International Journal of Engineering Innovation & Research
Volume 1, Issue 2, ISSN : 2277 – 5668

Automatic Shape Annotation Using Rough Sets and Decision Trees

Manoj P. Patil
Department of Computer Science
North Maharashtra University, Jalgaon, (M. S.)
mpp145@gmail.com

Satish R.Kolhe
Department of Computer Science
North Maharashtra University, Jalgaon, (M. S.)
srkolhe2000@gmail.com

***Abstract* — Annotation of images automatically assigns tags to images by analyzing contents of images. Shape is the most important feature of images, by using this features tagging of images is possible, can be termed as automatic shape annotation. In this paper, a novel classifiers using machine learning techniques viz. Rough Set (RS) and Decision Tree (DT) are presented to classify shape images of a standard dataset for annotation purpose. Shape based features are extracted and organized to form a shape feature. Rough Set Exploration System (RSES) is used to develop decision tree based, rough set based classifiers for the tagging of shapes. The results obtained using these classifiers are presented and discussed. The RS classifier significantly improves the annotation performance.**

***Keywords* — Automatic image annotation, shape features, decision tree, rough sets.**

I. Introduction

The description of the object shape is an important task in image analysis and pattern recognition. The shapes occurring in the images have also a remarkable significance in image retrieval [1]. The ever growing number of images generated everyday is the reason to develop, evaluate and implement sophisticated automatic annotation system for the retrieval of images from large databases based on their content rather than their manual annotations. Although computers are still a long way from identifying and textually describing image concepts in the way humans do, it is possible to train computers on large previously annotated image databases, in order to learn the associations between visual image data and their textual descriptions [2].

These automatic image annotation systems have received intensive attention in the literature of image information retrieval since this area was started years ago, and consequently a broad range of techniques have been proposed. The algorithms used in these systems perform four tasks namely feature extraction, feature selection, training annotation system, and annotation of new images.

The extraction task transforms rich content of images into a set of features. Feature extraction is a special form of dimensionality reduction. The generated features are to be used in selecting a subset of features. Feature selection reduces the number of features provided to train the system. The features which are likely to assist in discrimination are selected and used in the annotation task. Features those are similar and cannot discriminate shapes are not selected and hence discarded. A set of features is end result of the extraction process commonly called a feature vector, which composes a representation of the image.

Among other generic image features like color and texture that are used to achieve the classification objective, shape is considered the most promising for the identification of entities in an image [3].

Shape is a fundamental image feature and one of the most important image feature used in Image Annotation and Retrieval. This feature alone provides capability to recognize, classify objects and retrieve similar images on the basis of their contents [4].

Among the classification algorithms decision tree algorithms is the most commonly used because it is easy to understand and cheap to implement. It provides a modeling technique that is easy for human to comprehend and simplifies the classification process [5]. A decision tree can be constructed from a set of instances by a divide-and conquer strategy. If all the instances belong to the same class, the tree is a leaf with that class as label. Otherwise, a test is chosen that has different outcomes for at least two of the instances, which are partitioned according to this outcome. The tree has as its root a node specifying the test and for each outcome in turn, the corresponding sub-tree is obtained by applying the same procedure to the subset of instances with that outcome.

Rough set theory can be regarded as a new mathematical tool for imperfect data analysis. Rough set philosophy is founded on the assumption that with every object of the universe of discourse some information (data, knowledge) is associated. Objects characterized by the same information are indiscernible (similar) in view of the available information about them. The in-discernibility relation generated in this way is the mathematical basis of rough set theory. Any set of all indiscernible (similar) objects is called an elementary set, and forms a basic granule (atom) of knowledge about the universe. Any union of some elementary sets is referred to as a crisp (precise) set – otherwise the set is rough (imprecise, vague).

In this paper automatic annotation of shapes using decision trees and rough sets techniques is discussed. A novel classifier using Rough Set (RS) is presented to classify shape images of a standard dataset for annotation purpose. Shape features are extracted from the input images and then classification is done. Decision tree generation, discretization and rule extraction for rough sets is accomplished using RSES. Classifiers using decision tree and rough sets techniques are formulated in RSES.

