OBJECT RECOGNITION BASED ON EMPIRICAL WAVELET TRANSFORM

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Abstract - Object recognition is the method of finding an object in an image. We recognize objects without any effort easily. It is a challenging task for computer vision systems due to the size, shape, and structure of objects in an image. In this paper, an efficient object recognition system is presented based on Empirical Wavelet Transform (EWT). The energy features obtained form the EWT decomposed image is used as features for the given object. As EWT, a multiresolution analysis, the given image is decomposed at various level of decomposition and the obtained features are analyzed at each level of decomposition. The evaluation of the system is carried on Columbia Object Image Library Dataset (COIL) which consists of 100 objects captured at different orientations. The classification is done with K-nearest neighbor (KNN) which gives 98.42% accuracy.

Keywords - Object recognition, Empirical wavelet transform, Energy Features, KNN classifier.

1. Introduction

Over the last few decades, object recognition has received a considerable attention in many computer vision applications and it is a still a challenging task due to the orientation of objects. Over the years, many approaches have been designed for the recognition of objects in an image. Learning strategy that models membership functions of the fuzzy attributes of surfaces is employed using GA [1] for object recognition. The objective function aims at enhancing recognition performance in terms of maximizing the degree of discrimination among classes. It is composed of three stages: retrieval and feature extraction of number of local parts from each model object, modeling the objects by feature vectors and similarity measurement.

An improved adaptive mean-shift algorithm is used to track the moving object in the follow up frames. The colors on the objects are used for object recognition in [2]. To achieve better object and scene recognition top down color attention method is developed where more features are taken from category specific color regions. An optimization model to continuously perform prototype selection and kernel dictionary learning is discussed in [3]. It can be easily used for online kernel dictionary learning on the represented matrix that are introduced to ensure that only a few samples are actually used to reconstruct the dictionary. A whole sequence convergent algorithm is developed to solve the optimization problem.

Hidden Markov model based object recognition system is described in [4], which is capable of dealing with severe part occlusions in different object recognition situations. Occlusion is dealt with separating shapes into parts through high curvature points, tangent angle signatures for each part and continuous wavelet transform for signatures. Data driven unfalsified control is implemented for solving the drawbacks in visual servoing for object recognition in [5]. It recognizes an object through matching image features. Supervisory visual servoing is implemented until an accord between the model and the selected features is achieved, so that model recognition and object tracking are done successfully.

A multi-linear supervised neighborhood embedding approach is used for the feature extraction, which is able to recognize objects [6]. It includes a normalized gradient for local region representation and an image representation framework along with multi-linear supervised neighborhood embedding analysis which can directly deal with object recognition. Partial object recognition based on the corner point effective mapping is discussed in [7]. The features are extracted by using the corner point analysis. Then, neural network is used for recognition. An action depiction based on local spatio-temporal oriented energy features are discussed in [8] for object recognition. An additive kernel support vector machine is used for classification.

A prototype robot is designed for pick and place an object in [9]. Image processing concepts are used for recognition using arduino and MATLAB. Object recognition based on illumination and rotation invariant is discussed in [10]. Using the adaptive binarization filter, a binary image reserving object edges are obtained. Then the objects are recognized using neural network, which is trained by the standard shape model represented on object class to evaluate the recognized object.

In this paper, an efficient object recognition system is presented using EWT and KNN. Section 2 gives the background of EWT and the next section illustrates the proposed system for object recognition. Section 4 gives the results obtained by the proposed system using EWT and KNN classifier and the final section concludes the achievement of the proposed system.

2. Empirical Wavelet Transform

Unlike in Fourier and wavelet transform, the basis filters of EWT are not predefined and are a signal dependent method [11]. It is based on the information content in the given image or signal. The Fourier spectrum in the range 0 to π is segmented into M number of parts. Band pass filters in each segment defines the empirical wavelets. The EWT decomposition on 2D images [12] is described as follows. Let x denotes the image and the EWT decomposition consists of the following steps;

[1] Compute 1D Fourier transform of each row r of x; X(r ; Ω) and columns c of x; X(Ω ; c) and calculate the *mean* row and column spectrum magnitudes as follows:

$$X_R = \frac{1}{N_{Rw}} \sum_{r=0}^{N_{Rw}} X(r,\Omega) \quad (1)$$

$$X_c = \frac{1}{N_{C1}} \sum_{C=0}^{N_{C1}} X(\Omega,c) \quad (2)$$

where number of rows and columns are denoted by N_{RW} and N_{Cl} respectively.

