FACE RECOGNITION USING DUAL TREE COMPLEX WAVELET TRANSFORM

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ABSTRACT

We propose a novel face recognition using Dual Tree Complex Wavelet Transform (DTCWT), which is used to extract features from face images. The Complex Wavelet Transform is a tool that uses a dual tree of wavelet filters to find the real and imaginary parts of complex wavelet coefficients. The DT-CWT is, however, less redundant and computationally efficient. CWT is a relatively recent enhancement to the discrete wavelet transform (DWT). We show that it is a well-suited basis for this problem as it is directionally selective, smoothly shift invariant, optimally decimated at coarse scales and invertible (no loss of information). Our face recognition scheme is fast because of the decimated nature of the DTCWT. Dual Tree methods are based on image at different resolution. Normalization is done to reduce dimensionality which will reduce memory problem and computation time. Here Principal Component Analysis which is a linear dimensionality reduction technique, that attempt to represent data in lower dimensions, is used to perform the face recognition. PCA is applied that deals with the decomposition of the training set into the Eigenvectors called Eigen faces. Various discrimination analyzes such as, Euclidean, L1, L2 and Cosine similarity are used for the recognition of face images.

KEYWORDS

Dual Tree Complex Wavelet Transform, Principal Component Analysis, Dual Tree Discrete Wavelet Transform.

1 INTRODUCTION

In recent years face recognition received more attention in the field of biometric authentication. Biometrics refers to the automatic identification of a person based on his/her physiological or behavioral characteristics. This method of identification offers several advantages over traditional methods involving such as security systems, credit card verification, scene Surveillance including commercial and law enforcement applications for various reasons: 1.The person to be identified is required to be physically present at the point-of-identification.

Face recognition problem has become one of the most relevant research areas in pattern recognition. There is several recognition algorithms transform the original image into critically sampled domain such as Discrete Real Wavelet Transform (DWT) [3, 4], principal components analysis, Discrete Cosine Transform (DCT) or Discrete Fourier Transform (DFT). Gabor wavelet-based representation provides an excellent solution when one considers all the above desirable properties. For this reason, Gabor wavelets have been extensively implemented in many face recognition approaches [6-9]. In Complex Wavelet representation is 4 times redundant in 2 dimensions and the redundancy is independent of the number of scales used. Some face recognition algorithms have been proposed to solve the face recognition problem with only a single training image with various mode of process [2].

In this paper we propose main approach taken for face recognition is to compare some data present in a database with that of the probe image obtained from the person to be recognized. We systematically study complex wavelets for face recognition problem. Specifically we employ the recently developed dual-tree complex wavelet transform and a new single-tree complex wavelet transform with improved shift invariance and directional selectivity properties. First, Gabor wavelet and complex wavelet-based representation of face images are obtained. For all the transform, the representations encompass 4 levels and 6 directions. PCA is employed to further reduce the dimensionality of the derived feature vectors. Finally, 3 types of similarity measures used for identification. Results of experiments carried out on FERET and ORL databases indicate that complex wavelets indeed constitute and excellent alternative to Gabor wavelets in face image representation and recognition. The goal in most face recognition approaches is to find a similarity measure invariant to illumination changes, head pose and facial expressions so that images of faces can be successfully matched in spite of these variations. In order to capture multi-orientation information in face images better. Therefore, each face image is described by a subset of band filtered images containing DT-CWT coefficients which characterize the face textures. We divide the DT-CWT sub-bands into small sub-blocks, from which we extract compact and meaningful features vectors using simple statistical measures.

The rest of the paper is organized as follows. Sections 2 and 3 briefly give an overview of image decomposition using DWT, and DT-CWT. Section 4 describes the proposed method. Section 5describes the wavelet transform and multiscale analysis and section 6 discuss the simulation results.

2 IMAGE DECOMPOSITION USING DWT

The discrete wavelet transform used here is identical to hierarchical sub-band system. Next, the filtering is done for each column of the intermediate data.

The resulting two-dimensional array of coefficients contains 4 bands of data. Each labeled as LL, LH, HL, and HH.

