International Conference on Information and Communication Technology
ICICT 2007, 7-9 March 2007, Dhaka, Bangladesh

AN APPROACH OF CONTEXT ONTOLOGY FOR ROBUST FACE RECOGNITION AGAINST ILLUMINATION VARIATIONS

M.Rezaul Bashar, Yan Li** and Phill Kyu Rhee****

* Dept. of Information and Communication Technology, Islamic University, Kushtia, Bangladesh
** Department of Mathematics and Computing, University of South Queensland, Australia.
*** Department of Computer Science & Information Technology, Inha University, Korea

E-mail: mrb_iuc@yahoo.com, liyan@usq.edu.au

ABSTRACT

This paper proposes a face recognition method that is robust against image variations due to arbitrary lighting condition. Though many researches have been carried out on face recognition system, however; there exist some limitations such as illumination, pose, alignment, occlusion, etc. This paper presents a context ontology model making a robust face recognition system on different illumination situations. Our proposed system works on two phases: environmental context ontology building (modelling) and recognition using context ontology. Context ontology is built using context acquisition, context learning and context categorization. The recognition approach is implemented on illumination variant face recognition that takes identified context as input and performs recognition with usual process such as pre-processing, feature extraction, learning, and recognition. We have tested the recognition performance of our proposed model with an international standard FERET face database (our produced synthesized FERET images) and we have achieved a success rate of more than 92%.

1. INTRODUCTION

Viewing properties or appearance of a face image changes drastically when imaging conditions such as illumination and pose are varied, creating serious difficulties in identifying the resulting image. When illumination changes, its effects prevail the unique properties of individual features and thus greatly degrades the performance of state-of-art systems [1,2].

Recently, the process of building ontologies [3] becomes a research topic of interest. The term, ontology [3,4], is first developed for controlling vocabulary, later on, it is organized into taxonomy where key concepts are identified, and now these days, ontology is a rising research area in the field of pattern classification, data mining, and other purposes. Usually, the goal of building ontology is to create a logical framework, a classification, or to develop a common understanding related to some objects. The aim of this paper is to build ontology on variant illumination to improve the accuracy of vision system using ontological context modelling.

In this paper, we present context ontology method to introduce the novel concept of image context model to organize images in certain way to achieve high efficient face recognition. It distinguishes the environmental illumination variations of input image using unsupervised learning method repeatedly and derives context ontology. The system also constructs a classifier system for each context category using genetic algorithm (GA). The structure of classifier system is encoded in terms of artificial chromosome, called action reconfiguration chromosome. GA is used to explore the 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 (Knowledge). Once sufficient context knowledge is accumulated, the method can react to such variations in real-time.

2. ENVIRONMENTAL CONTEXT ONTOLOGY

In this research, environmental context identification and categorization produce context ontology. Environmental data is categorized as context data and action data. For example, all the relevant visual information in an environment is context data while only limited data those produce any operation is action data. Input context data need to be identified (context identification), and used to validate the most effective classifier for a given action data. Since there is no direct way to find context modeling, we used unsupervised learning method repeatedly for each context. The resulting context produces context ontology. The proposed method controls the classifier system selection (selection of proper fiducial points for Gabor feature extraction) based on the identified data context category. Context modeling produces several context categories from context data. An unsupervised learning algorithm such as self-organising map (SOM) [5], Fuzzy Art [5], K-means [5] etc. can perform context modelling. Context categorization determines the context into existing context category of a given context data. Context categorization can be carried out by employing a normal pattern classification method such as NN, K-nn, SVM, cosine distance, etc.

2.1 Context Knowledge Acquisition

It is important to mention about the importance of knowledge building for an intelligent system that is either digital or natural. For our experiment, context knowledge accumulation process consists four tasks. These are domain taxonomy acquisition, domain knowledge base, context data sampling and manually selected fiducial points on context data as shown in Fig. 1.

