OBJECT RECOGNITION USING COMBINED BLUR AND AFFINE MOMENT INVARIANTS

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Abstract

Recognition of objects which are invariant under object plane transformations such as rotation, scale and translation as well as blur is one of the active research areas in the field of robotics. Object recognition system using Combined Blur and Affine Moment Invariants is proposed in this paper. Combined Blur and Affine Moment Invariants are selected for feature extraction of objects because they are invariant with respect to object plane transformations, affine distortions as well as blur. Because of the invariant properties, the obtained features can be used to identify objects under affine distortions as well as blur. Euclidean distance is used as classifier in the proposed approach. Simulation results are carried out by considering standard database images. It is observed from the simulation results that this approach provide better recognition rate even under different affine distortions on image as well as blur.

Keywords: *Object Recognition, Combined Blur and Affine Moment invariants, Feature Extraction*

1. INTRODUCTION

Object recognition is one of the active research areas which have attracted the attention of because of number of applications such as automation, medical image diagnosis and analysis, biometrics, surveillance and security systems, content based image retrieval, robotics, artificial intelligence and intelligent vehicle systems. Robotics is the branch of technology that deals with the design, construction, operation, and application of robots, as well as computer systems for their control, sensory feedback, information processing and retrieval. Automated machine design requires invariant features. The main important areas in robotics are the object recognition and pattern recognition. Object recognition refers recognition of recognition of particular specific object in the scenery. There is rapid use of robots during the last few years. At present, robotics is a rapidly growing field, as technological advances to cater the needs of industry and automation.

Takacs et a. [1] presented a method for rotation invariant image matching with the concept of histogram of gradient. David G. Lowe developed an algorithm for scale invariant feature extraction by using key point localization, which are invariant to rotation, translation and scaling [2]. Montero et al. [3] proposed another method for shape recognition based on line segment detection andextraction of edge contour from colored images. Jan Flusser et al. [4] used geometric moments and their invariants for object recognition. Huang [5] computed the exact geometric moments for gray level images and introduced the overlapped rectangle image representation. Object detection using Geometric moment invariant method is proposed in [9]. Geometric moments are non-orthogonal and obtained features are not accurate. Venkataramana et al. [11] proposed an object recognition method using Legendre moment invariants. Geometric moment invariants and Legendre moment invariants provide invariant properties for image rotation, translation and scale only. These methods cannot work for affine distortions as well as blurring.

In order to increase the recognition rate under image affine distortions as well as blur, an object recognition system using Combined Blur and Affine Moment Invariants is presented in this paper. Combined Blur and Affine Moment Invariants are selected for feature extraction of objects because they are invariant with respect to object plane transformations, affine distortions as well as blur. Euclidean distance classifier is one of the simplest classifier and hence used as classifier in the proposed approach. The organization of paper is as follows: Section 2 presents Combined Blur and Affine Moment Invariants. The proposed method is presented in section 3. Simulation results are reported in section 4. Finally, conclusions about the work are presented in the last section.

2. COMBINED BLUR AND AFFINE MOMENT INVARIANTS

Combine Blur and Affine Moment Invariants [12] are derived based on Geometric Moments. Hence, an overview on Geometric Moments is presented in this section first.

2.1 Overview on Geometric Moments

Geometric moments of order (p, q) for an image $f(x, y)$ are given [12] as

$$M_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p\, y^q\, f(x, y)\, dx\, dy \qquad (1)$$

where $p, q = 0,1,2,........., \infty$

In order to suit the dynamic range of M_{pq} suitable for different size images, the N x M image plane is first mapped onto a square defined by $x \in [-1, +1]$, $y \in [-1, +1]$. Then eq. (1) can be written as

$$M_{pq} = \int_{-1}^{1}\int_{-1}^{1} x^p\, y^q\, f(x, y)\, dx\, dy \qquad (2)$$

The discrete form representation of above expression can be written as

$$M_{pq} = \sum_{i=0}^{N-1}\sum_{j=0}^{M-1} x_i^p\, y_j^q\, f(x_i, y_j)\, \Delta x\, \Delta y \qquad (3)$$

where (x_i, y_j) is the centre of (i, j) pixel and $\Delta x = x_i - x_{i-1}$, $\Delta y = y_j - y_{j-1}$ are the sampling intervals in the 'x' and 'y' directions respectively. N x M represents the size of the image.