1. The LL band can be decomposed once again.
2. DWT decomposed sub-bands. This can be done up to any level.

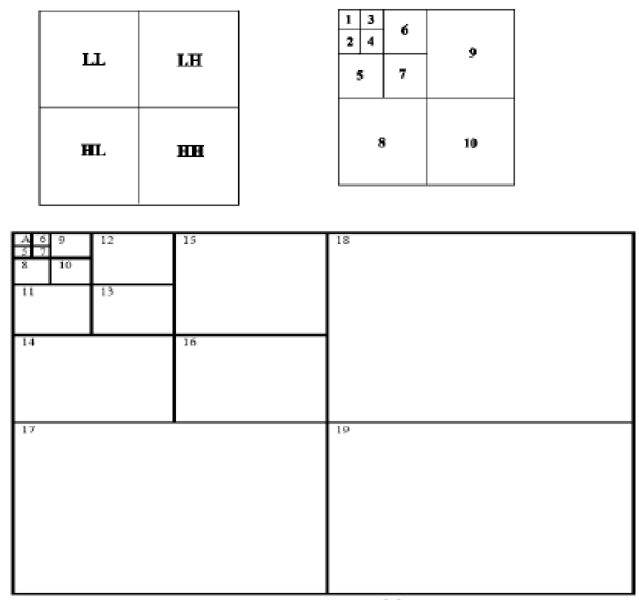


Figure 1: (a) 1-level wavelet decomposition and (b) 3-level wavelet decomposition and 6-level wavelet decomposition, the band A is decomposed one time again.

There by resulting in a pyramidal decomposition as shown in figure

3 DUAL-TREE COMPLEX WAVELET TRANSFORMS

The Dual-Tree Complex Wavelet Transform (DT-CWT), comprising two trees of real filters, Tree a and b, produce the real and imaginary parts of the complex coefficients. Odd and even length bi-orthogonal linear-phase filters are placed as shown to achieve the correct relative signal delays. The properties of the DT-CWT can be summarized as 1) approximate shift invariance;

2) good directional selectivity in 2 dimensions; 3) phase information; 4) perfect reconstruction using short linear-phase filters; 5) limited redundancy, independent of the number of scales, 2:1 for 1D (2m : 1 for mD); 6) efficient order-N computation-computation-only twice the simple DWT for 1D (2m times for mD).

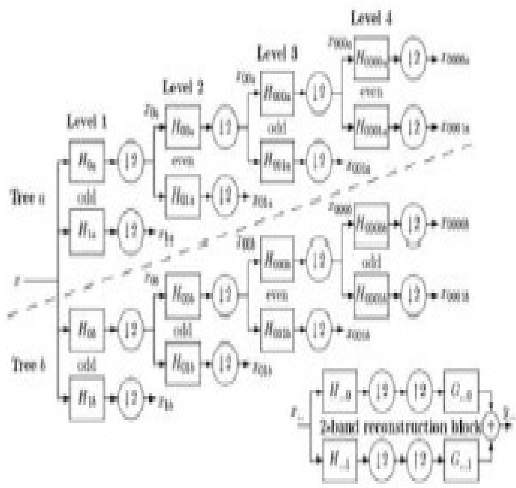
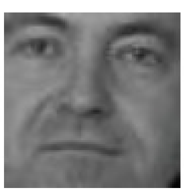
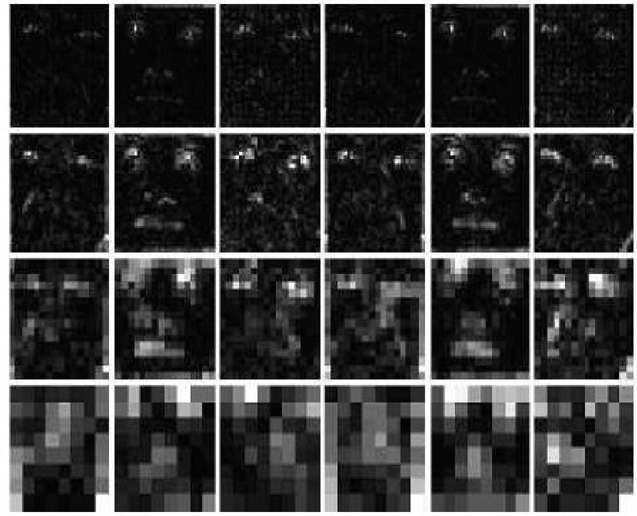


Figure 1.Dual-Tree Complex Wavelet Transform

It has the ability to differentiate positive and negative frequencies and produces six sub bands oriented in ±15, ±45, ±75. This figure shows the magnitude and real part of face image processed using the DT-CWT. it is called ‘fuzzy-fuzzy set’. As the type 1 gives only sub optimal solution, type 2 fuzzy is good in dealing with uncertainty, which is usual in Cloud ambience.



