

Survey on Feature Extraction methods in Object Recognition.

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Abstract— Feature extraction is the key process in any pattern recognition issues. There is no exception in object recognition. In this paper, several feature extraction approaches in the field of object recognition are summed up. Zernike and Hu are two invariant moments and geodesic descriptors are applied directly to binary images and so we can have more information about the general shape of the object. The extracted vectors are put together to form a unique input data to the Neural network for object recognition.

Keywords—component;Neural Network; Zernike moments; Hu moments; Geodesic descriptors; 3D object recognition.

I. INTRODUCTION

The recognition of objects from imagery may be accomplished for many applications by identifying an unknown object as a member of a set of well-known objects. Various object recognition techniques utilize abstract characterizations for efficient object representation and comparison. Such characterizations are typically defined by measurable object features extracted from various types of imagery and any a priori knowledge available. Similarity between characterizations is interpreted as similarity between the objects themselves, therefore, the ability of a given technique to uniquely represent the object from the available information determines the effectiveness of the technique for the given application. Since no one representation technique will be effective for all recognition problems, the choice of object characterization is driven by the requirements and obstacles of a specific recognition task.

Transforming the input data into the set of features is called features extraction[1]. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.Feature can be defined as quantitative description of input within a lower dimensional space. It plays an important role in object recognition systems since the information related to an object is contained within the extracted features. Computer vision has become one of the most appealing domains of research. Object Recognition stands for one of the main pillars of this science. In the classic pattern of shape recognition process we list two major steps:

1. Feature extraction
2. Classification

Feature extraction is a special form of size reduction, which involves simplifying the amount of resources, required to describe a large set of data accurately. When the input data of an algorithm is too large to be processed and it is suspected to be notoriously redundant. It will be hard to exploit them perfectly. Different techniques have been used, but the most commonly used are the invariant descriptors.

II. STUDY OF FEATURE EXTRACTION

The feature is defined as a function of one or more measurements, each of which specifies some quantifiable property of an object and is computed such that it quantifies some significant characteristics of the object. There are various features currently employed.

1) General features: Application independent features such as color, texture, and shape. According to the abstraction level, they can be further divided into:- Pixel-level features: Features calculated at each pixel, e.g. color, location.

- Local features: Features calculated over the results of subdivision of the image band on image segmentation or edge detection.
- Global features: Features calculated over the entire image or just regular sub-area of an image.

2) Domain-specific features: Application dependent features such as human faces, fingerprints, and conceptual features. These features are often a synthesis of low-level features for a specific domain. Selection of a feature extraction method is important factor in achieving high recognition performance. The performance also depends on the type of classifier used, different feature types may need different types of classifier. Feature extraction of an image can be classified into three types which are spectral features (color, tone, ratio, spectral), geometric features (edges, lines), and textural features (pattern, homogeneity, spatial frequency). The feature extraction methods Template matching, Deformable templates, Unitary image transforms, Graph description, Projection histograms, Contour profiles, Zoning, Geometric moment invariants, Zernike moments, Spline curve approximation, and Fourier descriptors are applied on Gray level images or Binary images.Zernike moments, which are proven to have very good image feature

representation capabilities, are based on the orthogonal Zernike radial polynomials. They are effectively used in pattern recognition since their rotational invariants can be easily constructed[1].

Moments are scalar quantities used to characterize a function and to capture its significant features. They have been widely used in statistics for description of the shape of a probability density function. The two dimensional moments of order (p+q) of a density distribution function f(x,y) as follows:

$$m_{pq} = \iint x^p y^q \quad (1)$$

The integration is calculated over the area of the object. Generally each other pixel based feature instead of the gray value could be used to calculate the moments of the object. Moments are generally classified by the order of the moments. The order of a moment depends on the indices p and q of the moment m_{pq} and vice versa. The sum p + q of the indices is the order of the moment

Considering this, the following moments are defined:
zero order moment ((p,q) = (0, 0))

$$m_{0,0} = \iint dx dy h(x,y) \quad (2)$$

The zero order moment describes the area A of the object.
first order moments ((p,q) = (1, 0) or (0, 1))

$$m_{1,0} = \iint dx dy xf(x,y) \\ m_{0,1} = \iint dx dy yf(x,y) \quad (3)$$

Moments and functions of moments of image intensity values have been widely used in image processing and analysis such as invariant pattern recognition, image reconstruction , robust line fitting, edge detection, and image recognition. Among the different types of moments, the Cartesian geometric moments are most widely used due essentially to their simplicity and their explicit geometric meaning. However, the geometric moments are not orthogonal, thus it is difficult to reconstruct the image from them. Teague introduced the Legendre and Zernike moments using the corresponding orthogonal functions as kernels. It was proven that the orthogonal moments possess better image feature representation and are more robust to image noise compared to geometric moments[2].