The Geometric central moments [12] are given by

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x - \bar{x})^p\, (y - \bar{y})^q\, f(x, y)\, dx\, dy \quad (4)$$

Where the centroid $\bar{x} = \dfrac{M_{10}}{M_{00}}$ and $\bar{y} = \dfrac{M_{01}}{M_{00}}$ (5)

Geometric central moments for digital images can be written as

$$\mu_{pq} = \sum_{i=0}^{N-1}\sum_{j=0}^{M-1} (x_i - \bar{x})^p\, (y_j - \bar{y})^q\, f(x_i, y_j)\, \Delta x\, \Delta y \quad (6)$$

The normalized central moments [12] are given by

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \qquad (7)$$

In which $\gamma = \dfrac{p+q}{2} + 1$ for $p + q = 2,3,.....$

2.2 Combined Blur and Affine Moment Invariants

Combined Blur and Affine Moment Invariants derived by Thomas Suk et al. [12] are invariant under different image distortions and hence, presented in this subsection. The main advantage of these invariants is there is no need for any image restoration and combined invariants are capable of recognizing objects in the degraded scene as well as affine distortions. The Combined Blur and Affine Moment Invariants (CBAMI) are given below [12].

$$\begin{aligned} \text{Invariant}_1 = {} & \mu^2_{30}\,\mu^2_{03} - 6\,\mu_{30}\,\mu_{21}\,\mu_{12}\,\mu_{03} \\ & + 4\,\mu_{30}\,\mu^3_{12} + 4\,\mu^3_{21}\,\mu_{03} - 3\,\mu^2_{21}\,\mu^2_{12})/\,\mu^{10}_{00}. \end{aligned} \tag{8}$$

$$\begin{aligned} \text{Invariant}_2 = {} & \mu^2_{50}\,\mu^2_{05} - 10\,\mu_{50}\,\mu_{41}\,\mu_{14}\,\mu_{05} + 4\,\mu_{50}\,\mu_{32}\,\mu_{23}\,\mu_{05} \\ & + 16\,\mu_{50}\,\mu_{32}\,\mu^2_{14} - 12\,\mu_{50}\,\mu_{14}\,\mu^2_{23} + 16\,\mu^2_{41}\,\mu_{23}\,\mu_{05} \\ & + 9\,\mu^2_{41}\,\mu^2_{14} - 12\,\mu_{41}\,\mu^2_{32}\,\mu_{05} - 72\,\mu_{32}\,\mu_{41}\,\mu_{14}\,\mu_{23} \\ & + 48\,\mu^3_{23}\,\mu_{41} + 48\,\mu_{14}\,\mu^3_{32} - 32\,\mu^2_{32}\,\mu^2_{23})\,/\,\mu^{14}_{00}. \end{aligned} \tag{9}$$

$$\begin{aligned} \text{Invariant}_3 = {} & (\mu^2_{30}\mu_{05}\,\mu_{12} - \mu^2_{30}\mu_{03}\,\mu_{14} - \mu_{30}\mu^2_{21}\,\mu_{05} \\ & - 2\,\mu_{30}\,\mu_{21}\,\mu_{12}\,\mu_{14} + 4\,\mu_{30}\,\mu_{21}\,\mu_{23}\,\mu_{03} + 2\,\mu_{30}\mu^2_{12}\,\mu_{23} \\ & - 4\,\mu_{30}\,\mu_{12}\,\mu_{32}\,\mu_{03} + \mu_{30}\mu^2_{03}\,\mu_{41} + 3\,\mu^3_{21}\,\mu_{14} \\ & - 6\,\mu^2_{21}\mu_{12}\,\mu_{23} - 2\,\mu^2_{21}\mu_{03}\,\mu_{32} + 6\,\mu_{21}\mu^2_{12}\,\mu_{32} \\ & + 2\,\mu_{12}\,\mu_{21}\,\mu_{41}\,\mu_{03} - \mu_{21}\mu^2_{03}\,\mu_{50} - 3\,\mu^3_{12}\,\mu_{41} + \mu^2_{12}\mu_{03}\,\mu_{50})\,/\,\mu^{11}_{00}. \end{aligned} \tag{10}$$