Sample image for transformation



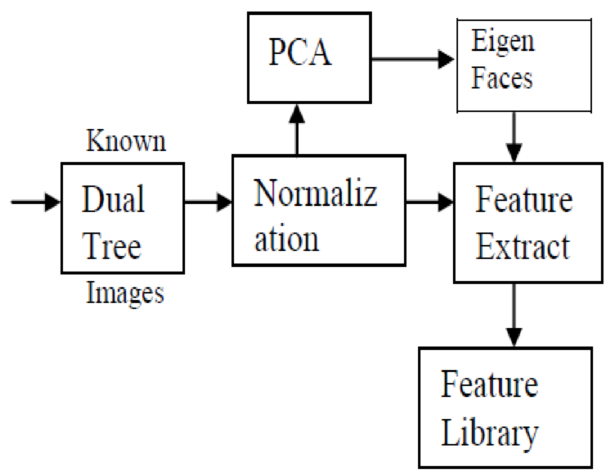
The magnitude of the transformation

4 PROPOSED FACE RECOGNITION SYSTEMS SUPPORT VECTOR MACHINES OF CLOUD

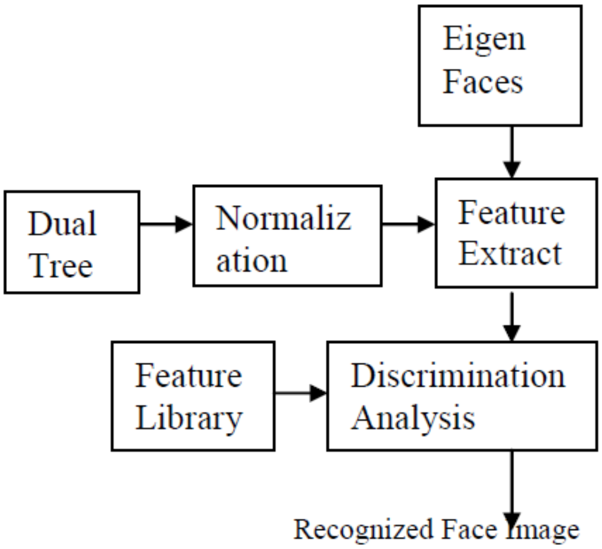
The face-based approach and it consists of 2 stages, namely

1. Training stages
2. Recognition stages

The block diagram of the proposed face recognition system is shown in the figure



Training Phase



Recognition Phase

5. DUAL TREE

5.1 The Wavelet Transform and multiscale analysis

The wavelet transform has been exploited with great success across the gamut of signal processing applications, in the process, often redefining the state-of-the-art performance. In the classical setting, the wavelets are stretched and shifted versions of a fundamental, real-valued bandpass wavelet$\psi(t)$. When carefully chosen and combined with shifts of a real-valued low-pass scaling function $\varphi(t)$, they form an orthonormal basis expansion for one-dimensional (1-D) real-valued continuous-time signals. That is, any finite energy analog signal $x(t)$ can be decomposed in terms of wavelets and scaling functions.

The scaling coefficients $c(n)$ and wavelet coefficients $d(j, n)$ are computed via the inner products.

There exists a very efficient, linear time complexity algorithm to compute the coefficients $c(n)$ and $d(j,n)$ from a fine-scale representation of the signal (often simply N samples) and vice versa based on two octave-band, discrete-time FBs that recursively apply a discrete-time low-pass filter $h0(n)$, a high-pass filter $h1(n)$, and upsampling and downsampling operations. These filters provide a convenient parameterization for designing wavelets and scaling functions with desirable properties, such as compact time support and fast frequency decay and orthogonally to low-order polynomials (vanishing moments).

5.2 Normalization

For Each input image wavelet transform output is about 40 images (for scale=5, orientation=8) which increase the size of the processing data. So to overcome the memory problem normalization is needed.

Steps involved in normalizing the each Dual output image and combining all to a single vector in the input space is as follows.

1. The Dual tree decomposed images are first down sampled by a factor, which is selected usually as low as possible (p=3).This is down sampling is done only to reduce the size of the processing data.
2. Then each down sampled image of 40 dual tree output images is normalized to zero mean and unit variance. Zero mean is obtained by subtracting the mean from its each element.
3. Then each zero mean normalized image is converted into the column vector. This is accomplished by concatenating the columns one after other. All the 40 dual tree output images are converted into column vector.
4. Then all 40 column vectors are concatenated one after another to form column vector. This vector is called the input feature vector of the corresponding input images.

The input feature space is formed by combining the entire input feature vector image as follows,

$$X = (O^{t}_{0,0} Ot_{0,1} \ldots O^{t}_{4,7}) t .$$

5.3 Principal component analysis

PCA is a useful statistical technique that has found applications in fields such as face recognition and image compression it is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in high dimensional data are hard to find due to the unavailability of graphical representation, PCA is a powerful tool for analyzing the data. PCA is applied to normalized vector which transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. Normally covariance matrix is calculated by, C= X X‟‟. Covariance matrix C is difficult to calculate due to its large size, which may leads to memory problem. Hence it can be calculated by indirect method. First, the matrix L is formed by, L=X „ X. Even vectors v for L is calculated. Eigen vectors v are sorted according to the Eigen values. Eigen vectors for C is calculated from v,(i.e.)u= Xv, where „u‟ is the eigenvectors of C.