III. FEATURE EXTRACTION METHODS

In general, moments describe numeric quantities at some distance from a reference point or axis. Moments are commonly used in statistics to characterize the distribution of random variables, and, similarly, in mechanics to characterize bodies by their spatial distribution of mass. The use of moments for image analysis is straightforward if we consider a grey level image segment as a two-dimensional density distribution function. In this way, moments may be used to to characterize an image segment and extract properties that have analogies in statistics and mechanics.

A. Zernike Moments

Teague introduced Zernike moments which could recover the image using the concept of orthogonal moments. The Zernike polynomials were introduced in 1934 by Zernike. Zernike moments are superior to other moments because of their insensitivity towards information content and image noise.

Zernike moment can also provide the properties of invariance to scale, position, and rotation. Zernike moment analysis is used to extract invariant features from image. This section gives brief description of the Zernike moment analysis. The magnitudes of Zernike moments have been treated as rotation-invariant features. It has also been shown that Zernike moments can have translation and scale invariant properties by their simple geometric transformations.

To derive orthogonal, rotationally invariant moments, Teague used the complex Zernike polynomials as the moment basis set. These moments are used for their characteristics:

- 1.Reduction of noise.
- 2.Invariance to rotation.
- 3.Reducing redundancies.

The Zernike moment is a series of calculations that transforms an image into vectors with real components . The geometrical moment of a function f(x, y) is by definition the projection of this function on the polynomials space denoted by $x_p y_q$ (p, q) $\in N^2$. However, the considered space is not generally orthogonal which reduces the control of redundancy that would appear during the projection[4].

Therefore, Zernike had introduced a set of complex polynomials which form an ortho-normal basis defined inside the unit disk, which means for $x^2+y^2 \leq 1$.

The polynomial is defined as follow:

$$V_{nm}^*(x,y) = V_{nm}(\rho,\theta) = R_{nm}(\rho) \cdot \exp(jm\theta) \quad (4)$$

Where:

- n: a positive integer (or null).
- m: an integer with $|m| \leq n$.
- r : the vector length (distance between the origin and the pixel at (x,y)).
- θ : Angle formed by vectors p and x axis.
- Rnm : radial polynomial.
- $V^*(x,y)$: complex polynomial, which is the projection of f(x,y) on the complex polynomials space.

B. Hu Moments

The first significant work considering moments for pattern recognition was performed by Hu. Hu derived relative and absolute combinations of moment values that are invariant with respect to scale, position, and orientation based on the theories of invariant algebra that deal with the properties of certain classes of algebraic expressions which remain invariant under general linear transformations.

The moments are often used in physics to describe the distribution of mass in a body. By combining the gray level of an image point to the mass of a body at each point, we can resume the same formalism to describe the distribution of gray levels in an object[4].

The centroid (x_0, y_0) of the function I is given by $(x_0 = m_{1,0} / m_{0,0}, y_0 = m_{0,1} / m_{0,0})$. The centered image $IT(x, y) = I(x + x_0, y + y_0)$ is invariant under translation. The central moments are invariant. The normalized moment is defined as follow:

$$M_{pq} = \frac{\sum x^p y^q I(x, y)}{m_{0,0}} \quad (5)$$

Where: $\gamma = 1 + (p+q)/2$

$$\begin{aligned} \mu_1 &= M_{2,0} + M_{0,2} \\ \mu_2 &= (M_{2,0} + M_{0,2})^2 + 4M_{1,1}^2 \\ \mu_3 &= (M_{3,0} - 3M_{1,2})^2 + (3M_{2,1} - M_{0,3})^2 \end{aligned} \quad (6)$$

These moments are invariants under translation, rotation and scaling. The moments of Hu are calculated via the normalized moments and they remain invariant under translation, rotation or scaling:

C. Geodesic Descriptors

Geodesic descriptors that are invariant under geodesic isometries, and quasi-invariant to shape articulations and bendings. This is especially relevant to perform robust retrieval on articulated shapes, such as animal or human with varying poses. The Geodesic descriptors are calculated after detection of the center of the Object. We select a set of end points; here we locate them on the boundary of the shapes.

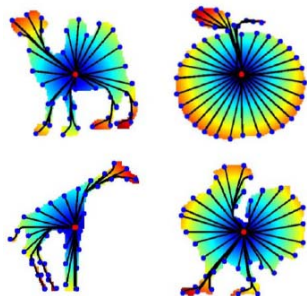


Figure 1. Example of geodesic distance between the center and boundary points.

Figure 1 give an example of geodesic distance and between the center and boundary points. Here we call “Geodesic Descriptors” the vector composed by the different geodesic distances between the center and boundary points[4].

The input vector is composed of Hu & Zernike moments of each level of gray and geodesic descriptors on binary image to form a input of the Artificial Neural Network which is used for object Recognition.

IV. CONCLUSION

Simple moments are not orthogonal, thus it is difficult to reconstruct the image from them. To overcome this drawback and to get the distribution of gray levels in the color image combination of Zernike and Hu moments is used. Zernike moments are used for less information redundancy. It allow a better description of objects than simple moments. These moments are joined together with Geodesic descriptors to get boundary of the object. .

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