The description of the use of various machine learning techniques for classification is provided in Section 2.

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Experimental data set information is presented in Section 3. Section 4 describes the development of automatic annotation systems (classifiers) by elaborating feature extraction process followed by classifier design. Results are presented and discussed in Section 5 followed by conclusions in Section 6.

II. Related Work

The content of an image can be represented by the feature vectors in different feature classes, such as color, texture, shape, or text annotation. Using similarity some of the methods for shape features are given by R. Mehrotra and J. E. Gary [6]. S. Loncaric given survey shape analysis techniques [7]. L. J. Latecki and R. Lakamper given idea about different shape measures [8]. D. Zhang and G. Lu given a review of the work using shape as a feature [9]. P. S. Hiremath and Jagadeesh Pujari described Content Based Image Retrieval based on Color, Texture and Shape features [10].

The shape features aims to measure geometric attributes of an object to be used for classifying, matching, and recognizing objects. There are available several techniques for shape representation that are summarized in [11], such as Fourier descriptors [12][13], Wavelet descriptors, grid-based, Delaunay triangulation [14], among others. The study in [11] classifies the shape description techniques into boundary based and region based methods. Boundary based methods use only the contour of the objects' shape, while the region based methods use the internal details in addition to the contour.

Decision tree algorithm is a data mining induction techniques that recursively partitions a data set of records using depth-first greedy approach [15] or breadth-first approach [16] until all the data items belong to a particular class. A decision tree structure is made of root, internal and leaf nodes. The tree structure is used in classifying unknown data records. At each internal node of the tree, a decision of best split is made using impurity measures [17]. Michie et al. compare alternative classifier-learning methodologies (including several based on decision trees) [18] on applications in industry and commerce. Some of the earliest work is reported by Hunt et al. [15], and Russell and Norvig and Winston give excellent tutorial overviews of inductive learning [19][20].

Nunes et. al. proposed the use of a reduced set of features to describe 2D shapes and retrieval and recognition tasks using decision trees (DT), k-nearest neighbor (kNN) and support vector machines (SVM)[21].

Rough set concept was introduced by Polish logician, Professor Zdzisław Pawlak in early eighties [22]. Banza et. al. presented some algorithms, based on rough set theory, that can be used for the problem of classification [23]. Shailendra Singh proposed a novel rough set based image classification method which uses RGB color histogram as features to classify images of different themes [24]. A good source of information about the most recent rough set literature mostly with short abstracts provides the Rough Set Database System [25][26]. The RSES is software that provides the means for analysis of data sets with use of various methods, in particular those based on Rough Set Theory[27].

III. Automatic Shape Annotation System

A. System Architecture

This system performs two basic operations, one to build the feature vector and the other is to train and test the system. As shown in Fig. 1 the system takes input image from MPEG7 CE-Shape-1 Part-B image database.

The input in the first phase describes boundary of the object as a binary image. This is done for the extraction of shape features. As a result of the extraction, vector is prepared out of which some selected features are used to create a shape feature vector. The shape feature vector is input for training and testing machine learning technique. The output generated from the classifier is tagged shape.

B. Dataset

The standard dataset created by the MPEG-7 committee for evaluation of shape similarity measures offers an excellent opportunity for objective experimental comparison of existing approaches and to develop and experiment new approaches. The database MPEG7_CE-Shape-1_Part_B consists of 1400 images of shapes with 70 image categories. Some examples are given in Fig. 2.

IV. Feature Extraction

Shape-based image retrieval consists of measuring the similarity between shapes represented by their features. Some simple geometric features can be used to describe shapes. Usually, the simple geometric features can only discriminate shapes with large differences therefore they are used as filters to eliminate false hits or combined with other shape descriptors to discriminate shapes.