5.4 Eigenfaces for face recognitions

Eigenface is the eigenvector obtained from PCA. Each training image is transformed into a vector by row concatenation. The covariance matrix is constructed by a set of training images.

5.5 Feature extraction

Feature extraction is the projected co-ordinates of each image along each eigenvector axis. This can be accomplished by, F=u‟‟ X. The u and F are stored in feature library. F contains the coefficients of each Eigenvectors for a particular image. If total no of images is M, no of coefficients for each image is also M. So the dimension of F is M x M. Thus large set of correlated feature space is reduced to smallest of uncorrelated eigenvectors. The feature vector formed after normalization is called as feature space. By using this Eigen faces and Feature faces, each face is projected into a point in the face space in which each eigenvector is considered as the mutually orthogonal coordinate axes. After projection of the all the input faces in the training set, their projected feature vector are stored in feature library and further used in recognition phase.

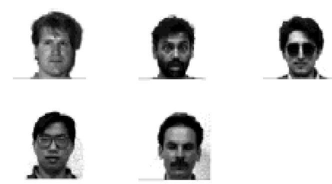
5.6 Recognition phase

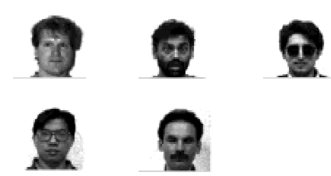
Dual tree transform of the given testing face images are taken and 40(8 x 5) images are obtained as output. Then, each output image is down sampled by a factor. All the column vectors are then concatenated to form a single column vector. Feature extracted vector is obtained as, Fr = u „X r where X r is the test image.

6. FACE RECOGNITION EXPERIMENTAL RESULTS FOR FERET DATABASE

The face recognition results obtained with 50,100 and 200 persons of FERET database for Gabor Decomposition (scale=5; Orientation=8). The training images are given.

Input Images





Normalized Training Images

PCA obtained Mean and Variance

Eigen faces

Feature Extraction Results

7 CONCLUSIONS

In this paper, we proposed a new technique, based on dual tree in using PCA for human face recognition. The proposed algorithm is yet to be tested for all Databases. FERET and Yale datasets are used, which contains the face images with different orientations, expressions and illumination. In our approach, the input face image is decomposed using dual tree complex wavelet transform. The recognition is done on the basis of Euclidean distance measure on CWT. We observe the results of face recognition using this approach are very good and encouraging. Furthermore, only one image per person is used for training which makes it useful for practical face recognition applications.

8 REFERENCES

1. A. Abbas and T. Tran, “Fast approximations of the orthogonal dual-tree wavelet bases,” in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Processing (ICASSP).*

2. W.Zhao, R.Chellappa, A.Rosenfeld, and P.J.Phillips, “Face Recognition: A Literature Survey”, Technical Report CAR-TR-948, Univ. of Maryland, CFAR(2000).

3. R.Brunelli,T.Poggio,Face recognition:features versus templates,IEEE transactions on Pattern Analysis and Machine Intelligence.

4. P. Nicholl and A. Amira, “DWT/PCA face recognition using automatic coefficient selection”, in Proceedings of the 4th IEEE International Worksho[on Electronic Design, Test and Applications (DELTS “08), pp.390-393, Honh Kong, Janurary 2008.

5. L. Shen, Z.Ji, L.Bai, and C.Xu, “DWT based HMM for face recognition”, Journal of Electronics, Vol.24, no.6, pp. 835-837, 2007.

6. Michael J. Lyons, Julien Budynek, and Shigeru Akamatsu(1999),”Automatic Classification of Single Facial Images”, IEEE Transactions on Pattern Analysis and Machine Intelligence,Vol.21,No.12.

7. L. Shen, L.Bai, and M.Fairhurst, “Gabor wavelets and general discriminant analysis for face identification and verification,” Image and Vision Computiong, vol.25, no.5, pp.553-563, 2007.

8. Chengjun Liu, and Harryechsler. (Jul 2003) Independent Component Analysis of Gabor Features for Face Recognition IEEE Transactions on Neural Networks, vol.14.

9. Aleix M. MartoAnez and Avinash C.Kak(2001),”PCA Versus LDA”,IEEE Transactions on Pattern Analysis and Machine Intelligence,Vol.23,No.2.

10. Jian Yang,David Zhang,Alejandro F.Frangi,and Jing-yu Yang(2004),”Two-Dimensional PCA:A New Approach to Appearance-Based Face Representation and Recognition”, IEEE Transactions on Pattern Analysis and Machine Intelligence,Vol.26,No.1.

