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Foreword

Alhamdulillah. First of all a big thank you and congratulations to the Editorial Board of *Esteem Academic Journal* of Universiti Teknologi MARA (UiTM), Pulau Pinang for their diligent work in producing this issue. I also would like to thank the academicians for their contributions and the reviewers for their meticulous vetting of the manuscripts. A special thanks to University Publication Centre (UPENA) of UiTM for giving us this precious opportunity to publish this first issue of volume 5. In this engineering issue we have upgraded the standard of the manuscript reviewing process by inviting more reviewers from our university as well as other universities in Malaysia. We have embarked from previous volume to establish a firm benchmark and create a journal of quality and this current issue remarks a new height of the journal quality. Instead of publishing once in every two years, now *Esteem* publishes two issues annually.

In this issue, we have compiled an array of 13 interesting engineering research and technical based articles for your reading. The first article is entitled "The Response of Tube Splitting on Circular Tubes by Using Various Types of Semi-angles Dies and Slits". The authors, Mohd Rozaiman Aziz and Roslan Ahmad investigated the axial splitting and curling behavior of aluminum circular metal tubes which was compressed axially under static loading using three types of dies with different semi-angles. The authors concluded that the introduction of slit to the specimen is necessary to initiate slitting rather than inversion.

Salina Budin, Aznifa Mahyam Zaharudin, and Sugeng Priyanto presents a model of energy conversion and impact energy generation during collision based on free falling experiment, which is closely resembles direct collision between ball and inner wall of the vial. Simulation results from the proposed impact energy model demonstrated that the impact energy generated during the collision is strongly influenced by the thickness of the work materials and reaches zero at certain value of the work materials thickness, which increases with an increase of falling height.

Salina Alias, Caroline Marajan and Mohamad Azrul Jemain wrote an article that looks at adsorption of zinc from waste water using bladderwort (*Utricularia vulgaris*). In batch adsorption studies, data show that dried bladderwort has considerable potential in the removal of metal ions from aqueous solution. The fourth article written by

Muhammad Khusairi Osman et al. looked at 3D object recognition using affine moment invariants and Multiple Adaptive Network Based Fuzzy Inference System (MANFIS). The experimental results show that Affine Moment Invariants combined with MANFIS network attain the best performance in both recognitions, polyhedral and free-form objects.

The article entitled "Construction Waste Management Methods Used by Contractors in the Northern Region" authored by Siti Hafizan Hassan, Nadira Ahzahar and Mohd Nasrul Nizam Nasri reports an ongoing study on the use of construction waste management methods by contractors and its impact on waste reduction in the Northern Region. In conclusion, the sizing and amount of materials to be ordered to reduce wastage is significant in reducing construction waste generation waste, alleviating the burden associated with its management and disposal. The sixth article by Muhammad Sofian Abdullah et al. examined on the performance of Performance of Palm Oil Fuel Ash (POFA) with lime as stabilizing agent for soil improvement. The authors concluded that POFA can be used to treat the silty soil as well as to reduce the environmental problem.

The seventh article penned by Soffian Noor Mat Saliah, Noorsuhada Md. Nor and Megat Azmi Megat Johari presents the results of an experimental study on the interfacial bond strength (IBS) of polypropylene fiber concrete (PFC). It was found that the interfacial bond strength between concrete and reinforcement bar was not affected by the inclusion of polypropylene fibers. However, concrete containing fibers exhibited no breaking of concrete and no debonding of reinforcement. The article by Juliana Zaabar and Rusnani measures, evaluates and analyzes the network link performance of fiber optic cable using OTDR. The authors suggested that the major loss for these measurements is connector loss. Preventive maintenance will increase the life time of fiber optic. From some of the findings, the PVC dust cap has been identified as a main source of contamination for the SC connector.