These shape parameters are center of gravity, axis of least inertia, digital bending energy, eccentricity, circularity ratio, elliptic variance, rectangularity, convexity, solidity, euler number, profiles, hole area ratio. These all features are filtered to have selected features in the final feature vector. Fig. 3 shows feature extraction phase in the system. These extracted features are normalized so that all values are in a range of 0 to 1.

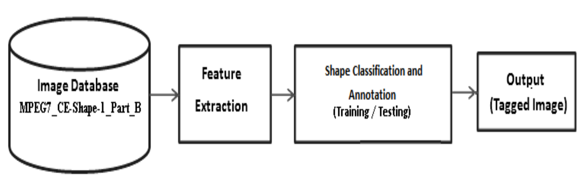

Fig. 1 System Frame Work

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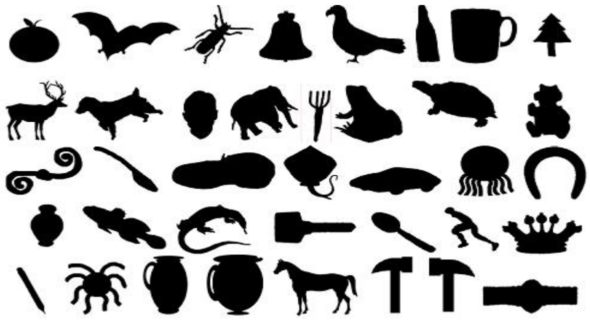

Fig.2 Sample shapes from MPEG7_CE-Shape-1_Part_B Database.

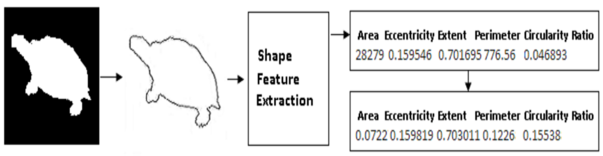

Fig.3 Shape boundary and feature extraction. Following

features are selected to form final feature vector.

Area: The actual number of pixels in the region.

Eccentricity: Eccentricity is the measure of aspect ratio. It is the ratio of the length of major axis to the length of minor axis.

Extent: Extent is the proportion of the pixels in the bounding box that are also in the region.

$$Extent = A_S / A_B \quad (1)$$

Where A_S= Area of shape

A_B=Area of bounding rectangle

Perimeter: Perimeter is the distance between each adjoining pair of pixels around the border of the region.

Circularity Ratio: Circularity ratio represents how the shape is similar to circle.

$$Circularity\ Ratio = A_S / A_C \quad (2)$$

Where A_S= Area of shape

A_C=Area of bounding circle

V. Classifier Design

The classification is the key issue of the automatic shape annotation system where learning of the system is the objective with accurate classification.

C. Decision Tree based Classifier

A decision tree is formalism for expressing attribute values to class mappings. A tree is either a leaf node labeled with a class or a structure consisting of a test node linked to two or more sub trees. A test node computes some outcome based on the attribute values of an instance, where each possible outcome is associated with one of the sub trees. An instance is classified by starting at the root node of the tree. If this node is a test, the outcome for the instance is determined and the process continues using the appropriate sub tree. When a leaf is eventually encountered, its label gives the predicted class of the instance[17].

A decision tree is generated using the training dataset of shape feature vector. From the training dataset rule based tree is generated and it is applied to test data for generating the object class. Fig. 4 shows the process carried out on shape feature vector using decision tree.