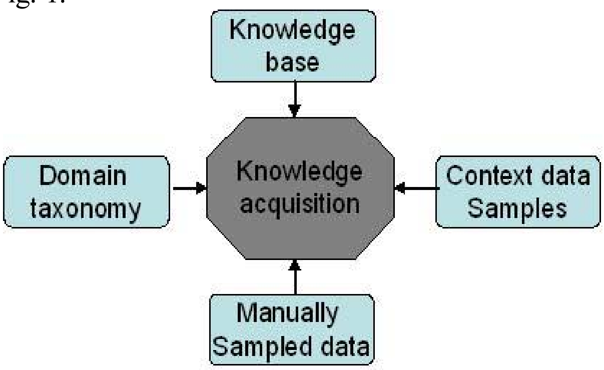

Fig 1. Symbolic structure of knowledge acquisition

Definition 1: Let ε be the set of all images and ℘ is a partial order between images. $\forall$ $(O_i, O_j) \in \varepsilon$, O_i ℘ O_j means that object O_i is a sub concept of O_j.
Definition 2: Let φ be the set of clusters. $A \in \varepsilon$ is the set of cluster attributes where A is predefined cluster attribute. For a cluster $\alpha \in \varphi$, $A_\alpha \subseteq A$ is the set of attributes of α. $℘_\varphi$ is a partial order between clusters. We define S: $\varphi \rightarrow \varphi$, so that S(α) is the set of subparts of α.
Definition 3: Let a is an attribute (feature) of an image where $a \in A_\alpha$. We define $\Im$: $A_\alpha \rightarrow \varepsilon$, so that $\Im(a)$ is the set of values of a and so that $\forall O_i \in \Im(a)$.

Definition 4: Let ϖ be the set of manual fiducial points. We define $\kappa_\varphi: \varphi \rightarrow \varpi$, so that $\kappa_\varphi(\alpha)$ is the set of representative region of a cluster α.

The complete ontology is composed of FERET synthesized images (described in section 5.1). The depth of this ontological tree is 4. Depending on the application domain this ontology can be extendible. Numerical features are the basic contents of an environmental context data. 32 fiducial points with 32 x 32 kernels are associated with feature extraction. For example, FERET for a cluster left_top, α = {Left_top}, S(α) = {Left_90, left_25}, A_α = {direction, moment, mean}. Attribute value direction is defined as $\Im$(direction) = {Neg} /{Pos} .

2.2 Context Learning

Context learning learns environmental context data during knowledge acquisition phase. The example of context learning task is to learn how to detect a particular context in an environment.

Context learning consists of a training set of contexts C = $\{c_i\}$ to recognize context within context ontology. Context ontology is used because the learning process is done in a hierarchical way using ontological tree structure. Context learning is composed of three steps: training set building, feature selection and training.

A training set T_i is associated with context set $O_i \in \varepsilon$. A training set is a set of N labelled vector $x_i \in R^n$. Training set building uses the set of training vectors $X = \{x_i, O_i\}$. Feature selection chooses the most characterizing features for better context identification. We use hybrid scanning algorithm to perform feature selection and K-means clustering algorithm for learning that produces any defined number of contexts (clusters).

2.3 Context Categorization

Cosine distance is a popular distance measure for comparing documents in the information retrieval literature. We adapt cosine distance to match peaks within a tolerance window to account for calibration error between experimental and theoretical spectra. For two vectors, A and B, the similarity measure

$$D_{\cos}(A,B) = \frac{\sum_i match(a_i, b_i)}{|A|.|B|} \quad \ldots\ldots (1)$$

The structure of environmental context ontology is represented in Fig 2.

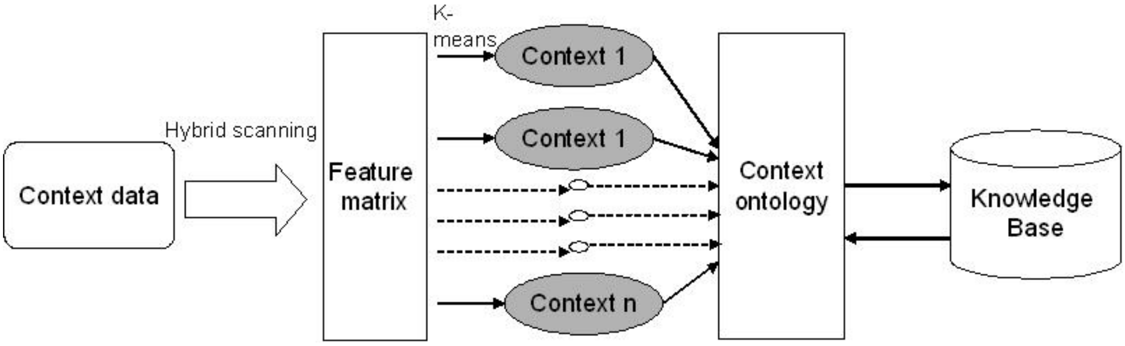

Fig 2. Structure of environmental context ontology

3. CONSTRUCTION OF CONTEXT ONTOLOGY

Ontology is an explicit specification of a conceptualization [3]. It has a long history in philosophy, in which it refers to the subject of existence. Ontology can be thought as description of the relational structure of concepts for enabling knowledge sharing and reuse. Ontology is often equated with taxonomic hierarchies of classes regarding its usage.