$$\begin{aligned} \text{Invariant}_4 = {} & (2\,\mu_{30}\,\mu_{12}\,\mu_{41}\,\mu_{05} - 8\,\mu_{30}\,\mu_{12}\,\mu_{32}\,\mu_{14} + 6\,\mu_{30}\,\mu_{12}\,\mu^2_{23} \\ & -\mu_{30}\,\mu_{03}\,\mu_{50}\,\mu_{05} + 3\,\mu_{30}\,\mu_{03}\,\mu_{41}\,\mu_{14} - 2\,\mu_{30}\,\mu_{03}\,\mu_{23}\,\mu_{32} \\ & - 2\,\mu^2_{21}\mu_{41}\,\mu_{05} + 8\,\mu^2_{21}\mu_{32}\,\mu_{14} - 6\,\mu^2_{21}\,\mu^2_{23} + \mu_{21}\,\mu_{12}\,\mu_{50}\,\mu_{05} \\ & - 3\,\mu_{21}\,\mu_{12}\,\mu_{41}\,\mu_{14} + 2\,\mu_{21}\,\mu_{12}\,\mu_{32}\,\mu_{23} + 2\,\mu_{21}\,\mu_{03}\,\mu_{50}\,\mu_{14} \\ & - 8\,\mu_{21}\,\mu_{03}\,\mu_{41}\,\mu_{23} + 6\,\mu_{21}\,\mu_{03}\,\mu^2_{32} - 2\,\mu^2_{12}\mu_{50}\,\mu_{14} + 8\,\mu^2_{12}\mu_{41}\,\mu_{23} \\ & - 6\,\mu^2_{12}\,\mu^2_{32})\,/\,\mu^{12}_{00}. \end{aligned} \tag{11}$$

$$\begin{aligned} \text{Invariant}_5 = {} & (\mu_{30}\,\mu_{41}\,\mu_{23}\,\mu_{05} - \mu_{30}\,\mu_{41}\,\mu^2_{14} - \mu_{30}\mu^2_{32}\,\mu_{05} + 2\,\mu_{30}\,\mu_{32}\,\mu_{23}\,\mu_{14} \\ & - \mu_{30}\,\mu^3_{23} - \mu_{21}\,\mu_{50}\,\mu_{23}\,\mu_{05} + \mu_{21}\,\mu_{50}\,\mu^2_{14} + \mu_{21}\,\mu_{41}\,\mu_{32}\,\mu_{05} \\ & - \mu_{21}\,\mu_{41}\,\mu_{23}\,\mu_{14} - \mu_{21}\mu^2_{32}\,\mu_{14} + \mu_{21}\,\mu_{32}\,\mu^2_{23} + \mu_{12}\,\mu_{50}\,\mu_{32}\,\mu_{05} \\ & - \mu_{12}\,\mu_{50}\,\mu_{23}\,\mu_{14} - \mu_{12}\mu^2_{41}\,\mu_{05} + \mu_{12}\,\mu_{41}\,\mu_{32}\,\mu_{14} + \mu_{12}\,\mu_{41}\,\mu^2_{23} \\ & - \mu_{12}\mu^2_{32}\,\mu_{23} - \mu_{03}\,\mu_{50}\,\mu_{32}\,\mu_{14} + \mu_{03}\,\mu_{50}\,\mu^2_{23} + \mu_{03}\mu^2_{41}\,\mu_{14} \\ & -2\,\mu_{03}\,\mu_{41}\,\mu_{23}\,\mu_{32} + \mu_{03}\,\mu^3_{32})\,/\,\mu^{13}_{00}. \end{aligned} \tag{12}$$