The article entitled "Symbolic Programming of Finite Element Equation Solving for Plane Truss Problem" by Syahrul Fithry Senin proposed a plane truss problem to be solved by finite element method using MAPLE 12 software. The numerical solution computed by the author was almost matched with the commercial finite element software solution, LUSAS. The tenth article by Nor Azlan Othman, Nor Salwa Damanhuri and Visakan Kadirkamanathan presents a detail review of fault diagnosis in rotating machinery using pattern recognition technique. The authors proposed a solution based on artificial neural network (ANNs) which is Multi-Layer Perceptron (MLP). The authors concluded that the proposed methods are suitable for rotating machinery on fault detection and diagnosis.

The eleventh article is entitled "RAS Index as a Tool to Predict Sinkhole Failures in Limestone Formation Areas in Malaysia". Damanhuri Jamalludin et al. found that, using the RAS classification method, the prediction of sinkhole occurrences can be easily be made by simply knowing the weekly rainfall especially in areas having limestone as the bedrock. The twelfth by Muhammad Hafeez Osman et al. explores cases regarding the histories of rock slope repair and stabilization of unstable boulder along the road from Bukit Cincin to Genting Highland and along the road from Gap to Fraser Hill. The last article is "Soil Nail and Guniting Works in Pahang". The authors, Damanhuri Jamalludin et al. concluded that if the stability of the embankment needs to be improved, soil nails can be installed and embankment surface can be covered with gunite to prevent erosion.

We do hope that you not only have an enjoyable time reading the articles but would also find them useful. Thank you.

Mohd Aminudin Murad
Chief Editor
Esteem, Vol. 5, No. 1, 2009
(Engineering)

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3D Object Recognition Using Affine Moment Invariants and Multiple Adaptive Network Based Fuzzy Inference System

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ABSTRACT

This paper addresses a performance analysis of Affine Moment Invariants for 3D object recognition. Affine Moment Invariants are commonly used as shape feature for 2D object or pattern recognition. However, this study proves that with some adaptation to multiple views technique, Affine Moment Invariants are sufficient to model 3D objects. In addition, the simplicity of moments calculation reduces the processing time for feature extraction, hence increases the system efficiency. In the recognition stage, this study used a neuro-fuzzy classifier called Multiple Adaptive Network based Fuzzy Inference System (MANFIS) for matching and classification. The proposed method was tested using two groups of object; polyhedral and free-form objects. The experimental

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results show that Affine Moment Invariants combined with MANFIS network attain the best performance in both recognitions, polyhedral and free-form objects.

Keywords: *3D object recognition, multiple views technique, affine moment invariants, neuro-fuzzy system*

Introduction

In computer vision, the process of recognition typically involves some sorts of sensors, a model database which contains all the information about the objects representations and a decision making capability. Sensors, for instance, laser range finders, ultrasonic sensors, infrared sensors and charge-coupled device (CCD) cameras are used to gather images and information from a scene of interest. Then the digitized image is processed to represent it in the same way as the models are represented in the database. Finally, a recognition algorithm is applied to find the model to which the object best matches. The method is also known as model-based recognition system, and it is the most common system for shape or object recognition. Figure 1 depicts the interaction and information flow among different components of the system.

Human performs object recognition effortlessly and instantaneously, but an algorithmic description of this task for implementation on computers has been very difficult especially for 3D objects. Developing a 3D object recognition system is much harder compared to a flat 2D recognition system, since it allows additional degrees of freedom for the orientation of the object in space (Büker & Hartmann, 1996). In addition, objects may be partially occluded each other and only one side of the object can be seen from any given viewpoint, which is sometimes insufficient to distinguish similar objects.