D. Rough Set based Classifier

In the discretization of a decision table $\mathbb{A} = (U, A \cup \{d\})$ where Va==(va, wa) is an interval of real's, we search for a partition P_a of V_a for any $a \in A$. Any partition of V_a is defined by a sequence of the so-called cuts v1<v2<v3<…vk from V_a. Hence, any family of partitions $\{P_a\}_{a \in A}$ can be identified with a set of cuts. The discretization process was targeted to

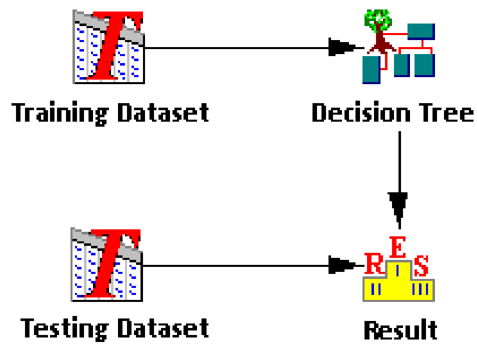

Fig.4 Decision Tree based Classifier.

search for a set of cuts satisfying some natural conditions[25].

Let $X \subseteq U$ be a target set that is represented using attribute subset P; that is, it is to be expressed with an arbitrary set of objects X comprising a single class, and this class (i.e., this subset) is to be expressed using the equivalence class induced by attribute subset P. In general, X cannot be expressed exactly, because the set may include and exclude objects which are indistinguishable on the basis of attributes P.

However, the target set X can be approximated using only the information contained within P by constructing the P-lower and P-upper approximations of X:

$$\underline{P}X = \{x \mid [x]_P \subseteq X\} \quad (3)$$

$$\overline{P}X = \{x \mid [x]_P \cap X \neq \emptyset\} \quad (4)$$

The tuple $\langle \underline{P}X, \overline{P}X \rangle$ composed of the lower and upper approximation is called a rough set; thus, a rough set is composed of two crisp sets, one representing a lower boundary of the target set X, and the other representing an upper boundary of the target set X.

The training dataset of shape vector is used to find cut set for generating discretize dataset of training and testing data. From the training dataset rule set is generated and it is applied to test data for generating the object class. Fig. 5 shows the process carried out on shape feature vector using rough sets.

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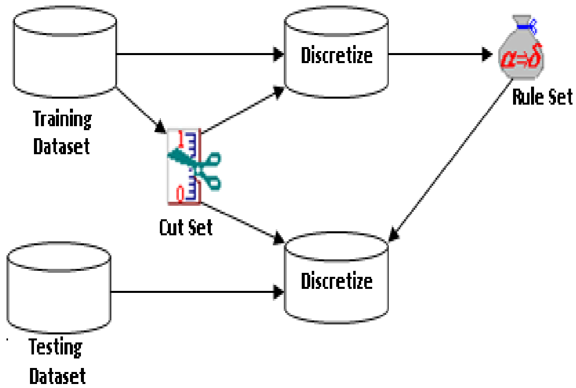

Fig. 5 Rough Set based Classifier.

VI. EXPERIMENTAL RESULTS AND OBSERVATIONS

Shape dataset described in section 3 is used for automatic image annotation experimentations. For experiments out of 1400 images, 1120 images are used for training purpose whereas remaining 280 shape images are used for testing, while with other machine learning techniques 10 fold cross validation is applied with 10 iterations. The images are distinguished due to variations in eccentricity, circularity ratio and extent in shape contour.

As the features selected in final feature vector are proportion of the shape properties, the representation of shape in feature form is rotation, translation and scaling invariant so it is easy for neural network to classify. The shape boundaries of distinct categories like bottle, cellular phone, fork, octopus, rat, watch exhibit sufficiently different features so that a classifier can differentiate a category from other.

DT based classifier generates decision tree with total 63 nodes for every fold of training data set. The decision tree for 10th fold is as shown in Fig. 6. Every node in this tree corresponds to a decision. The decision rule at a node is shown in Fig. 6. This tree contains 63 rules to classify 140 test image objects in the respective fold. The classifier could classify maximum 60.71% objects correctly with the fold wise average classification 56.07%. It is observed that DT classifier cannot classify all 140 objects i.e. coverage of this classifier is average 69.65% for all folds. The fold wise performance is as shown in Table 2.