11. N.G. Kingsbury. Complex wavelets for shift invariant analysis and filtering of signals. J. of Appl. And Comp. Harm. Analysis.

12. I.W. Selesnick, R.G. Baraniuk, and N.G. Kingsbury. The dual-tree complex wavelet transform. IEEE Signal Process.

13. J.Yang, Y.wang, W.Xu, and Q.Dai. Image coding using dual-tree discrete wavelet transform. IEEE Trans. Process.

VM is a Machine Learning Technique developed on statistical learning theory. For machine learning tasks involving pattern classification, multi sensors information fusion, non-linear system control etc, SVMs have become an increasingly popular tool. SVMs are a set of related supervised learning methods used for *classification* and regression. Viewing input *data* as two sets of *vectors* in an *n-dimensional space*, an SVM will construct a separating hyper plane in that *space,* which maximizes the *margin* between the two data sets. To calculate the margin, two *parallel* hyper planes are constructed, one on each side of the separating hyper plane, which are "pushed up against" the two data sets. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the neighboring data points of both classes, since in general the larger the margin the better the *generalization error* of the classifier [5], [8]. This could be implemented to identify the nodes in Cloud through optimal path.

4.1 Multi class support vector machine

For the conventional SVM an *n* class problem is converted into *n* two-class problem and for the *i*th two class problem, class *i* is separated from remaining class with decision function that classifies class *i* and remaining classes be

$$D_i(\mathbf{x}) = w_i^t\mathbf{x} + b_i , \qquad (1)$$

SVM, if for the input vector **x** *Di* (**x**) > 0 is classified for *i*, **x** is classified in to class *i*. Let the decision function for class *i* against class, with the maximum margin [4], [5] be

$$D_{ij}(\mathbf{x}) = w_{ij}^t \mathbf{x} + b_{ij}, \qquad (2)$$

where $D_{ij}(\mathbf{x}) = D_{ji}(\mathbf{x})$ for the input vector $\mathbf{x}$ can be calculated

$$D_i(\mathbf{x}) = \sum_{i=1}^{n} sign(D_{ij}(\mathbf{x})) \qquad (3)$$

and classify $\mathbf{x}$ into the class

$$\arg\max_{i=1}^{n} D_i(\mathbf{x}). \qquad (4)$$

4.2 Fuzzy support vector machine (FSVM)

An SVM learns the decision surface from two distinct classes of the input points. In many applications, each input point may not be fully assigned to one of these two classes. In this paper, a fuzzy membership is applied to each node in the path and the SVMs are reformulated so that different nodes in the Cloud can make different contribution to the learning of decision surface. Class *i* is defined as a one dimensional membership functions *mii*(**x**) on the direction orthogonal to the optimal separating hyper planes Dj(**x**) = 0 as given below

$$1.\ \text{For } i = j \quad m_{ij}(\mathbf{x}) = \begin{cases} 1 & \text{for } D_j(\mathbf{x}) > 1, \\ D_i(\mathbf{x}) & \text{otherwise,} \end{cases} \qquad (5)$$

$$2.\ \text{For } i \neq j \quad m_{ij}(\mathbf{x}) = \begin{cases} 1 & \text{for } D_j(\mathbf{x}) < -1, \\ -D_j(\mathbf{x}) & \text{otherwise.} \end{cases} \qquad (6)$$

The class i membership function of $\mathbf{x}$ is defined using the minimum operator for

$$m_i(\mathbf{x}) = \min_{j=1}^{n} m_{ij}(\mathbf{x}). \qquad (7)$$

Now the datum $\mathbf{x}$ is classified in to the class $\arg\max_{i=1}^{n} m_i(\mathbf{x})$ if x satisfied

$$D_k(\mathbf{x}) \begin{cases} > 0, & \text{for } k = i, \\ \leq 0, & \text{for } k \neq i,\ k = 1, \cdots, n \end{cases} \qquad (8)$$

and $m_k(\mathbf{x})$ is given by

$$1.\ k \in i_1, \quad m_k(x) = \min_{\substack{j=i_1 \\ j \neq k}}^{i_1} \left(-D_j(x)\right), \qquad (9)$$

$$2.\ k \neq j, (j = i_1, \cdots, i_1), \quad m_k(x) = \min_{j=i_1}^{i_1} \left(-D_j(x)\right), \qquad (10)$$

Thus the maximum degree of membership is achieved among $m_k(\mathbf{x})$, $k = i_1, \cdots, i_1$ (*Fig. 2*) [4], [5].