[2] Perform boundaries detection on X_R and X_C and build the corresponding filter bank $\left\{\xi_1^R, \left\{\varsigma_m^R\right\}_{m=1}^{N_R}\right\}$ *and* $\left\{\xi_1^C, \left\{\varsigma_m^C\right\}_{m=1}^{N_C}\right\}$ respectively. N_R and N_C are the number of *mean* row and column sub-band respectively.

[3] Filter *x* along the rows $\left\{\xi_1^R, \left\{\varsigma_m^R\right\}_{m=1}^{N_R}\right\}$ which provides (N_R+1) output images.

[4] Filter (NR+1) output images along the columns with $\left\{\xi_1^C, \left\{\varsigma_m^C\right\}_{m=1}^{N_C}\right\}$ this provides (N_R+1) (N_C+1) sub-band images.

In this study, EWT is used as a feature extraction technique. EWT is used for the diagnosis of glaucoma in medical image processing [13] and several extensions for the 1D adaptive wavelet frames to 2D signals (images) for EWT is explained in [12].

3. Proposed System

The proposed system for object recognition using EWT consists of two stages; Feature extraction and classification. In the former stage, the features are extracted using EWT and in the later stage they are used for training the classifier. Figure 1 gives the overall view of the proposed EWT based object recognition system.

In the feature extraction stage, features are extracted from the training objects using EWT and stored in the database which is used later for testing the unknown objects. At first, the given object image is converted into gray format and then EWT is applied on it to decompose it. The decomposition produces components of different frequency bands. From the components, energy features are extracted. It is defined by the following equation

$$EWT_k = \frac{1}{RC} \sum_{i=1}^{R} \sum_{j=1}^{C} \left| x_k(i,j) \right| \quad (3)$$

where x_k is the k^{th} component of EWT decomposed image. *R* and *C* are the height and width of the image. From (3), EWT energy features are obtained for different frequency bands. All the training images are used to make a database which contains discriminant features of different objects for classification and also with their identity i.e., the class of objects. After constructing the feature database, unknown objects are tested using KNN classifier. It computes the Euclidean distance between the testing objects features with the database. The identity of object which has the minimum distance is retuned by the classifier. It is an instant based classifier and there is no separate training stage required

