Adaptive Classifier Selection on Hierarchical Context Modeling for Robust Vision Systems

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Abstract. This paper proposes a hierarchical image context based adaptable classifier ensemble for efficient visual information processing under uneven illumination environments. In the proposed method, classifier ensemble is constructed in two stages: i) it distinguishes the illumination context of input image in terms of hierarchical context modeling and ii) constructs classifier ensemble using the genetic algorithm (GA). It stores its experiences in terms of the illumination context hieratical manner and derives artificial chromosome so that the context knowledge can be accumulated and used for identification purpose. The proposed method operates in two modes: the learning mode and the action mode. It can improve its performance incrementally using GA in the learning mode. Once sufficient context knowledge is accumulated, the method can operate in real-time. The proposed method has been evaluated in the area of face recognition. The superiority of the proposed method has been shown using international face database FERET.

Keywords: context awareness, face recognition, classifier ensemble, evolvable classifier selection, hierarchical context modeling, and genetic algorithm.

1 Introduction

The aim of this paper is to improve the accuracy of vision system using hierarchical context modeling and adaptive classifier ensemble. The difficulty of object recognition can be understood by observing Fig. 1 where the same person looks different under varying environments. Efficient interpretation or understanding of images in vision systems frequently relies on some priori knowledge. Several vision systems using prior knowledge have been proposed in the past. Most of them require knowledge bases specifically designed for the application domain, and designing such knowledge bases requires very time consuming process.

In this paper, we focus on the variation of illumination in input images referred as image context that affect the performance of object recognition. However, the proposed method can be readily applied or extended to other kinds of variations. It constructs the most effective structure of classifier system for individual illumination environmental ontology, called hierarchical context modeling, using unsupervised learning method.

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A general classifier system for object recognition can be thought to having multiple stages. Each stage consists of several competitive action primitives. The action primitives are basic functional elements and the same functional elements with different behavior by changing parameters, threshold, etc. are treated as different action primitives. Simple model for object recognition can be divided into three stages: preprocessing, feature representation, and class decision. The preprocessing action primitives are histogram equalization, end-in contrast stretching, Retnix, Hormomorphic filter, etc. The feature representation action primitives are PCA [22], FLD [22], Gabor wavelet [11], etc. The class decision action primitives are Bayesian classifier, neural network, SVM, etc. General Classifier selection scheme can be thought to select action primitive and associated parameters in each stage, and produces an efficient classifier system for a given operational environment.

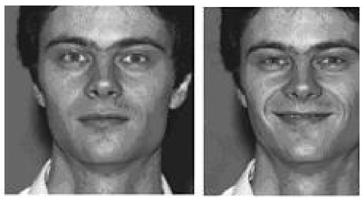


Fig 1. The face images of the same person with different facial expressions

The framework of classifier ensemble can be formalized as follows. Let $PP=\{pp_1, pp_2,..., pp_s\}$ be a set of preprocessing action primitives. Let $FR=\{fr_1, fr_2,..., fr_t\}$ be a set of feature representation action primitives. Let $CD=\{cd_1, cd_2,..., cd_n\}$ be a set of class decision action primitives. Assume that there is k possible $classes=\{\omega_1, \omega_2,..., \omega_k\}$. Let R^n be an input space. The input of each classifier system is represented by input vector $x \in R^n$, i.e. $x=\{x_1, x_2,..., x_n\}^T$. Individual classifier system assigns class label from Ω to an input vector x. That is, $CLS_i : R^n \rightarrow \Omega$ with i = 1, . . ., c. The set of all possible classifier systems are expressed as follows:

$$CLS = PP \times FR \times CD \tag{1}$$

Total $k = s \times t \times u$ classifier systems can be produced. For example, a classifier can be denoted as follows.

$$CLS_i = [pp_j, fr_k, cd_l] \tag{2}$$

The output of classifier $CLS_i(x)$ can be represented as a vector in the following.

$$CLS_i(x) = [O_{i,1}(x), O_{i,2(x)}, ...O_{i,c}(x)], \tag{3}$$

where $O_{i,j}(x)$ is the output derived from CLS_i using the input vector x.

