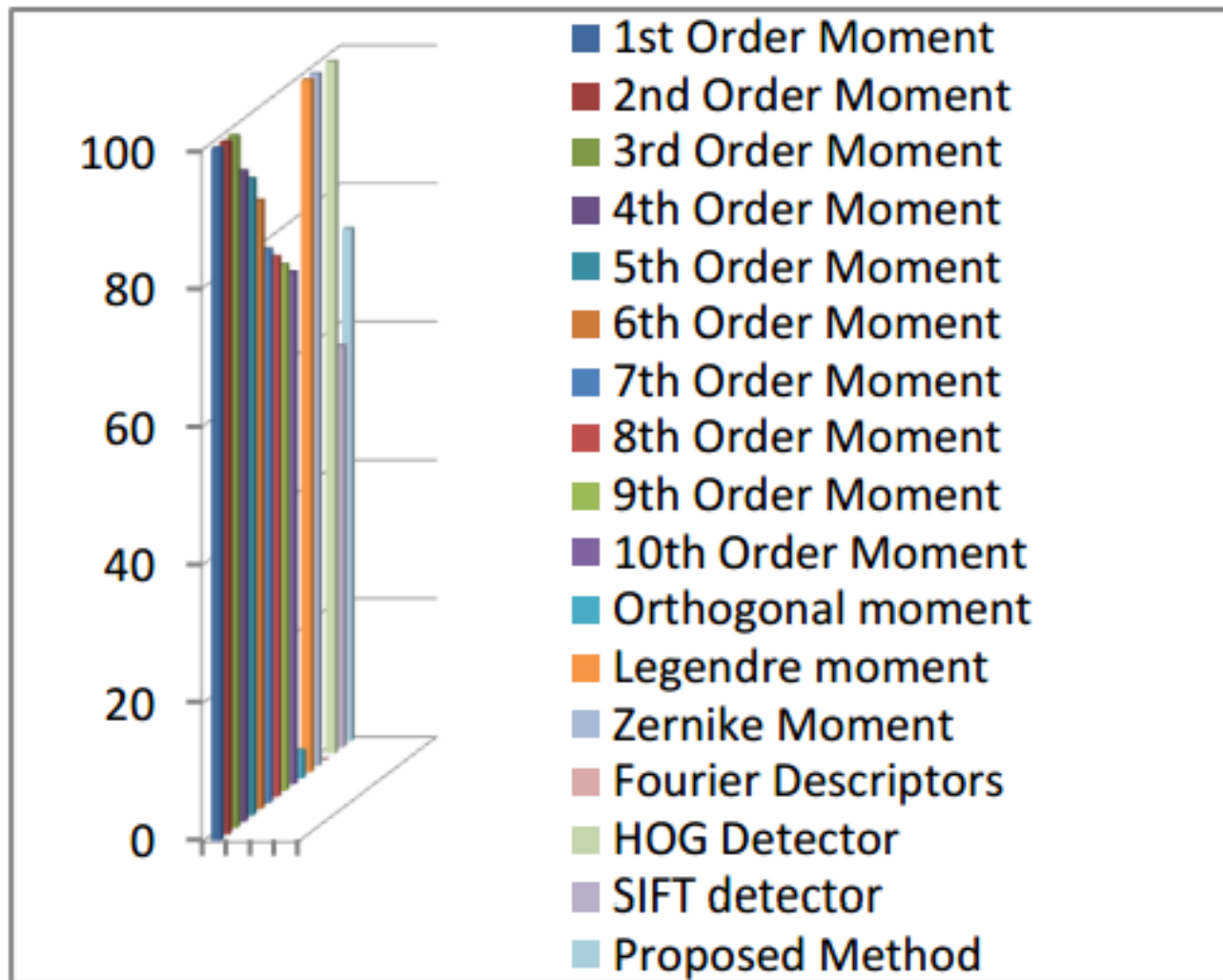


Figure 4. Accuracy of negative images for different methods (in %)