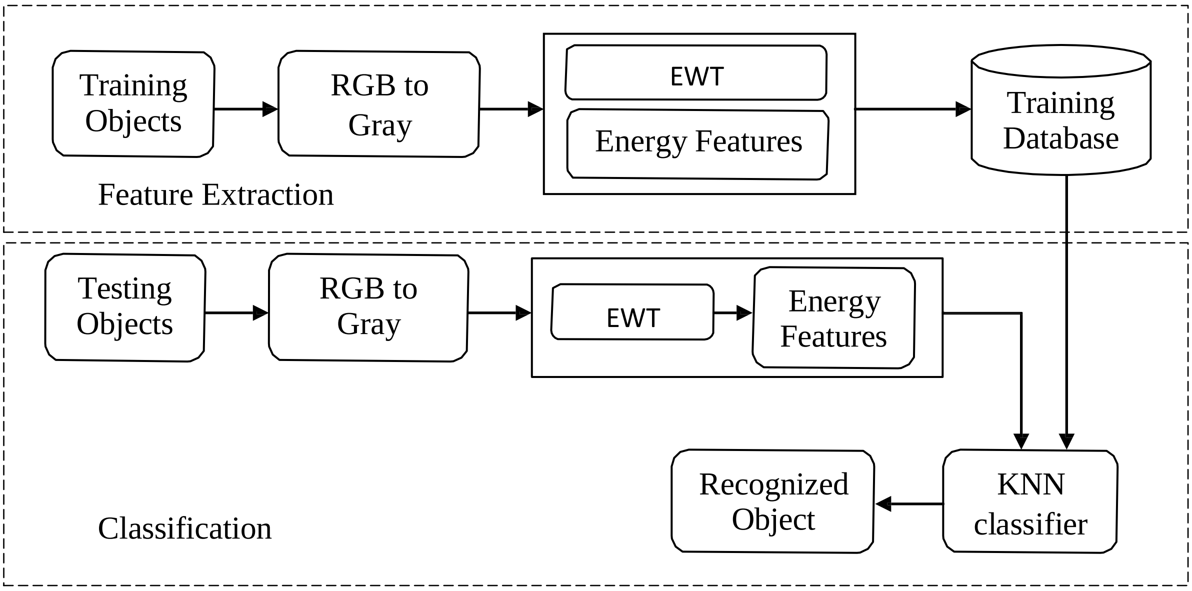

Figure 1 overall view of the proposed EWT based object recognition system

4. Results and Discussions

The proposed EWT based object recognition system is tested on COIL-100 database which is downloadable from [14]. Figure 2 shows the whole objects in the database. The description of COIL-100 database is as follows: A CCD color camera with a 25mm lens was fixed to a rigid stand about 1feet from its base. A motorized turntable was placed about 2feet from the base of the stand. The turntable was rotated through 360 degrees and 72 images were taken per object; one at every 5 degrees of rotation. The size of image in the database is 128 x128 pixels and the number of objects is 100.

Figure 2 COIL Database

As the proposed system is considered as a pattern recognition system, the COIL-100 database is divided into two sets; training and testing sets. The former set is used to extract the discriminant features which are stored in the database for training the classifier. The latter one is used to analyze the performance of the proposed EWT based object recognition system. The division of these two sets is based on the turntable rotation. The images captured at predefined turntable rotation are used for making the training sets and the remaining are used for testing. In this study, six predefined turntable rotations such as 10, 20, 30, 45, 60, and 90 are used for making training images and their corresponding testing images are tested by the proposed system. Table 1 shows the accuracy obtained by the proposed EWT based system. It gives the average accuracy of 100 objects.

Table 1 Performance of the EWT based object recognition system

EWT Decomposition Level	**Average accuracy in percentage (%)**					
	10^0	20^0	30^0	45^0	60^0	90^0
2	86.64	78.50	73.00	66.19	59.79	52.25
3	86.78	77.72	71.85	65.63	56.77	50.44
4	89.31	80.65	75.98	69.23	62.92	57.37
5	94.92	88.24	82.13	73.81	67.52	60.25
6	98.42	93.50	88.68	82.41	75.71	68.31

It is inferred from table 1 that the proposed EWT based object recognition system provides 98.42% accuracy while using the energy features obtained at 6th decomposition level. It is noted that the accuracy of the system gradually increases from lower level decomposition to higher level as more discriminant information captured at higher level. Table 2 shows the individual objects accuracy obtained by the EWT based object recognition system using the EWT energy features obtained at 6th decomposition level.

Table 2 Individual objects accuracy obtained by the EWT based object recognition system

#Object	Accuracy (%)	#Object	Accuracy (%)	#Object	Accuracy (%)	#Object	Accuracy (%)
1	100	26	100	51	100	76	99.31
2	100	27	95.14	52	100	77	100
3	100	28	100	53	100	78	100
4	100	29	100	54	100	79	96.53
5	100	30	100	55	100	80	97.22
6	100	31	99.31	56	100	81	100
7	100	32	100	57	100	82	99.31
8	100	33	100	58	100	83	100
9	100	34	100	59	100	84	92.36
10	100	35	100	60	100	85	100
11	100	36	100	61	100	86	100

12	100	37	100	62	100	87	100
13	91.67	38	100	63	100	88	100
14	100	39	100	64	100	89	100
15	91.67	40	100	65	94.44	90	100
16	100	41	100	66	100	91	77.08
17	100	42	100	67	87.50	92	100
18	100	43	100	68	95.14	93	100
19	99.31	44	86.81	69	74.31	94	100
20	100	45	100	70	100	95	100
21	81.25	46	100	71	100	96	100
22	99.31	47	100	72	100	97	100
23	92.36	48	100	73	100	98	91.67
24	100	49	100	74	100	99	100
25	100	50	100	75	100	100	100
Average							98.42

5. Conclusion

In this paper, an efficient object recognition system based on EWT is proposed. The energy features obtained from the EWT decomposed image are considered as features and given to KNN classifier for classification. As the decomposition of EWT is a signal dependent, it provides better information content than the DWT. COIL-100 database is used for the evaluation. Results show that the proposed object recognition system provides promising results for recognition objects in the given image. It is concluded that EWT energy features are useful for object recognition

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