$$\begin{aligned} \text{Invariant}_6 = {} & (\mu^2_{70}\,\mu^2_{07} - 14\,\mu_{70}\,\mu_{61}\,\mu_{16}\,\mu_{07} + 18\,\mu_{70}\,\mu_{52}\,\mu_{25}\,\mu_{07} \\ & + 24\,\mu_{70}\,\mu_{52}\,\mu^2_{16} - 10\,\mu_{70}\,\mu_{43}\,\mu_{34}\,\mu_{07} - 60\,\mu_{70}\,\mu_{43}\,\mu_{25}\,\mu_{16} \\ & -234\,\mu_{61}\,\mu_{52}\,\mu_{25}\,\mu_{16} + 40\,\mu_{61}\mu^2_{43}\,\mu_{07} + 50\,\mu_{61}\,\mu_{43}\,\mu_{34}\,\mu_{16} \\ & + 360\,\mu_{61}\,\mu_{43}\,\mu^2_{25} - 240\,\mu_{61}\mu^2_{34}\,\mu_{25} + 360\,\mu^2_{52}\mu_{34}\,\mu_{16} \\ & + 81\,\mu^2_{52}\,\mu^2_{25} - 240\,\mu_{52}\mu^2_{43}\,\mu_{16} - 990\,\mu_{52}\,\mu_{43}\,\mu_{34}\,\mu_{25} \\ & + 600\mu_{52}\,\mu^3_{34} + 600\mu^3_{43}\,\mu_{25} - 375\,\mu^2_{43}\,\mu^2_{34}\,)\,/\,\mu^{18}_{00}. \end{aligned} \tag{13}$$

The above six expressions are invariant to image scale, translation, rotation, affine distortions as well as blur.

3. PROPOSED METHOD

The proposed approach consists of sequence of steps namely gray scale conversion of RGB images, feature extraction and classification and is shown in Fig.1.

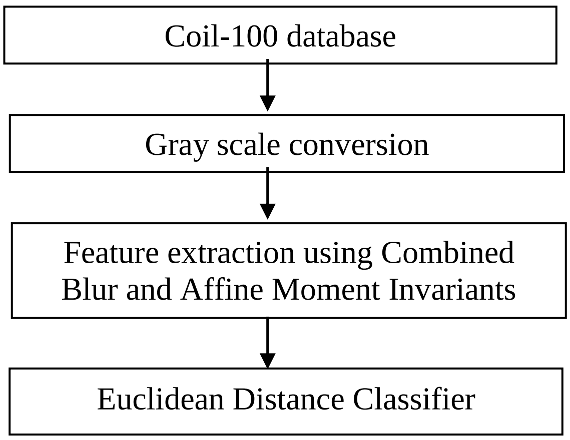

Fig.1. Proposed Approach

Gray scale conversion: The objects in the scenery are normally captured using color camera. Hence, the captured RGB color objects are converted in to gray scale objects as a first step in this work.

Feature extraction: Feature extraction and selection plays a vital role for object recognition. An optimum feature set should have capability of extracting the properties of objects under different distortions as well as blur and must have discriminating features. In this work, Combined Blur and Affine Moment Invariants which are invariant to object plane transformation such as rotation, scale, translation and affine distortion as well as blur are used for feature extraction.

Classification: The computed features using eqs.(8) to (13) are then applied for Euclidean distance classifier. This classifier is a simple classifier and hence, used in this work.

4. SIMULATION RESULTS

In order to test this method of object recognition, we have selected Coil-100 database which is freely available online. This database consists of 100 different objects with different viewpoints and noticeable change in scale, angle and translation. A total of 20 objects are selected in the simulations. Some of the sample objects are shown in Fig.2.

Fig.2. Some sample objects of Coil-100 database

The Combined Blur and Affine Moment Invariants features are computed using eqs. (8) to (13) for objects. MATLAB software is used to implement the proposed method because MATLAB is a high performance language for education and research purposes. Stirmark Software is used to generate different distortions on an image. Recognition rate is calculated as the ratio of number of correctly matched images to the total number of test images. Recognition rate is 97%.

5. CONCLUSIONS

A method for object recognition for robotic applications using Combined Blur and Affine Moment Invariants is presented in this paper. Combined Blur and Affine Moment Invariants are selected in this work for obtaining features of different objects since the computed features are invariant under different affine distortions as well as blur. From the simulation results, it is observed that the proposed method provide better recognition rate even under different image distortions as well as blur.

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