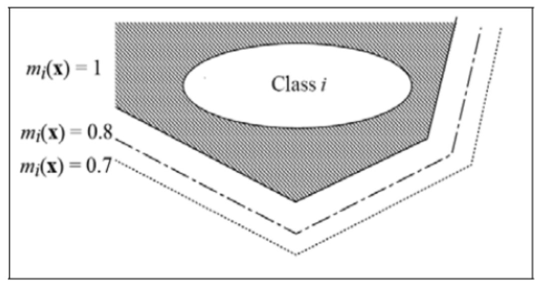


Fig. 2. Contour lines of the class *i* membership function

5. IMPLEMENTATION DETAILS

Architecture: The Cloud architecture consists of three layers. The Resource Layer is a collection of nodes communicating with the Cloud's hardware resources so as CPU Cycles and memory. One module can be shared by two or more Brokers, which reduces redundancy in coding. The development tools used is Java language.

5.1 Multi-agent system

Fig. *3* depicts the simplified diagram representing the Abstract-Owner system using a AO Broker/Agent.

The agent basically interacts with the other components of the Cloud system by manipulating information on the agent. The information on the agent may represent facts, assumptions, and deductions made by the system during the course of solving the problem by the consumers. An agent is a partial problem solver, which may employ a different negotiation strategy and contribute to the interaction of consumers and providers by viewing the information on the AO agent. Note that the arrows in Fig. *3* represent the flow of information. The diagram shows that the Owner and job shop is allowed to read/write information on the AO agent. AO agents basically execute their tasks independently using the information on the interface agent and posts any result back to the interface agent [6].

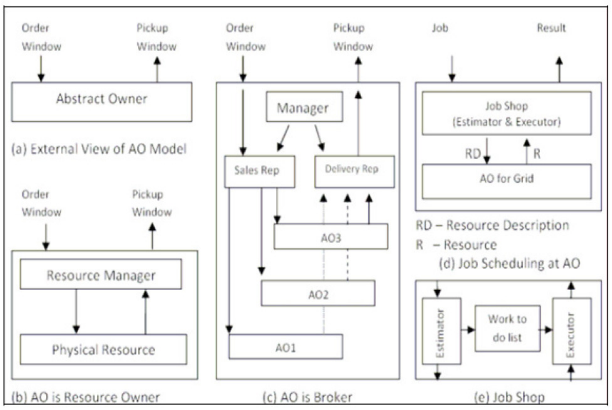


Fig. 3. Grid resource management architecture

5.2 Intelligent AO Agents/Brokers Fuzzy SVM based Collision Avoidance

The agent called the Fuzzy Collision Detector [9], [1] is a fuzzy SVM –based Collision Avoidance Controller, which is used in sensing Robotic movements. In this paper, a fuzzy membership is applied to each node in the Cloud-computing ambience and the SVMs are reformulated so that different input points can make different contributions to the learning of decision surface and hence pave the way for efficient Cloud interaction. The fuzzy-based agent is fed with CPU Cycles or memory as an input, acquired from a set of Cloud nodes. The values that are stored in the AO Broker in terms of CPU cycles and Memory availability (near, medium, and far) are considered for the optimal Cloud interactions thus avoiding the collision. The CPU cycles of the processors is shown in Fig. *4*.

For the operation of a computational Cloud, the broker discovers properties of resources that the user can access through the Cloud information server(s), negotiates with (Cloud-enabled) resources or their agents using middleware services, maps tasks to Computational Resources (scheduling), stages the application and data for processing (deployment) and finally gathers results [10]. It is also responsible for monitoring application execution progress along with managing changes in the Cloud infrastructure and resource failures. *Fig. 5* shows the high-level view of Cloud where the computational resources use both brokers and information services.

Computational resource navigation

A method for uniquely detecting the resource availability on a heavy traffic high performance network; separately sensing packets scattered from the congested segment region indicative of a traffic delay and producing signals representative thereof; normalizing the signal from node with respect to the consumer to indicate availability [7].