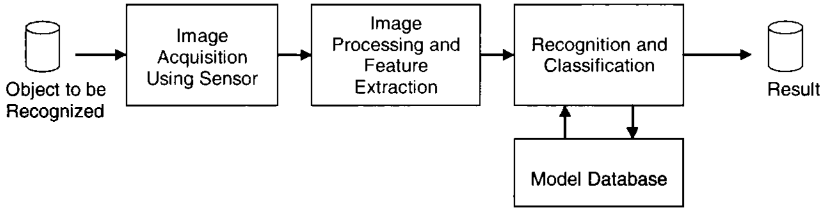

Figure 1: Block Diagram of a Typical Object Recognition System

Earlier works in 3D object recognition system considered the problem of recognizing objects from the image of a single view (Besl & Jain, 1985; Chin & Dyer, 1986; Flynn & Jain, 1991; Zisserman et al., 1995). A single view may not be sufficient to recognize an object unambiguously since only one side of an object can be seen from any given viewpoint (Büker & Hartmann, 1996). Sometimes, two objects may have all views in common with respect to a given feature set, and maybe distinguished only through a sequence of views (Roy et al., 2003). In addition, because of the single dependency on image view, this method requires complex features to represent the object.

To overcome these problems, 3D objects recognition using multiple views technique was proposed by recent researchers (Li et al., 2001; Roy et al., 2003; Selinger, 2001). This study proposed using multiple view techniques for image acquisition. Affine Moment Invariants were extracted from the image. Although moments are commonly applied to 2D object or pattern recognition, an adaptation with the multiple views technique enables this method to be used for 3D object modeling. In addition, the simplicity of 2D moment calculation will reduce processing time, hence increases the system efficiency. The moments are then fed into a neuro-fuzzy classifier called Multiple Adaptive Network based Fuzzy Inference System (MANFIS) to perform the recognition. A neuro-fuzzy classifier combines fuzzy reasoning system and neural networks into an integrated functional model (Lin & Lee, 1996). The integrated system will possess the advantages of both neural networks and fuzzy system.

Related Research

One of the basic problems in the design of a 3D object recognition system relates to the method of modeling and representing the objects. Earlier works make use of object-centered method which attempted to describe the full 3D shape before performing recognition task. One example of a system which used the object-centered approach was reported in Besl & Jain (1985). It used the wire-frame and surface-edge-vertex (SEV) representation. A wire-frame model consists of object edges and it represents an object using possible edge junction.

Another proposal is the appearance-based approach. According to this idea, 3D object is described using a set of 2D characteristic views and stored in the model database either explicitly as images or in some abstracted form such as an eigenspace representation. The set of images representing the model is acquired for the range of viewing conditions under which the object is to be recognized. One advantage of appearance-based methods is that objects of any shape, even with no obvious features can be modeled, provided that a sufficient number of images of the object is taken. Some of the examples were reported by Paggio and Edelman (1990) and Murase and Nayar (1995). Paggio and Edelman (1990) showed that 3D objects can be recognized from the raw intensity values in 2D images, using a network or generalized radial basis functions. They demonstrated that a full 3D structure of an object can be estimated if enough 2D views of the object are provided. Murase and Nayar (1995) developed a parametric eigenspace method to recognize 3D objects directly from their appearance. Eigenvectors are computed from a set of images in which the object appears in different poses.

The third approach uses invariants for shape representation. An invariant is a quantity that can be computed from an object image features and has the same value for all viewpoints of the object. Rothwell et al. (1995) used projective algebraic invariants as index function to identify planar objects. Their system deals with a class of co-planar lines and conics. Meanwhile, Abdallah (2000) constructed a robust canonical frames from image features of 3D objects. Invariants that are useful for indexing a model-based are then extracted from these canonical frames to recognize 3D objects in scenes with clutter and partial occlusion.

Another type of invariants is moment invariants. The first significant discussion on the application of moments was published by Hu (1962). He used geometric moments to generate a set of invariants features which were used for automatic character recognition. The dominant advantage of geometric moments is image coordinate transformations can be easily expressed and analyzed in terms of the corresponding transformation in the moment space. The Hu moments are invariant under changes in translation, rotation and scale but not under general 2D affine transformation. Affine moment invariants were introduced by Flusser and Suk (1993) to address the problem. Teague (1980) introduced orthogonal moments, and provided the basis concepts and applications of Zernike moments. This moment values has additional properties of being more robust in the presence of image noise, having a nearly zero value of redundancy measure in a moment set and higher degree of information content (Pang et al., 2004). Moments and functions of moments have been widely and commonly used for 2D object recognition. For 3D object recognition, extended 3D moments were used to represent the objects (Yang et al., 1997) . However, 3D moments are complex and incurred high computational cost. To avoid these problems, the current work proposed to used 2D moments adapted with multiple views technique for object representation. Affine Moment Invariants were used for the analyses.

