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An Efficient Approach for Object Recognition Using Empirical Wavelet Transform

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Abstract

Object recognition is a challenging task in many computer vision systems. In order to ease the task of identifying an object in a digital image, an efficient object recognition system is presented in this paper. The proposed approach uses Empirical Wavelet Transform (EWT) which is a signal dependent analysis for extracting information content in the given image. From the low frequency and high frequency EWT components, different entropies such as Shannon, log entropy, and sure entropy are computed as features. A simple K Nearest Neighbor (KNN) classifier is designed for the classification. The experimental results show promising results with 98.97% accuracy on a Columbia Object Image Library Dataset (COIL) that consists of 100 objects

Keywords: *Object recognition, empirical wavelets, entropy, nearest neighbor.*

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. Discriminative robust ternary pattern and discriminative robust local binary pattern for object recognition is discussed in [1]. These two patterns overcome the drawback of local binary pattern and local ternary pattern. They solve the discrimination problems between a bright object against a dark background and vice-versa.

A group-sensitive multiple kernel learning technique is used for object recognition to accommodate the inter-class correlation and intra-class diversity in [2]. A midway representation between the individual images and object category is obtained. An approach for object recognition using principal component analysis and KNN algorithm with Scale Invariant Feature Transform (SIFT) is discussed in [3]. It consists of three steps. The first step is the feature extraction of the input images by SIFT descriptor. The second step is the extraction of Eigen values and Eigen vectors for each image. In the final step a design of nearest neighbor classifier is introduced for classifying the images based on the extracted features.

Context model based object recognition is discussed in [4]. It gives an efficient model that captures the information for more than a hundred object categories using a tree structure. It improves the performance of the system and also a coherent interpretation of a scene is obtained. A task driven progressive part localization method for fine-grained object recognition is discussed in [5]. The part detector should be jointly constructed and gradually refined with the object classifier so that the detected image can give the most distinctive features for final object recognition system.

Multiple kernel learning (MKL) is an approach for selecting and combining kernels functions for a given recognition task. For solving the optimization problems, the state of MKL including different formulations and algorithms are discussed in [6] which focus on their applications to object recognition. Kernel dictionary learning method has become a very efficient strategy for object recognition. An optimization model to concurrently perform kernel dictionary learning and prototype selection is discussed in [7]. The representation matrix is implemented to ensure that only a few samples are actually used to reconstruct the dictionary. So a convergent algorithm is employed to resolve the formulated non-convex optimization problem.

A self adaptive module is discussed in [8] for object recognition. It consists of one selector and four passes. Among the four passes, two are direct passes; one residual pass and one maxout pass with different receptive fields and depths. And the selector is designed to help the user to choose reasonable output. Data driven un-falsified control is implemented for solving the drawbacks in visual servoing for object recognition in [9]. 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.

In this paper, an efficient object recognition system is presented using EWT and KNN. Section 2 gives the methods and materials used in the proposed object recognition system Section 3 gives the results obtained by the proposed system using KNN classifier and in the final section conclusion is made based on the results of the proposed system.

2. MATERIALS AND METHODS:

The overall design of the proposed EWT and KNN based object recognition system is shown in Figure 1.

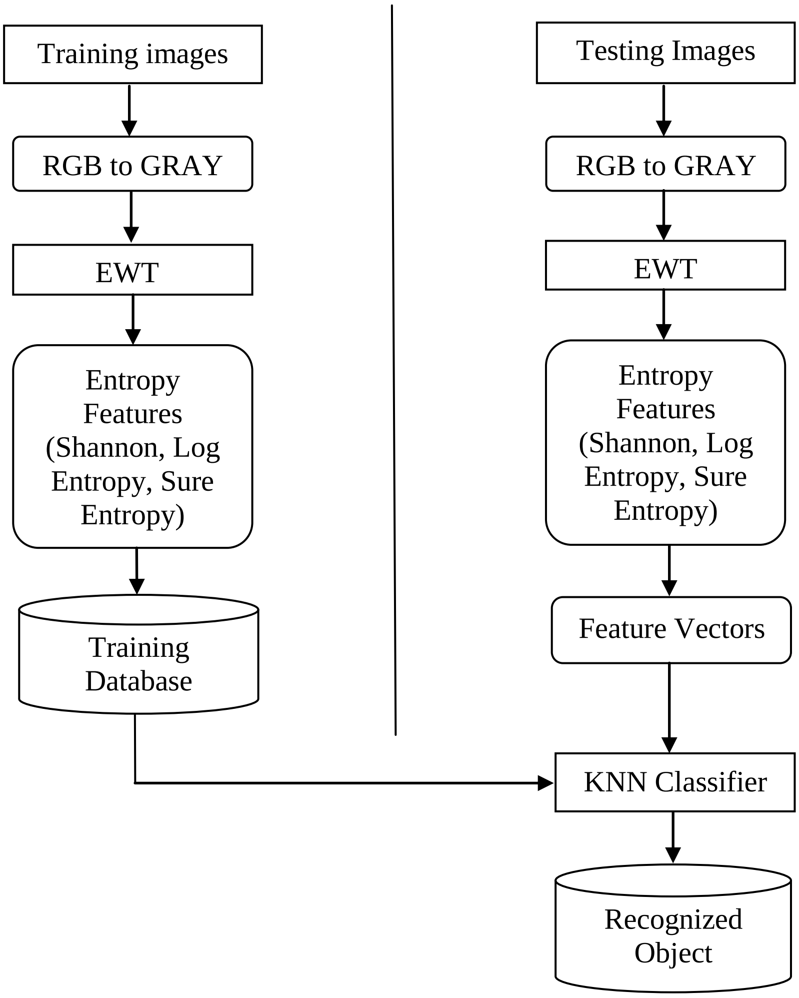

Figure 1 Overall design of the proposed EWT and KNN based object recognition system

Usually a classification system mainly consists of feature extraction and classification phases. Similarly, the proposed object recognition system also consists of the aforementioned phases where EWT and KNN are used for feature extraction and classification respectively. Before feature extraction, all the images are converted into gray format.