In this paper, we present a novel classifier selection method by introducing the novel concept of hierarchical image context model to achieve high efficient object recognition. It distinguishes the illumination variations of input image using unsupervised learning method repeatedly and derives a hierarchical illumination image category, called hierarchical context modeling. It constructs a classifier system for each illumination category for effective exploration of the GA search space of various classifier systems. Classifier system structure is encoded in terms of artificial chromosome, called action reconfiguration chromosome. GA is used to explore a most effective classifier system structure for each identified data context category. The proposed method adopts the novel strategy of context knowledge accumulation. The knowledge of an individual context category and its associated chromosomes of effective classifiers are stored in the context knowledge base. Similar research can be found by [7]. Once sufficient context knowledge is accumulated, the method can react to such variations in real-time.

2 Hierarchical Context Modeling and Adaptive Classifier Selection

In this session, we will discuss about context knowledge modeling that is derived from context data using unsupervised learning method. Context data is defined as any observable and relevant attributes that affect system behavior, and its interaction with other entities and/or surrounding environment at an instance of time [15]. We limit the context data as the variation of images due to illumination change. It can be, however, extended to various configurations, computing resource availability, dynamic task requirement, application condition, application related environment, etc. [15].

2.1 Hierarchical Context Modeling and Adaptive Classifier Selection

In this research, Context-awareness is carried out based on the hierarchical context modeling and identification of context data. Input context data need to be identified (context identification), and used to validate a most effective classifier for a given action data. Thus, context data should be modeled in association with input action data as much as possible. Since there is no direct way to find context modeling, we used unsupervised learning method repeatedly for each context. The resulting context cluster hierarchy is called hierarchical context model. The proposed method controls the classifier system selection (reconfiguration) based on the identified data context category. Context modeling clusters context data set into several data context categories. Context modeling can be performed by an unsupervised learning algorithm such as SOM, Fuzzy Art, K-means etc. [16, 17]. Context identification is to determine the context category of a given context data **[17]**. Context identification can be carried out by employing a normal pattern classification method such as NN, K-nn, SVM, etc.

2.2 Context Knowledge Accumulation Using GA

Context knowledge describes a trigger of system action (combined classifier system output) in association with an identified context stored in the context knowledge base over a period of time [8]. Initially, the proposed method learns and accumulates the knowledge of context-action configuration chromosome associations, and stores them in the CKB. The knowledge of context-action association denotes that of a most effective classifier system for an identified context. The AM configures the action configuration chromosome and our method decides the fitness of the GA.

The proposed method adopts the novel strategy of context knowledge accumulation. The knowledge of an individual context category and its associated chromosomes of effective classifier systems are stored in the context knowledge base. In addition, once the context knowledge is constructed, the system can react to changing environments at run-time [17].

2.3 Adaptive Classifier Selection Using Hierarchical Context Modeling

The proposed Evolvable Classifier Selection (ECS) method uses two types of data: context data and action data as inputs. The action data, denoted by **x**, is a normal data being processed. The context data, denoted by **y**, is used to identify a data context of x, the normal input. The proposed method controls classifier selection based on the identified data context. Action data itself can be used as context data. We assume that the context data can be modeled in association with the input action data. We need identify a data context (category) firstly, and select a best classifier system based on the data category. The classifier selection is formalized as follows.

$$ECS(x, y) = CKO(y)(CLS_1(x), CLS_2(x),...., CLS_k(x)) , \tag{4}$$

where, CKO is a context-aware knowledge operator. CKO selects the best classifier from total k classifier systems. The implementation of CKO can be done by some learning method and hierarchical context knowledge base. We use a single input image as both context and action data in this paper. The proposed method consists of the context identification module (CIM), the action control module (ACM), the action module (AM), the evolution control module (ECM), and the context knowledge base (CKB) (see Fig. 2).

The proposed method tries to distinguish the data characteristics of input image (data contexts) and selects a classifier system accordingly using the genetic algorithm (GA). It stores its experiences in terms of the data context category and the artificial chromosome, called action configuration chromosome, so that the context knowledge can be accumulated and used later. Each chromosome represents the encoding of the structure of an optimal AM for corresponding data context category. Data context is identified by the CIM. The ACM searches for a best combining structure of action primitives (i.e. classifier system) for an identified data context. The action configuration chromosomes of optimal actions are stored in the CKB with the corresponding data context category. Our method evolves itself by accumulating the knowledge which classifier system guarantees an optimal performance for each identified data context. The ECM manages the evolution. It operates in two modes: the evolution mode and action mode, and the details are described in the following sub section.