Using other shape based features the performance of DT classifier can be improved [21]. But from rough set theory it is learn that approximation of upper and lower bound by making crisp set can improve performance. Therefore a novel RS based classifier is proposed for shape annotation. For RS based classifier more than 400 decision rules are generated for every fold of training data set. These rules are used to classify 140 test image objects in the respective fold. For the 10th fold it is observed that 515 rules are generated the sample rules are listed below.

Rule 1
attr0="(0.0176904,0.0256749)")&(attr1="(0.926158976,0.959491008)")&(attr2="(-Inf,0.628161024)")
&(attr5="(0.142508,0.244596992)")
=>(attr6=carriage[18]) 18
Rule 2
attr0="(0.0566444,0.0734632)")&(attr1="(0.545681984,0.691417024)")&(attr5="(0.329627008,0.478323008)")=>(a ttr6=teddy[18]) 18
Rule 3
attr0="(-Inf,0.0176904)")&(attr1="(0.959491008,Inf)")&(attr2="(0.756294016,0.847793024)")&(attr5="(0.329627008,0.478323008)")=> (attr6= children[17]) 17
Rule 4
(attr0="(0.258416,Inf)")&(attr3="(0.784579968,Inf)")=>(attr6=device3[17]) 17
(attr1="(0.146943008,0.545681984)")&(attr5="(0.478323008,Inf)")&(attr0="(0.0734632,0.107135)")=>(attr6=apple[15]) 15
Rule 5
(attr1="(0.959491008,Inf)")&(attr2="(-Inf,0.628161024)")&(attr3="(-Inf,0.277504992)")&(attr5="(0.142508,0.244596992)")=>(attr6=bone[15]) 15

The category wise distribution of rules is shown in Fig 7. The classifier could classify maximum 75.71% objects correctly with the fold wise average classification 61.78%.

It is observed that coverage of RS classifier is average 64.65%. The fold wise performance is as shown in Table 3.

Table 5 shows performance analysis of overall classification (correct annotation) of DT, RS. Thus annotation using DT is 56.07%. Rule extraction using rough sets improves the performance to 61.78%. Here the classifiers have stability as demonstrated by standard deviation (Std. Dev.)

The term 'coverage' is used to represent the number of classified (either correct or wrong) objects. It is observed that the coverage using decision tree and rough sets is not 100%. With rough sets, even though cut supported discretized feature vector based rules could not adequate enough to cover all unseen objects.

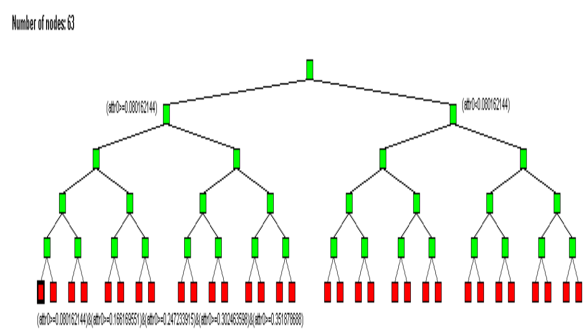

Fig.6 Decision Tree for 10th fold.

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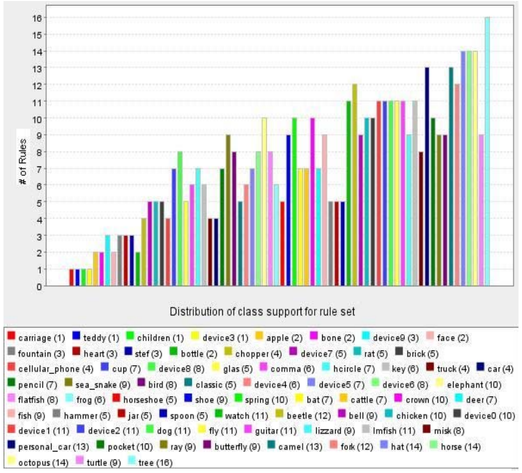

Fig.7 Rough Set based Classifier

CONCLUSION

In this paper the authors have put forward analysis of annotation performance using Decision Trees and Rough Sets. The annotation performance is significantly improved using RS classifier. With decision trees the decision making at every node is done in binary, RS uses boundary approximation and then with respect to upper and lower bound the decision is made and hence the performance is improved as compare to DT classifier. The performance can be further improved with selection of more effective shape features.