2.1 Feature Extraction

In feature extraction, the training object images are given as an input in order to extract the discriminant features. In this study, the discriminant features of objects are obtained from the EWT at various levels. AT first, the given image is decomposed by using EWT. Unlike in Fourier and wavelet transform, the basis filters of EWT are not predefined and are a signal dependent method [10]. It is based on the information content in the given image or signal. The Fourier spectrum in the range 0 to is segmented into M number of parts. Band pass filters in each segment defines the empirical wavelets. The EWT decomposition on 2D images [11] 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 $\left\{\varsigma_1^R, \left\{\varsigma_m^R\right\}_{m=1}^{N_R}\right\}$ *and* $\left\{\varsigma_1^C, \left\{\varsigma_m^C\right\}_{m=1}^{N_C}\right\}$ respectively. N_R and N_C are the number of *mean* row and column sub-band respectively.

[3] Filter *x* along the rows $\left\{\varsigma_1^R, \left\{\varsigma_m^R\right\}_{m=1}^{N_R}\right\}$ which provides (N_R+1) output images.

[4] Filter (NR+1) output images along the columns with $\left\{\varsigma_1^C, \left\{\varsigma_m^C\right\}_{m=1}^{N_C}\right\}$ this provides (N_R+1) (N_C+1) sub-band images.

After EWT decomposition, three different entropy measures; Shannon, log entropy and sure entropy are computed as features from the components of it. They are defined in the following equations.

$$\text{Shannon} = -\sum_i C_i^2 \log\left(C_i^2\right) \quad (3)$$

$$\text{Log Entropy} = \sum_i \log\left(C_i^2\right) \quad (4)$$

$$\text{Sure Entropy} = \left|C_i\right| \le \varepsilon \rightarrow e(s) = \sum_i \min\left(C_i^2, \varepsilon^2\right) \quad (5)$$

where C_i is the coefficients of a particular component i with log(0) = 0 and is a positive threshold. It is obtained using the principle of Steins unbiased risk estimate [12]. These three entropy features are extracted for all the training images and stored for the next stage.

2.2 Classification

The proposed EWT based object recognition system uses KNN classifier to classify the given unknown object. It is instance based classifier and hence there is no need for separate training stage. For testing, the database obtained from the feature extraction phase is given as one of the input the classifier. K-nearest neighbor classification is performed by finding K nearest neighbors in the feature space defined by the given training feature database. Each neighbor votes on the classification of the unknown object. Each vote may be counted equally or more priority may be given to votes of the closest neighbors. 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.

2.3 Database

The COIL-100 database is used for the evaluation which is downloadable from [13]. 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

3. RESULTS AND DISCUSSION:

This section gives the performance of the proposed EWT based object recognition system discussed in the methods and materials section. At first, the COIL-100 database is divided into two sets; training set and testing set based on the turntable rotation. The images in the training set are used to generate the feature database and the testing set images are used for testing the classifier. In this study, six predefined turntable rotations such as 10, 20, 30, 45, 60, and 90 are used for making training set. 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	87.19	78.09	72.18	65.94	57.08	50.74
3	87.33	78.87	73.33	66.50	60.09	52.54
4	89.86	81.02	76.32	69.55	63.23	57.66
5	95.47	88.61	82.47	74.13	67.82	60.54
6	98.97	93.87	89.02	82.72	76.02	68.60

It is inferred from table 1 that the proposed EWT based object recognition system provides 98.97% accuracy while using the entropy 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 entropy 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	100.00	26	100.00	51	100.00	76	100.00
2	100.00	27	97.92	52	100.00	77	100.00
3	100.00	28	100.00	53	100.00	78	100.00
4	100.00	29	100.00	54	100.00	79	99.31
5	100.00	30	100.00	55	100.00	80	97.22
6	100.00	31	100.00	56	100.00	81	100.00
7	100.00	32	100.00	57	100.00	82	100.00
8	100.00	33	100.00	58	100.00	83	100.00
9	100.00	34	100.00	59	100.00	84	95.14
10	100.00	35	100.00	60	100.00	85	100.00
11	100.00	36	100.00	61	100.00	86	100.00
12	100.00	37	100.00	62	100.00	87	100.00
13	94.44	38	100.00	63	99.31	88	100.00
14	100.00	39	100.00	64	100.00	89	100.00
15	94.44	40	100.00	65	97.22	90	100.00
16	100.00	41	100.00	66	100.00	91	83.33
17	100.00	42	100.00	67	89.58	92	100.00
18	100.00	43	100.00	68	96.53	93	100.00
19	100.00	44	92.36	69	84.72	94	100.00
20	100.00	45	100.00	70	100.00	95	100.00
21	86.11	46	100.00	71	100.00	96	100.00
22	100.00	47	100.00	72	100.00	97	100.00
23	95.14	48	100.00	73	100.00	98	94.44
24	100.00	49	100.00	74	100.00	99	100.00
25	100.00	50	100.00	75	100.00	100	100.00
						Average	98.97

4. CONCLUSION:

In this paper, EWT entropy features are analyzed for object recognition. Firstly, the object images are decomposed using EWT and then three different entropy measures; Shannon, log entropy, and sure entropy are extracted from levels (2-6). The gray images are considered in this study. KNN classifier is employed for the classification of objects using Euclidean distance measure. The results on the COIL-100 database showed the effectiveness of the proposed object recognition system.

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