2.4 The Action Mode

In the action mode, data context is identified by the CIM. The ACM searches the action configuration chromosome for the identified data context in the CKB (see Fig. 2). The AM is reconfigured by the ACM, if necessary. Then, the reconfigured AM performs its task using the action data, and produces the response of the ECS. Whenever the ACM identifies that the data context is changed, the system reconfigures the AM. If our method measures the performance being fell down below a predefined criterion, our method activates the evolution mode, or it may evolve the system periodically.

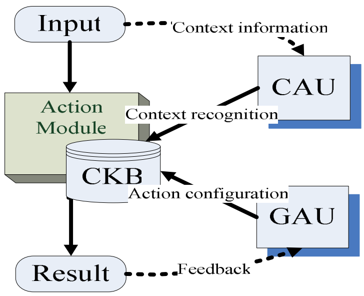


Fig. 2. Block diagram of the proposed architecture for object recognition

2.5 The Evolution Mode

In the evolution mode, the training data are clustered into data context categories by the CIM (see Fig. 2). The training data of each data context category are used to accumulate the knowledge of the action configuration chromosome of the AM. The evolution process is controlled by the ECM, and the details will be discussed in the next session. The determined action configuration chromosome with its corresponding data context category is stored in the CKB.

3 Object Recognition Using ECS Method

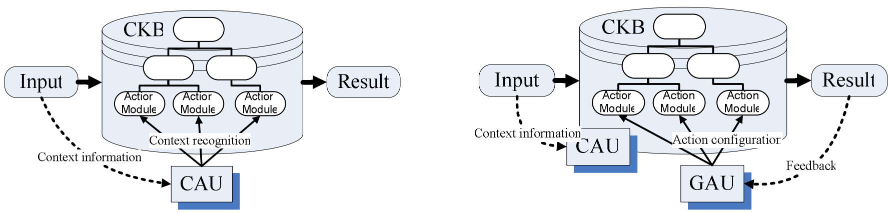
The proposed ECS method has been tested in the area of object recognition. We employ the ECS strategy where the face recognition system structure is allowed to evolve in accordance with changing quality of input image data, i.e. data context. The data sets Inha, FERRET, and Yale were used in our experiments.

3.1 The Design of ECS Based Face Recognition

The AM of ECS based face recognition consists of three stages: the preprocessing, feature representation, and class decision. Preprocessing is performed for providing stable quality images as much as possible for face recognition. The action primitives employed for preprocessing stage here is the histogram equalization, the Retnix, and the end-in contrast stretching [17]. We adopt Gabor vectors [17] with different weight values of individual fiducial points as the action primitives of feature representation.

For the simplicity, we adopt non-parametric classification method k-nn's with different threshold values as the action primitives of the class decision stage. The architecture of face recognition using the proposed method is shown in Fig. 3.

In hierarchical context based face recognition, the input images are used as the action data as well as the context data. We assume that the training set of input face image is provided. In the action mode, and the data context category of input face image is identified by the CIM. If the data context category is the same as the previous one, the ACM activates the AM. Otherwise, the ACM gets the action reconfiguration chromosome from the CKB, and the AM reconfigures itself using the information in the chromosome. In other words, a classifier system that is optimized for the data context of the input image is selected (or reconfigured). Finally, the AM produce the recognition result using the action data (input face image).



(a) (b)

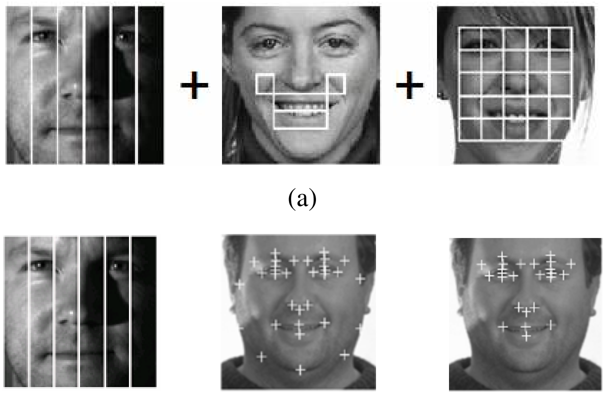
Fig. 3. Two modes of hierarchical context based face recognition: (a) the flow diagram of the action mode, and (b) the flow diagram of the evolution mode.