The methods of representing ontology are diverse and depend on the required level of detail and logic. In practice, a simple concept hierarchy may represent ontology. For example, context ontology, a terminological ontology, is a collection of categories organized in such an order where images are ordered according to their illumination [6], i,e. left directed illumination, right directed illumination, normal illumination, dark illumination, and so on. During learning for context identification, environmental context modelling clusters (models) face data images into several data context categories according to Section 2. Each cluster denotes one data context category and the cluster set are organized in hierarchy fashion. Figure 3 shows an example of context ontology based on illumination.

In this research, ontological approach is selected because of its hierarchical properties. Though there are several approaches for artificial knowledge construction methodologies i,e neural network, resonance theory, super vector machine etc., ontology produces proper classification categories based on illumination. As ontology produces tree structure, it takes very short time to select illumination category. Another advantage of ontology construction is that when there is a huge amount of data, ontology can be used for identifying clusters and then any knowledge construction method can be used for individual recognition.

4. EXPERIMENT MODEL

Experimental environment is organized in two parts: environmental context modelling and face recognition. Environmental context modelling is associated with knowledge acquisition, learning and context categorization. Hybrid scanning (horizontal + vertical scanning method) is considered for feature extraction on manually sample images, K-means algorithm is employed for learning i,e producing clustering and cosine distance measurement is used for categorizing the clusters. Face recognition consists of three stages: the pre-processing, feature representation, and class decision. Pre-processing is performed for providing stable quality images as much as possible for face recognition. The action primitives employed for pre-processing stage here is the histogram equalization. We adopt Gabor vectors [7, 8, 9] with different weight values of individual fiducial points as the action primitives of feature representation. There are 32 fiducial points per image and GA selects some strong feature for generating artificial chromosome to learn and finally GA creates knowledge data base. For the simplicity, we adopt non-parametric classification method k-nn's with different threshold values for the class decision stage. The architecture of face recognition using our proposed method is shown in Fig.4. At the learning phase of context ontology unit, the system tries to familiar with all possible context situations (illumination variation) may happen. And at the face recognition unit, system makes its knowledge using GA on registered face images. However, during action phase, the context ontology unit recognizes the current situation (cluster) and then face recognition unit determines its success or failure with the help of knowledge in terms of chromosome of GA.

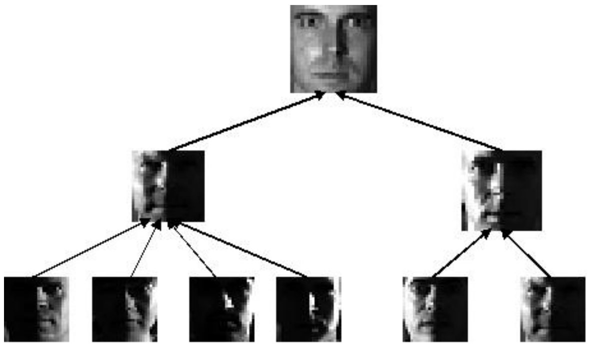

Fig 3. Context ontology based on illumination

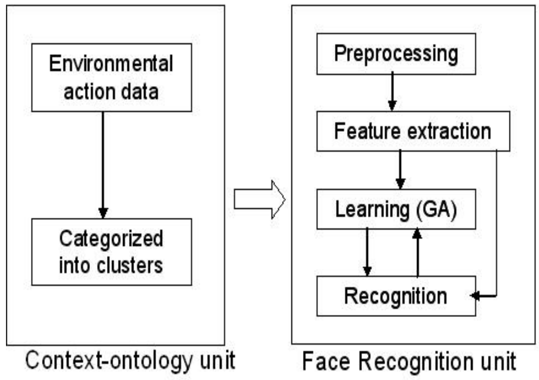

Fig 4. Block diagram of proposed context ontology based face recognition

5. EXPERIMENT RESULT

5.1 Dataset

The proposed system has been experimented on FERET [10] face database. In FERET dataset, two frontal views with normal illumination are taken. A synthesized image (illumination 1 to illumination 9) data set is generated by distinguishing the high, medium, and low brightness level and left, front, and right coarse lighting direction per each FERET image and we termed it as synthesized FERET image. We have trained our system with 90 synthesized face images (taking 10 images per cluster) and tested on 1038 synthesized images at random order with AMD Athlon 2.21GHz processor.

5.2 Result

First, we grouped the images into hierarchical context models by clustering using K-means algorithm. Extracted vectors using hybrid scanning are fed 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.

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 context ontology. We have explored our experiment with 4 parts to show the importance of a well organized ontology for recognition.

First case, the system is tested without ontology system and it produces the lowest success rate.

Second case, we have termed as 1 level ontology where test images are categorized into 6 clusters.

Third case, 2 level ontology where test images are categorized into 8 clusters.