Current trends in 3D object recognition have utilized neural networks and fuzzy system for their system (Mattone et al., 2000; Sahambi & Khorasani, 2003; Soodamani & Liu, 1998; Yuan & Niemann, 2003). The advantage of neural network is its adaptive learning capability. Neural networks can learn from the data, and automatically adjust their connection weights between the layers. On the other hand, the process of fuzzy logic is based on specific rules. Fuzzy logic does not have the capability to extract association between input and output variables during training. While the learning capability is an advantage from the viewpoint of fuzzy inference system, the formation of linguistic rule base will be an advantage from the viewpoint of neural networks. With the advantages and disadvantages of neural network and fuzzy logic approach, a neuro-fuzzy framework has emerged, by combining the learning ability of the neural network and the functionality of fuzzy logic.

This study proposed to use Affine Moment Invariants for 3D object recognition. Affine Moment Invariants are commonly used as shape feature for 2D object or pattern recognition. However, this study proved that with some adaptation to multiple views technique, Affine Moment Invariants are sufficient to model 3D objects. In addition, the simplicity of moments calculation reduces the processing time for feature extraction, hence increases the system efficiency. In the recognition stage, this study investigates the performance of neuro-fuzzy classifier called Multiple Adaptive Network based Fuzzy Inference System (MANFIS) for classification of 3D objects.

Image Acquisition and Thresholding

In this section, a proposed methodology for camera-object setup will be discussed. Each object to be recognized is placed in its stable condition at the centre of the turntable as illustrated in Figure 2. The turntable is a circular horizontal platform that can be rotated 360 degree. A, B and C represent the coordinate for the cameras around the turntable. Point A and B are located on the same horizontal plane, but differs about 90° from each other. Point C is perpendicular to the turntable. Figure 2(a)

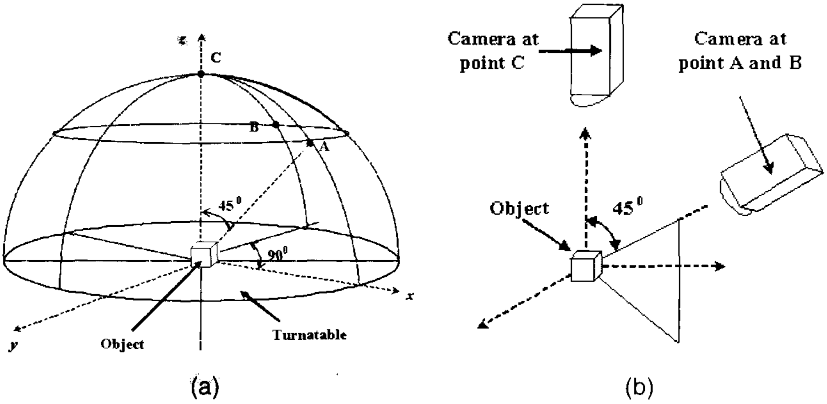

Figure 2: (a) Image Aacquisition Set-Up and (b) Camera Position for Point A, B and C

shows the location of the points and object. Since all points have the same distance from the centre of the turntable, all cameras must have the same focal lengths. The cameras at point A and B are proposed to be fixed at 45° from perpendicular view. Camera at point C is fixed at the top of the object. Figure 2(b) shows how all the cameras are positioned.

After an object of interest is placed at the centre of the turntable, the object's images are acquired. Then, the object will be rotated 5° and the same process is repeated. Each rotation will rotate the object for an angle of 5°, and so on until 360° is complete. Hence, for each object, there will be 72 image sets. These images are divided into two groups, 36 image sets for training data and 36 image sets for testing data. For training data, images with 0°, 10°, 20°, ... 350° condition are considered, and the rest of the images (image with 5°, 15°, 25°, ...355° condition) are used for testing. The training data set is used to build the 3D object model in the recognition stage. Captured images are then digitized and sent to the pre-processing, and feature extraction stage. In the pre-processing stage, images are thresholded automatically using iterative thresholding method (Riddler & Calvard, 1978). This method leads to a good separation between object and background in several applications (Klette & Zamperoni, 1996).