Comparison with other methods

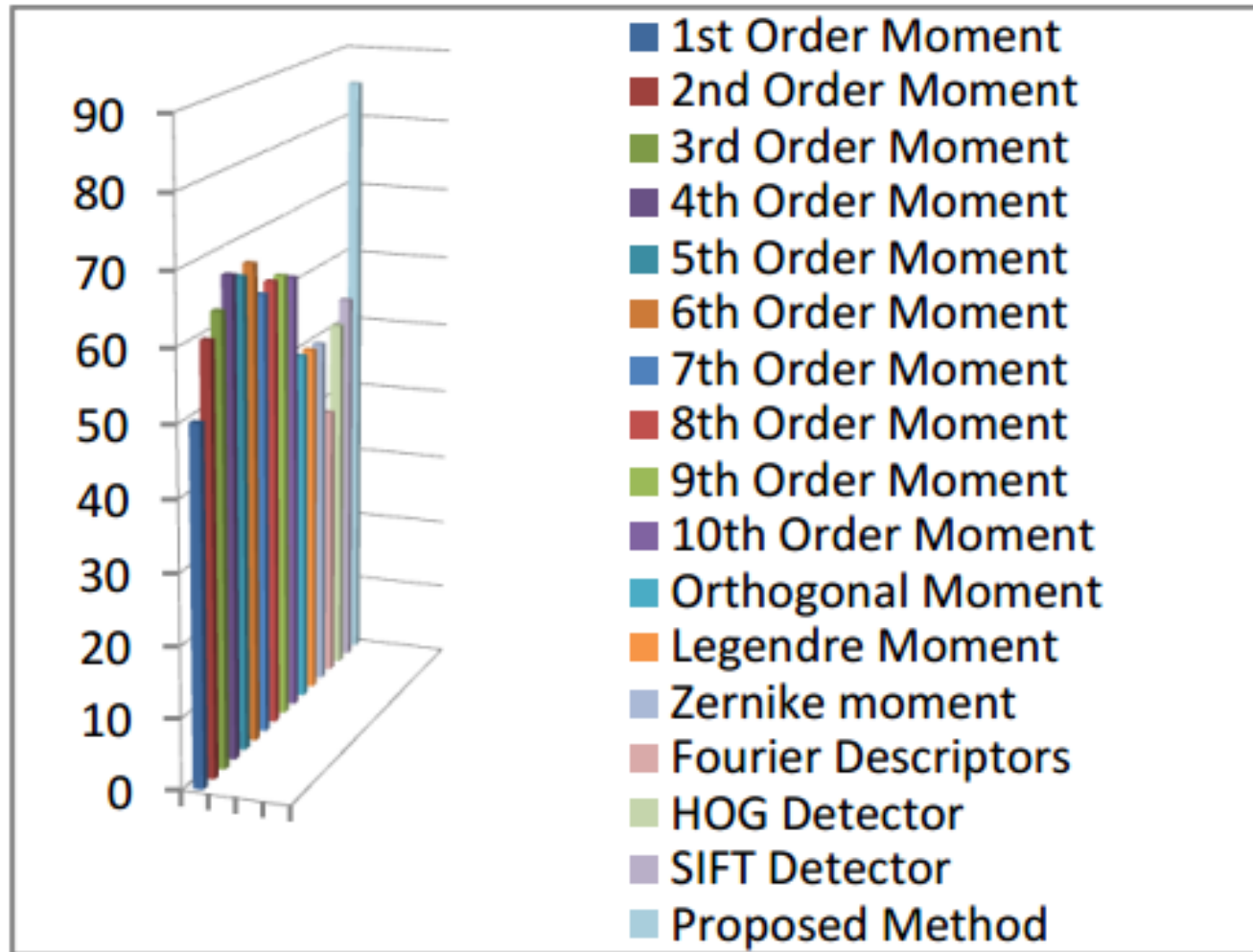


Figure 5. Average accuracy of images for different methods (in %)