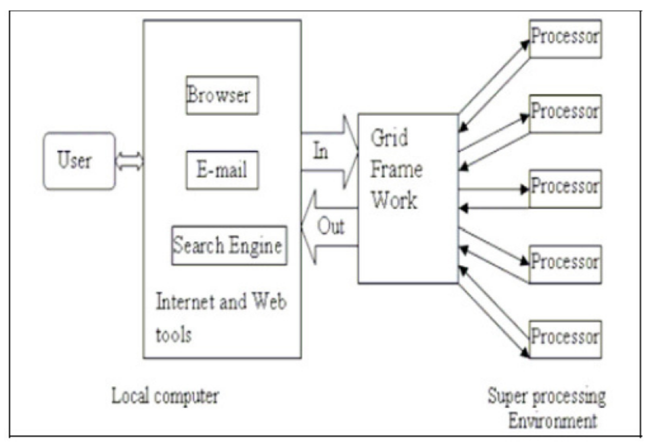


Fig. 4. Task split-up for grid interaction

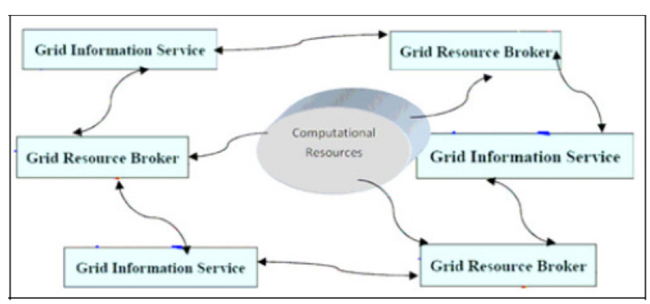


Fig. 5. High-level view of grid

Network monitor
The Network Monitoring Component monitors the remote clients for their availability. Availability of these clients is decided based on the amount of their CPU cycles [8] and their Memory capacity being used for any on-going executions. CPU Usage is the data that represents the amount of CPU cycles being spent at the remote client for local processes. This data is to be taken into account because busy processes should not be overloaded with more tasks, which may lead to system failure or hang up. It is calculated based on the Operating System versions. On Windows NT, CPU usage counter is '% Total processor time' whose index is 240 under 'System' object whose index is 2. And, in Win2K/XP, Microsoft moved that counter to '% processor time' whose index is 6 under 'Total' instance of 'Processor' object whose index is 238. The index value is specified as a parameter to the method that finds the CPU Usage information using performance counters. The above proposed algorithm can be implemented using Java and the performance is evaluated for this envisioned system. PERFCLOUD tool is used to analyze the CPU and memory usage of four nodes at the normal state. This is compared against values obtained for the CPU and memory usage by implementing the optimized IC Scheduling algorithm.

5.3 Multi-agent optimal path planning

Problems of multi-agent Cloud systems have got significance [6]. Each AO agent Cloud system has some transport subsystem, which consists of several nodes. The method based on graph optimization algorithms [11] has been applied to control the dynamic group of nodes. Novelty of the developed multi-agent path planning algorithm [12], [13] is as follows:

- Cloud participants are considered as dynamic obstacles;
- Graph representation of common distribution environment mode is used for path planning;
- The quickest path is planned (time optimization);
- Expert rules for speed and path correction are synthesized to provide Cloudlock avoidance.

These algorithms provide global optimality. Optimal Path Planning Approach to Cloud Environment also provides Cloudlock avoidance. *Ant colony optimization* also can be used to identify a group of nodes in Cloud.

6. EXPERIMENTATION AND RESULTS.

The algorithm schedules the eligible tasks so as to maximize the number of eligible tasks at each step of computation, thus making maximum utilization of the available resources in the Cloud Framework. The example job, which is used for evaluating the performance and thereby comparing the results is shown below;
Example Job: (((a+b)*(c+d))-((e+f)*(g+e))).
The above job was split into tasks using Job Splitter and the tasks are allocated to the four nodes based on their availability. This allocation was done using the Optimized IC Scheduling Algorithm. The CPU usage and Memory availability before and after implementing the algorithm was observed using PerfCloud Tool and the Network Monitor designed using Java. The Processor utilization in terms of percentage is tabulated in *Table I* as follows:

Table I

Network monitor

Resource Usage		PerfGrid	Network Monitor
CPU Usage %	Client 1	1.52	1.4
	Client 2	0.82	27.12
	Client 3	0.09	12.33
	Client 4	0.87	34.52

Fig. 6 represents the line graph, which depicts the percentage of CPU usage. For PerfCloud [11] the CPU usage is equal to zero for all the four clients, which means the CPU is not used as there are no processes allocated to these clients. However, there will be a significant value for memory availability because of the RAM usage even in the idle state of the machine. The time optimization algorithm [14] that plans and

responds a user request on auction-based resource allocation systems can be used for further improvement of Cloud broker services. Cloud System can also be enhanced with Incremental FSVM [8] with Kernel will give better result in group nodes/clusters. Since the Cloud ambience requires an optimized approach of scheduling resources, the proposed technique can further improved by a more robust hybrid algorithm [15], which actually provides a way for scheduling projects/tasks in resource constrained environment like the Cloud. Hence the combination of the approaches [14], [15] is believed to have better scheduling solutions which could be made as future enhancements..