In the evolution mode, the CIM clusters (models) face data images into several data context categories. The details of the data context modeling and identification will be discussed in the next sub-session. Each cluster denotes one data context category, and the ACM generates the corresponding action reconfiguration chromosome for each data context using the face images in each cluster, respectively.

3.2 Hierarchical Illumination Context Modeling

We used face image of 128 x 128 spatial resolution and 256 g ray levels as input context data **y** here (seethe session 3.1). Three methods of derived context feature were investigated here as shown in Fig. 4. In the vertical scanning method, the input context data, i.e. 128 x 128 face image is reduced into 6 x 6 images, and the reduced image is scanned in the vertical direction first (from top to bottom) and from left to right. Then, we generated dcfs [17] 1-D vector with 36 elements. The horizontal scan is carried out in a similar way except that the first scanning direction is horizontal. In the hybrid scan, three different scans are concatenated into 1-D dcf vector with 36 elements.

Next step, dcf's is clustered into several context categories in order to assign a data context category to each face images. Several types of unsupervised learning methods have been investigated for constructing the context model. However, SOM [22] is selected to be the most promising algorithm. SOM can be used to create an intuitive model of the important concepts contained in information [15, 16]. After a sufficient number of input vectors have been presented, network connection weights specify clusters, the point density function of which tends to approximate the probability density function of the input vectors. In addition, the connection weights will be organized such that topologically close nodes are sensitive to inputs that are similar. Fig. 5 shows hierarchical context model generated by the hybrid scan where images are categorized according to environmental situation.



(a)

(b) (c) (d)

Fig. 4. Facial geometry representation by hybrid scanning (a), vertical scanning (b), coordinates of facial feature points (c) and facial feature points excepting face edges (d)

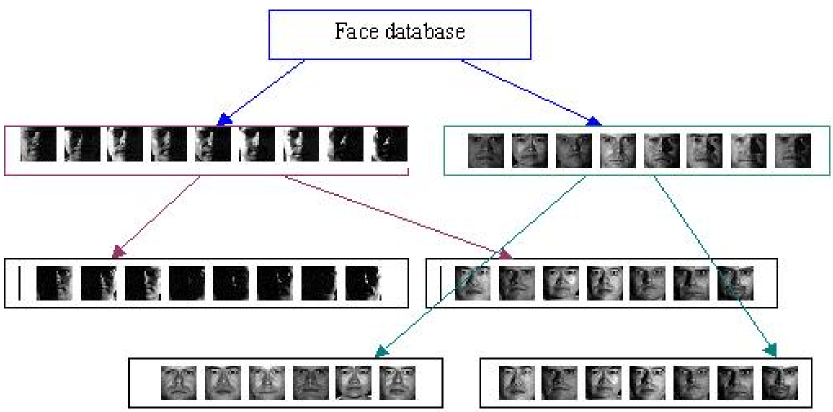


Fig. 5. Hierarchical context modeling using hybrid scanning

4 Experimental Results

The feasibility of the proposed hierarchical context modeling method has been tested in the area of face recognition using FERET [20] data sets. We used 2418 images from 1209 persons in FERET data set.

First, we clustered the images into context models by hierarchical clustering using K-means algorithm. Extracted vectors using hybrid scanning are feed into K-means clustering. Second, we evolve classifier systems for individual context models. Genetic algorithm evaluates the best classifier system for each context model using images in the corresponding cluster.

Table 1. Face recognition results on clustered data after GA adaptation. Face images are hierarchically clustered using K-means clustering repeatedly.

<table>
<tr><th rowspan="2"></th><th colspan="4">Recognition rate (Total number of images)</th></tr>
<tr><th>No clustering</th><th>K-means clustering (K = 6)</th><th>K-means clustering at two clusters</th><th>K-means clustering at a cluster</th></tr>
<tr><td>Cluster-0</td><td rowspan="10">93.13</td><td colspan="3">96.09% (228)</td></tr>
<tr><td>Cluster-1</td><td colspan="3">97.45% (157)</td></tr>
<tr><td>Cluster-2</td><td colspan="3">96.94% (131)</td></tr>
<tr><td rowspan="2">Cluster-3</td><td rowspan="2">95.27% (148)</td><td colspan="2">96.68%(87)</td></tr>
<tr><td colspan="2">94.56%(61)</td></tr>
<tr><td>Cluster-4</td><td colspan="3">99.36% (157)</td></tr>
<tr><td rowspan="3">Cluster-5</td><td rowspan="3">92.62% (217)</td><td colspan="2">96.15%(130)</td></tr>
<tr><td rowspan="2">90.8%(87)</td><td>90.91%(22)</td></tr>
<tr><td>92.30%(65)</td></tr>
<tr><td>Total</td><td>96.05%</td><td>96.23%</td><td>96.54%</td></tr>
</table>