Table 1. DT classifier Performance

	fold1	fold2	fold3	fold4	fold5	fold6	fold7	fold8	fold9	fold10
Correctly annotated	82	79	85	83	72	80	78	76	77	78
Annotation Accuracy (%)	58.57	56.42	60.71	59.28	51.42	57.14	55.71	54.28	55	55.71
Coverage (%)	73.6	63.6	68.6	69.3	70.7	71.4	67.1	71.4	70	65.7

Table 2. RS classifier Performance

	fold1	fold2	fold3	fold4	fold5	fold6	fold7	fold8	fold9	fold10
Correctly annotated	100	84	95	81	87	83	86	86	96	106
Annotation Accuracy (%)	71.42	60	67.85	57.85	62.14	59.28	61.42	61.42	68.57	75.71
Coverage (%)	66.4	64.3	65	62.9	60.7	61.4	65	62.1	70.7	72.9

Table 3. Analysis of Performance

Classifier	Min	Max	Mean	Std. Dev.
Decision Tree (10 fold)	51.42%	60.71%	56.07%	0.02
Rough Set Rule Extraction(10 fold)	57.85%	75.71%	61.78%	0.05

REFERENCES

[1] A. Del Bimbo, *Visual Information Retrieval,* Morgan Kaufmann Publishers, San Fransisco, California, 2001.

[2] Marius Renn, Joost van Beusekom, Daniel Keysers, Thomas M. Breuel, "Automatic Image Tagging using Community-Driven Online Image Databases", *Proceedings of 6th International Workshop on Adaptive Multimedia Retrieval*, 2008.

[3] Naif Alajlan Ibrahim El Rube, Mohamed S. Kamel and George Freeman, "Shape retrieval using triangle-area representation and dynamic space warping," *Pattern Recognition* Volume 40, Issue 7, July 2007, pp. 1911-1920.

[4] Xiaoliu Chen and Imran Shafiq Ahmad," Shape-Based Image Retrieval Using k-Means Clustering and Neural Networks," *Lecture Notes in Computer Science, Advances in Image and Video Technology*, Volume 4872/2007, 2007, pp. 893-904.

[5] Utgoff, P and Brodley, C.," An Incremental Method for Finding Multivariate Splits for Decision Trees,Machine Learning," *Proceedings of the Seventh International Conference,* 1990, pp.58.

[6] R. Mehrotra and J. E. Gary, "Similar-shape retrieval in shape data management," *IEEE Trans. On Computer Science*, 28(9), September 1995, pp 57-62.

[7] S. Loncaric, “A survey of shape analysis techniques,” *Pattern Recognition*, vol. 31(8), 1998, pp. 983- 1001.

[8] L. J. Latecki and R. Lakamper ,”Shape similarity measure based on correspondence of visual parts,” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 22(10), 2000, pp. 1185-1190.

[9] D. Zhang and G. Lu ,”Review of shape representation and description techniques,” *Pattern Recognition*, vol. 37, 2004, pp. 1-19.

[10] P. S. Hiremath and Jagadeesh Pujari ,”Content Based Image Retrieval based on Color, Texture and Shape features using Image and its complement,” *International Journal of Computer Science and Security*, vol.1(4), November/December 2007, pp.25-35.

[11] Mehtre, B., K. M. L. W., Shape measures for content based image retrieval: a comparison. *Information Processing and Management: an International Journal*, 1997, pp.33.

[12] Zhang, D., L. S., Content-Based Shape Retrieval Using Different Shape Descriptors: A Comparative Study. *IEEE International Conference on Multimedia and Expo (ICME2001)*, 2001.