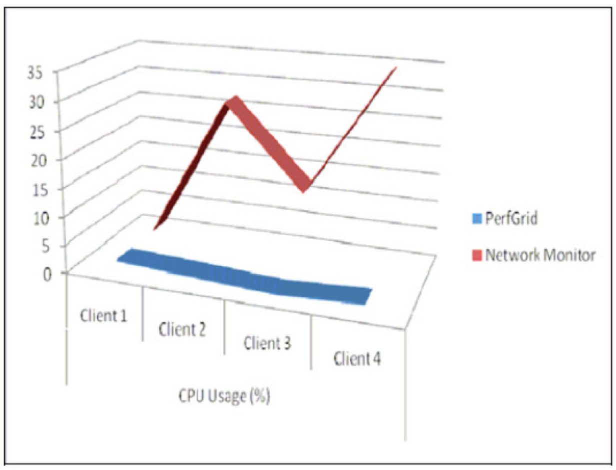


Fig. 6. CPU usage

7. CONCLUSIONS

The multi-agent and multi-agent optimal path planning approach provides an extra level intelligence. This paper deals with the real-time navigation made by the Cloud nodes in a totally uncertain environment called Cloud Ambience. Type 2 fuzzy gives a better approach to solve uncertainty. Based on fuzzy logic and Support Vector Machine, a collision free technique has been proposed that partitions a task and hence fed to the processors. This proposal has been validated in different unknown environments cluttered with static and dynamic obstacles and has proven to give the node, a means of to be an active Cloud participant. These techniques provide better scheduling solutions and hence make resource utilization more efficient.

8. REFERENCES

[1] Merchant-Cruz E. A., Morris A. S. Fuzzy-GA-based trajectory planner for robot manipulators sharing a common workspace, *IEEE Tr. Robotics*, Vol. 22, No. 4, 2006, pp. 613–624.

[2] Poornaselvan K. J., Gireesh Kmar T., Vijayan V. P. Agent based ground flight control using type-2 fuzzy logic and hybrid ant colony optimization to a dynamic environment, in *Proceeding of First International Conference on Emerging Trends in Engineering and Technology*, 16-18 July 2008, Nagpur, Maharashtra, India, pp. 38–42.

[3] Kumar T.G., Vijayan V. P. A multi-agent optimal path planning approach to robotics environment, in *Proceeding of International Conference on Computational Intelligence and Multimedia Applications*, 13-15 December 2007, Sivakasi, Tamil Nadu, India, pp. 400–404.

[4] Abe S., Inoue T. Fuzzy support vector machines for pattern classification, in *Proceeding ofInternational Joint Conference on Neural Networks* (IJCNN'01'), 15-19 July 2001,Washington DC, USA, Vol. 2, pp. 1449–1454.

[5] Abe S., Inoue T. Fuzzy support vector machines for multiclass problems, in *Proceedings onEuropean Symposium on Artificial Neural Networks*, 24-26 April 2002, Bruges, Belgium, pp. 113–118.

[6] Huq R., Mann G. K. I., Gosine R. G. Behavior-modulation technique in mobile robotics using fuzzy discrete event system, *IEEE Tr. Robotics*, Vol. 22, No. 5, 2006, pp. 903–916.

[7] Levine S. P., Bell D. A., Jaros L. A. Simpson R. C. Koren Y., Borenstein J. The NavChair assistive

wheelchair navigation system, *IEEE Tr. Rehabilitation Engineering*, Vol. 7, No. 4, 1999 pp. 443–451.
[8] Evgeniou T., Pontil M., Poggio T. Regularization networks and support vector machines, in *Advances in Large Margin Classifiers*, Cambridge, MA, MIT Press, 2000, pp. 171–204.
[9] Fayad C., Webb P. Optimized fuzzy logic based on algorithm for a mobile robot collision avoidance in an unknown environment, *7th European Congress on Intelligent Techniques and Soft Computing*, Aachen, Germany, 13-16 September 1999, pp. 26–33.
[10] Foster A., Kesselman C. (Ed.) The grid: blueprint for a future computing infrastructure,Morgan Kaufmann Publishers, USA, 1999.
[11] Abbas A. *Grid computed to technology and applying: A practical guide to technology & applications*, Firewall Media, New Delhi, India, 2009.
[12] Assistive Technology & Artificial Intelligence, Lecture Notes in Computer Science, KISS Institute for Practical Robotcs, Vol. 1458, 1998, Springer-Verlag, Berlin, 1998, pp. 126–136.
[13] Xiaolei Yin Y.,Go, Y., Bowling A. Navigability of multi-legged robots, *IEEE/ASME Tr. Mechatronics*, Vol. 11, No. 1, 2006, pp 1-8.
[14] Sulistio A., Buyya R., A time optimization algorithm for scheduling bag-of-task applications in auction-based proportional share systems, in *Proceedings of the 17th International Symposium on Computer Architecture on High Performance Computing* (SBAC-PAD '05), Rio de Janeiro, Brazil, 24-27 October 2005, pp. 235–242.
[15] Szendr_i E. A robust hybrid method for the multimode resource-constrained project scheduling problem, *Pollack Periodica*, Vol. 5, No. 3, 2010, pp. 175–184.