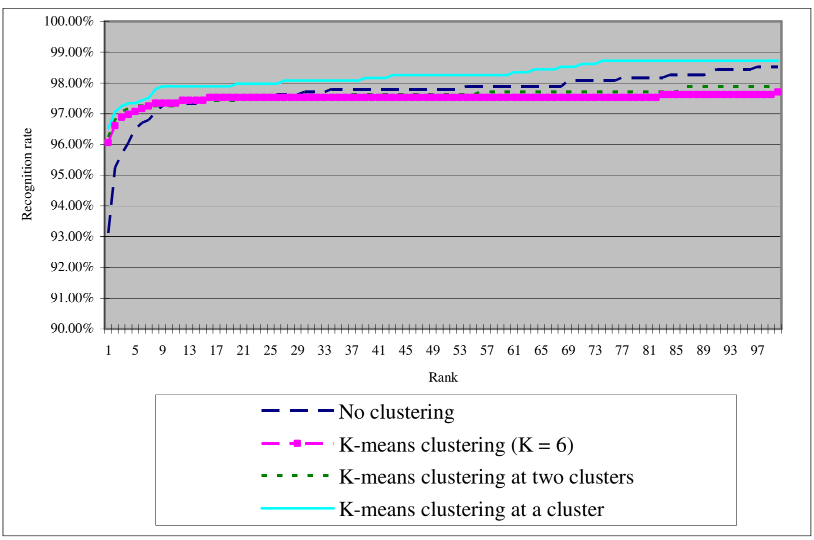


Fig. 6. The CMC curve shows the performance on clustered data after GA adaptation

In the process of clustering, K-means clustering is done repeatedly. Some clusters constructed by K-means algorithm are clustered by K-means algorithm again. Table 1 shows the performance of successful face recognition using hierarchical K-means clustering and adaptation. At first, whole test images are clustered to 6 clusters. Next, on some clusters, K-means clustering is done again. And this process is repeated. In the event, that enables hierarchical context modeling. As you can see in those tables, we can achieve better performance by hierarchical context modeling after adaptation using genetic algorithm. Fig. 6 is showing the CMC curve of the adaptable face recognition for each case of clustering.

In Table 2, one can find that the proposed method can achieve the highest performance. The superiority comes from the flexibility of our method since it has the capability of hierarchical ontology based context-awareness and adaptation.

Table 2. Performance comparison of the proposed system comparing with other approaches

Algorithm/Method	Recognition rate
arl_cor	0.827
arl_ef	0.797
Ef_hist_dev_anm	0.774
Ef_hist_dev_l1	0.772
ef_hist_dev_l2	0.716
ef_hist_dev_md	0.741
ef_hist_dev_ml1	0.733
ef_hist_dev_ml2	0.772
excalibur	0.794
mit_mar_95	0.834
mit_sep_96	0.948
umd_mar_97	0.962
usc_mar_97	0.95
Proposed method	0.9654

5 Conclusion

In this paper, a novel method of classifier combination using hierarchical image context-awareness is proposed and applied to object recognition problem. The proposed method tries to distinguish its input data context and evolves the classifier combination structure accordingly by Genetic algorithm (GA). It stores its experiences in terms of the data context category and the evolved artificial chromosome so that the evolutionary knowledge can be used later. The main difference of the proposed classifier selection method from other methods is that it can select classifiers in accordance with the identified context. In addition, once the context knowledge is constructed, the system can react to changing environments at run-time.

The proposed method has been evaluated in the area of face recognition. Data context-awareness, modeling and identification of input data as data context categories, is carried out using K-means algorithm. The face data context can be decided based on the image attributes such as, light direction, contrast, brightness, spectral composition, etc. The proposed scheme can optimize itself to a given data in real-time by using the identified data context and previously derived chromosome. The proposed method is tested using four datasets: Inha, FERET, and Yale. Its performance is evaluated through extensive experiments to be superior to those of most popular methods, especially in each cluster.

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