And finally, N level ontology is made using 9 clusters (same number of clusters of synthesized data). N level ontology is well organized ontology in comparison with 1, 2 or other level ontologies. It shows the best success rate. Figure 5 shows the average performance of different ontology level.

Table 1. Face recognition result with different ontology level on cluster basis

Ontology Level (OL)	Recognition rate (%) per cluster								
	Cls-01	Cls-02	Cls-03	Cls-04	Cls-05	Cls-06	Cls-07	Cls-08	Cls-09
OL-1					92.87				
OL-2	93.23	95.84	92.77	91.48	95.14	91.62	-	-	-
OL-3	93.58	95.19	94.37	92.08	95.89	92.15	94.72	95.06	
OL-N	95.48	95.96	93.91	95.26	96.38	94.81	96.03	94.86	96.73

5.3 Comparison

Our proposed context ontology system is innovative and we haven't found any existing system that is very close to our proposed system to compare. This is why, we are unable to show the superiority of our proposed system to others but there are many existing face recognition system on FERET dataset. P. Philips [10] has shown about the performance of face recognition on FERET database in his paper and we have found other performance rates at homepage of FRVT 2002. Comparing with these sources, we found that the success rate of our proposed context ontology based face recognition is superior to others.

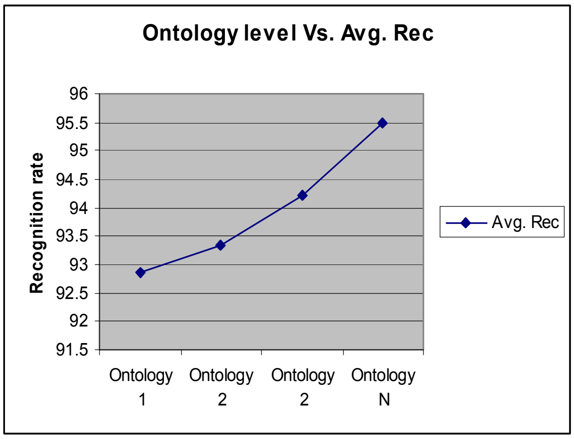

Fig 5. Recognition rate *vs* Ontology level

6 CONCLUSION

This paper presents an approach making context ontology on varying illuminations for a robust face recognition system and the importance of building well organized ontology. Context ontology is structured into three main phases: knowledge acquisition, context learning and context categorization. For face recognition cases, the system takes categorized context as input and GA assists for learning to build knowledge in association with artificial chromosome that selects the feature point of Gabor encoding. And finally, K-nn method recognizes the faces according to its knowledge.

We have applied this context ontology approach to face recognition scheme on FERET data set. We have achieved that our proposed well-organized model is superior to other existing system. The future trends of our paper will focus on distributed and real time ontology construction for dynamic changing environments.

REFERENCES

[1] Rui Ishiyama, asahiko Hamanaka, and Shizuo Sakamoto, "An Appearance Model Constructed on 3-D Surface for Robust Face Recognition Against Pose and Illumination Variations," IEEE Traansactions on Systems, Man, and Cybernatics-Part C: Applications and Reviews, vol 35, no. 3, pp 326-334, Aug 2005.

[2] Y. Adini, Y. Moses, and S. Ullman, "Face recogtion: The problem of compensating for changesin illumination direction," IEEE Transaction on Pattern and Machine Intelligent, vol 19, n0 7, pp 721-731, Jul.1997.

[3] Auncion Gomez, Mariano Fernandez, and Oscar Corch., Ontological Engineering, 2nd Edition, Springer-Verlag, Berlin Heidelberg New York 2004.

[4] Ruben Prieto-Diaz, "A Faceted Approach to Building Ontologies," IEEE International Conference on Information Reuse and Integration, 2003 pp 48-465.

[5] Richard O. Duda, Peter E. Hart, David G. Stork, Pattern Classification, Second Edition Wiley-Interscience Publications, New York, 2001

[6] Dang-Hui Liu, Kin-Man Lam, and Lan-sun Shen, "Illumination invariant face recognition," Journal of Pattern Recognition, 38 (2005) page no.1705 – 1716

[7] C. Liu and H. Wechsler, "Gabor Feature Classifier for Face Recognition," Computer Vision 8th IEEE International Conference, (2001) 270-275

[8] X. Wu, B. Bhanu, "Gabor wavelet representation for 3D object recognition", IEEE International Transaction on Image Processing, vol. 6 , no. 1, 1997.

[9] Wang and X. Tang, " A Unified Framework for Subspace Face Recognition," IEEE Trans. on PAMI, vol. 26, no. 9 (2004) 1222- 1228

[10] P. Phillips, "The FERET database and evolution procedure for face recognition algorithms," Image and Vision Computing, vol.16, no.5 (1999) 295-306.