[13] El-ghazal A. Basir O. & Belkasim S., Farthest point distance: A new shape signature for Fourier descriptors. *Image Commun., Elsevier Science Inc., (*2009), vol.24, pp. 572-586

[14] Shahabi C. & Safar M., An experimental study of alternative shapebased image retrieval techniques. *Multimedia Tools Appl., Kluwer Academic Publishers, (*2007), vol.32, pp. 29-48

[15] Hunt, E.B., Marin, J. and Stone,P.J., *Experiments in induction*, Academic Press, New York,1966.

[16] Shafer, J., Agrawal, R., and Mehta, M., “Sprint: A scalable parallel classifier for data mining” *Proceedings of the 22nd international conference on very large data base. Mumbai, India*, 1996.

[17] Quinlan, J. R., *C4.5: Programs for Machine Learning*. Morgan Kaufmann, San Mateo, CA., 1993.

[18] Michie, D., Spiegelhalter, D. J., and Taylor, C. C., *Machine Learning, Neural and Statistical Classification*, Ellis Horword. 1994.

[19] RUSSELL S., AND NORVIG P., *Artificial Intelligence: A Modern Approach*, Prentice Hall, Englewood Cliffs, NJ. 1995.

[20] WINSTON P. H., *Artificial Intelligence*, 3rd edition. Addison-Wesley, Reading, MA., 1992.

[21] Nunes, J.F., Moreira, P.M., Tavares, J.M.R.S., “Shape based image retrieval and classification”, Information Systems and Technologies (CISTI), 2010, pp. 1 – 6.

[22] Pawlak Z., “Rough sets”, *Int. J. Computer and Information Science*, vol. 11, pp.341-356, 1982.

[23] J. Bazan, H.S. Nguyen, S.H. Nguyen, P. Synak, J. Wr´oblewski, “Rough Set Algorithms in Classification Problem”. In: Polkowski, L., Tsumoto, S., Lin, T.Y. (eds.), *Rough Set Methods and Applications*. Physica Verlag, Berlin, 2000, pp. 49–58.

[24] Shailendra Singh, “RGB Color Histogram Feature based Image Classification: An Application of Rough Reasoning”, *IHCI 2009:Part2*, 2009, pp.102-112.

[25] J. Komorowski, Z. Pawlak, L. Polkowski, A. Skowron, “Rough Sets: A Tutorial” in S.K. Pal, A. Skowron (Eds.), *Rough Fuzzy Hybridization. A New Trend in Decision-Making, Springer-Verlag, Singapore*, 1999, pp. 3-98.

[26] A. Skowron , Z. Pawlak, J. Komorowski, L. Polkowski,” A rough set perspective on data and knowledge”, in W. Kloesgen, J. Żytkow (Eds.) Handbook of KDD, Oxford University Press, Oxford, 2002, pp. 134-149.

[27] Skowron A. , Bazan J. , Szczuka M. S., Wroblewski J. Rough Set Exploration System, version 2.2.2 (2009), http: //logic.mimuw.edu.pl/~rses/

AUTHOR’S PROFILE

Manoj P. Patil received the M.Sc.. degree in computer science from North Maharashtra University, Jalgaon, India, in 2001. He is currently an Assistant Professor with the Computer Science Department, North Maharashtra University. His research interests include digital image processing and machine learning. Prof. Patil is a Life Member of Indian Science Congress Association.

Satish R.Kolhe received the B.E. degree in computer engineering from Amaravati University, Amaravati, India, in 1991, the M.Tech. degree in engineering systems from Dayalbagh Educational Institute, Agra, India, in 1994, and the Ph.D. dgeree in computer engineering from North Maharashtra University, Jalgaon,India, in 2007. He is currently an Associate Professor with the Computer Science Department, North Maharashtra University. His research interests include artificial intelligence and pattern recognition. Prof. Kolhe is a Fellow Life Member of Institute of Electronics and Telecommunication Engineers, India, Life Member of Computer Society of India, India, Linguistic Society of India, and Indian Science Congress Association. He is also a member of Special Interest Group in Artificial Intelligence, India.