Comparison with other methods

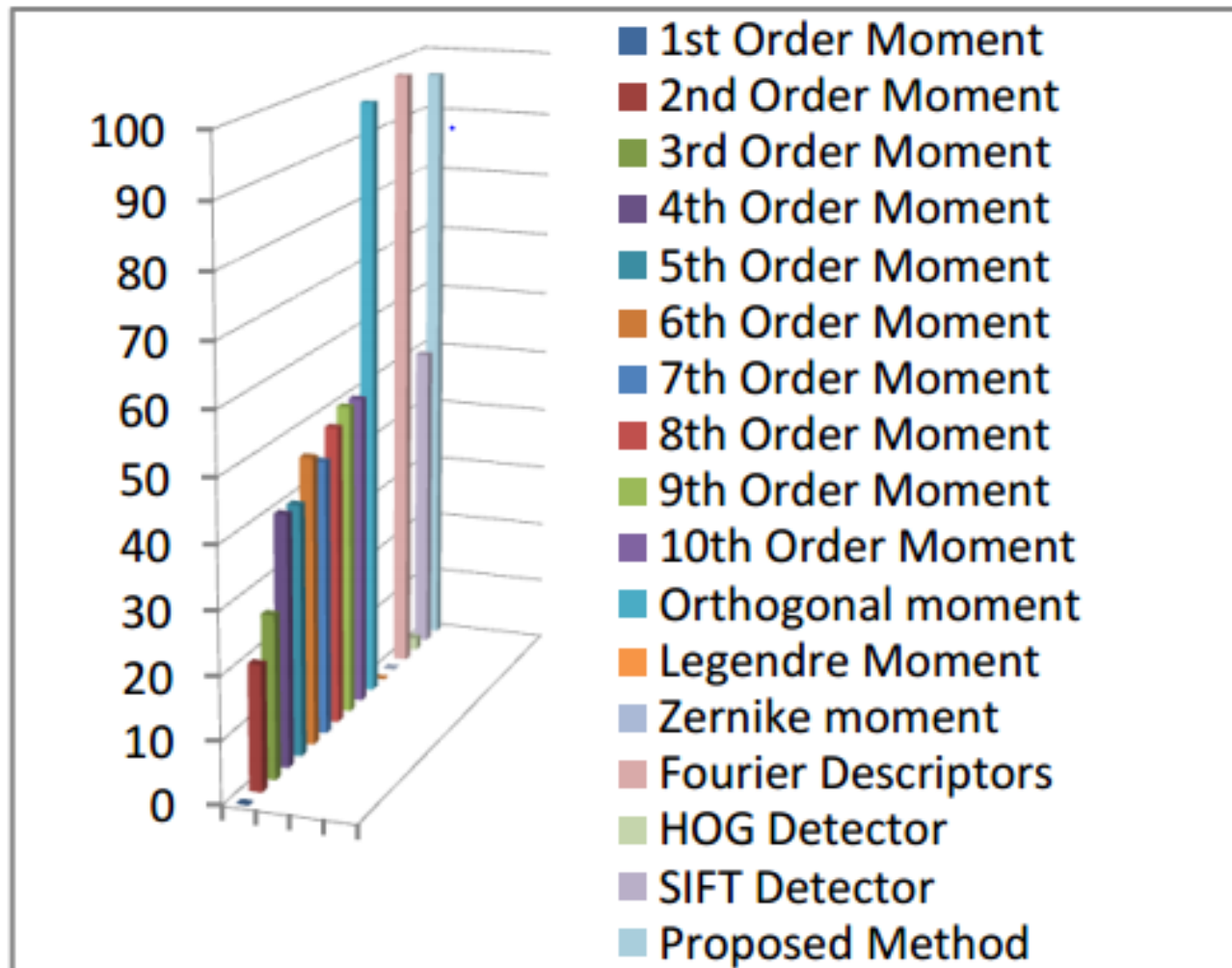


Figure 6. Recall value of different methods



Comparison with other methods

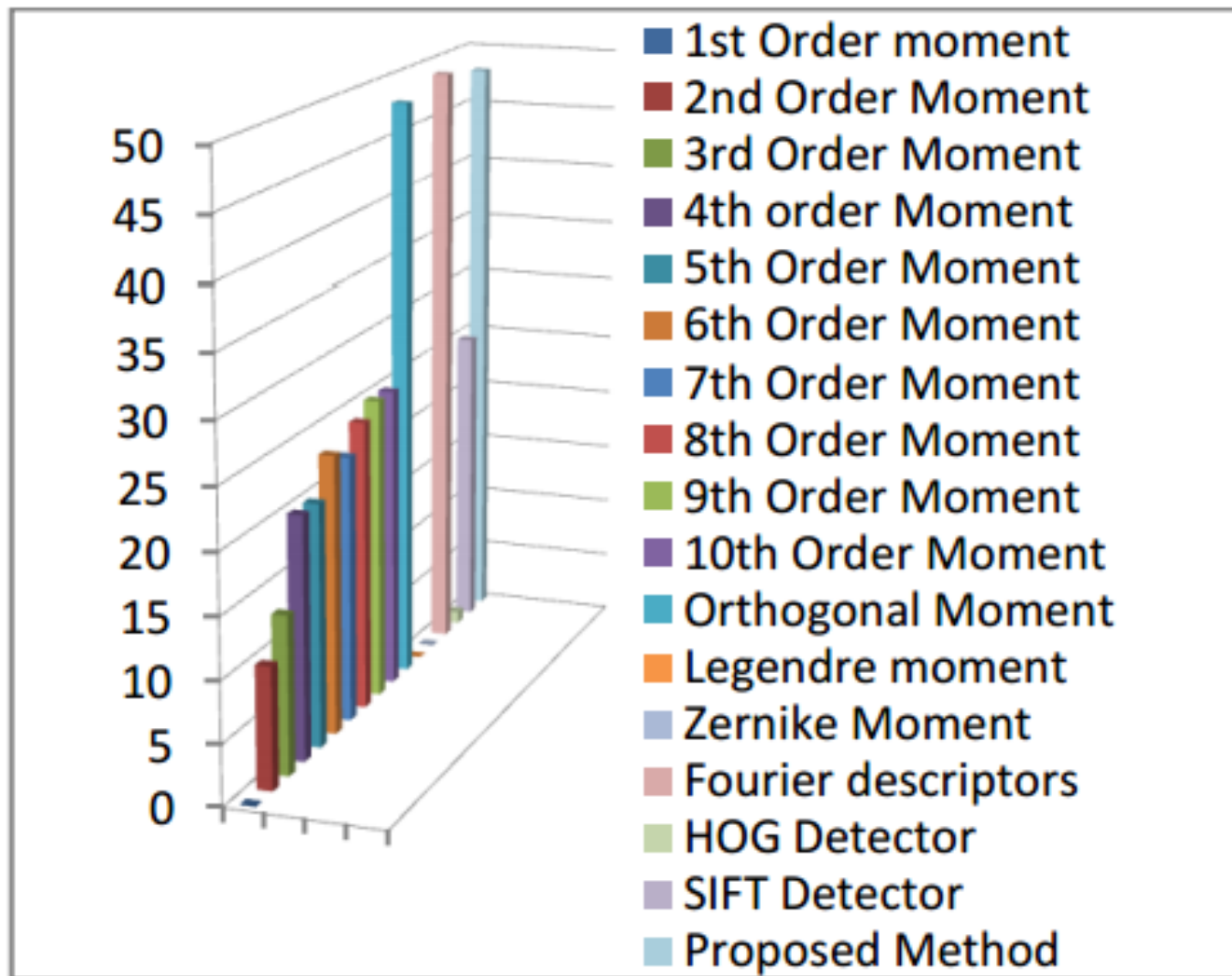


Figure 7. Precision value of different methods



Comparison with other methods

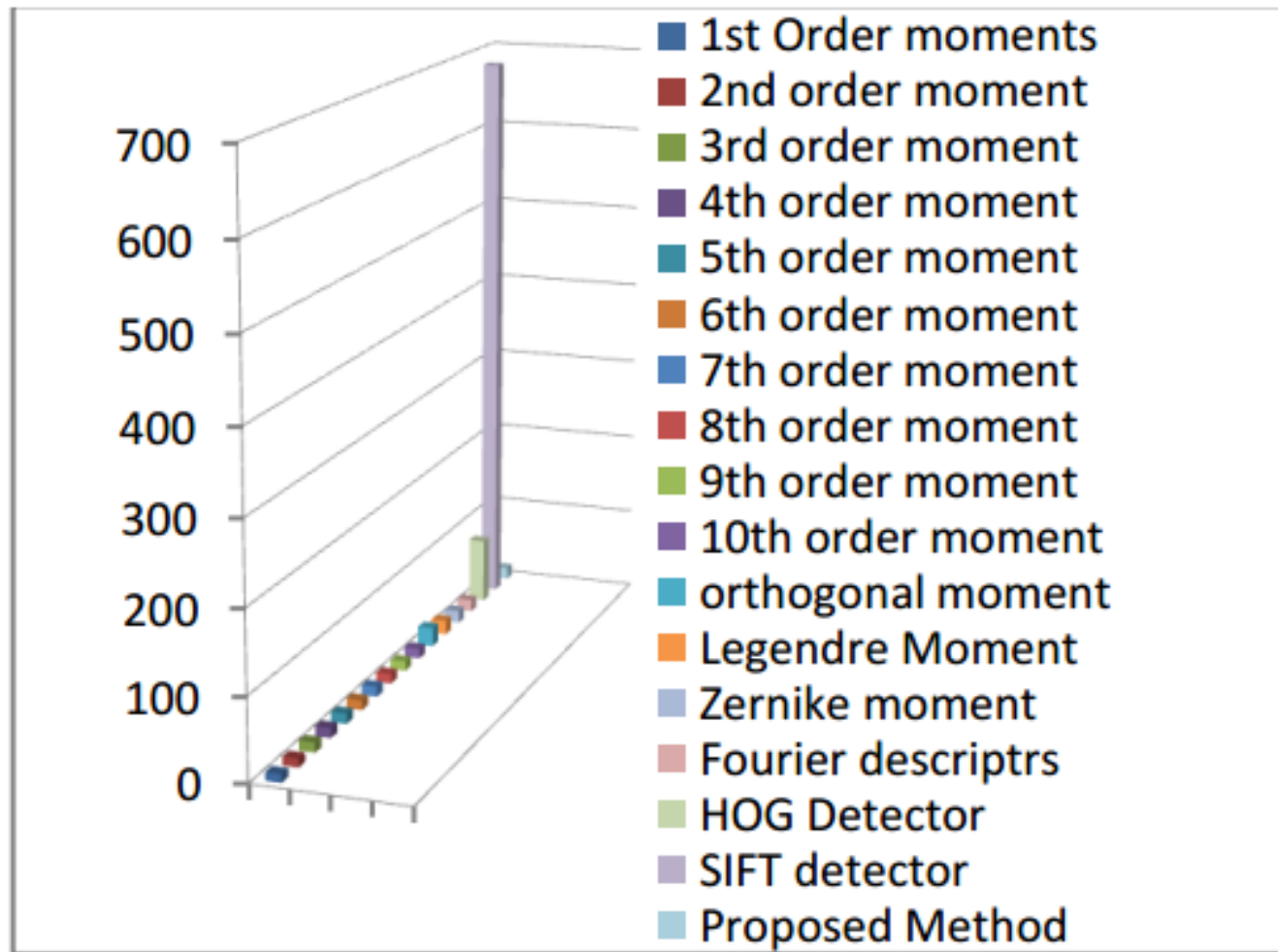


Figure 8. Efficiency of different methods (in seconds)



Measures for different recognition methods

Methods	Pos Acc	Neg Acc	Avg Acc	R	P	E
1 st Order Moment	0	100	50	0	0	10.19
2 nd Order Moment	20	100	60	20	10	10.61
3 rd Order Moment	26	100	63	26	13	11.90
4 th Order Moment	40	94	67	40	20	12.21
5 th Order Moment	40	92	66	40	20	12.59
6 th Order Moment	46	88	67	46	23	11.95
7 th Order Moment	44	80	62	44	22	12.27
8 th Order Moment	48	78	63	48	24	11.99
9 th Order Moment	50	76	63	50	25	11.90
10 th Order Moment	50	74	62	50	25	12.22
Orthogonal Moment	96	4	50	96	48	23.29
Legendre Moment	0	100	50	0	0	17.54
Zernike Moment	0	100	50	0	0	14.91
Fourier Descriptors	98	0	39	98	49	14.72
HOG Detector	2	100	51	2	1	78.9
SIFT Detector	50	58	54	50	25	72.4
Proposed Method	96	74	85	96	48	14.14



Conclusion

- This paper describe the development and demonstration of a new moment invariant approach for object recognition in real world. The invariance nature of moment invariants against linear transformation made it suitable for recognition of object of different pose and appearances. It achieved an average accuracy of 85% which is better than other methods.



Thank you all