Features Extraction Using Moments

Affine Moment Invariants

Let $f(i,j)$ be a digital image with $i = 1, 2, 3 \ldots M$ and $j = 1, 2, 3 \ldots N$. Two-dimensional moments, m_{pq} and central moments of order $(p+q)$ of $f(i, j)$, μ_{pq} are defined as:

$$m_{pq} = \sum_{i=1}^{M}\sum_{j=1}^{N} i^p j^q f(i,j) \tag{1}$$

$$\mu_{pq} = \sum_{i=1}^{M}\sum_{j=1}^{N} (i-\bar{i})^p (j-\bar{j})^q f(i,j) \tag{2}$$

where

$$\bar{i} = \frac{m_{10}}{m_{00}} \quad \text{and} \quad \bar{j} = \frac{m_{01}}{m_{00}} \tag{3}$$

The six Affine Moment Invariants were derived as follows (Kadyrov & Petrou, 2001):

$$I_1 = \frac{1}{\mu_{00}^4}(\mu_{20}\mu_{02} - \mu_{11}^2) \tag{4}$$

$$I_2 = \frac{1}{\mu_{00}^{10}}(\mu_{30}^2\mu_{03}^2 - 6\mu_{30}\mu_{21}\mu_{12}\mu_{03} + 4\mu_{30}\mu_{12}^3 + 4\mu_{03}\mu_{21}^3 - 3\mu_{21}^2\mu_{12}^2) \tag{5}$$

$$I_3 = \frac{1}{\mu_{00}^7}(\mu_{20}(\mu_{21}\mu_{03} - \mu_{12}^2) - \mu_{11}(\mu_{30}\mu_{03} - \mu_{21}\mu_{12}) + \mu_{02}$$

$$(\mu_{30}\mu_{12} - \mu_{21}^2)) \tag{6}$$

$$I_4 = \frac{1}{\mu_{00}^{11}}(\mu_{20}^3\mu_{03}^2 - 6\mu_{20}^2\mu_{11}\mu_{12}\mu_{03} - 6\mu_{20}^2\mu_{21}\mu_{02}\mu_{03} + 9\mu_{20}^2\mu_{02}\mu_{12}^2 \tag{7}$$

$$+ 12\mu_{20}\mu_{11}^2\mu_{03}\mu_{21} + 6\mu_{20}\mu_{11}\mu_{02}\mu_{30}\mu_{03} - 18\mu_{20}\mu_{11}\mu_{02}\mu_{21}\mu_{12} -$$

$$- 8\mu_{11}^3\mu_{03}\mu_{30} - 6\mu_{20}\mu_{02}^2\mu_{30}\mu_{12} + 9\mu_{20}\mu_{02}^2\mu_{21}^2 + 12\mu_{11}^2\mu_{02}\mu_{30}\mu_{12} -$$

$$6\mu_{11}^2\mu_{02}^2\mu_{30}\mu_{21} + \mu_{02}^3\mu_{30}^2)$$

$$I_5 = \frac{1}{\mu_{00}^6}(\mu_{40}^{04} - 4\mu_{31}\mu_{13} + 3\mu_{22}^2) \tag{8}$$

$$I_6 = \frac{1}{\mu_{00}^{9}}(\mu_{40}\mu_{04}\mu_{22} + 2\mu_{31}\mu_{22}\mu_{13} - \mu_{40}\mu_{13}^{2} - \mu_{04}\mu_{31}^{2} - \mu_{22}^{3}) \tag{9}$$

Recognition and Classification

In the recognition stage, we proposed to use a neuro-fuzzy classifier named Multiple Adaptive Networks Based Fuzzy Inference System (MANFIS). The MANFIS network contains a number of ANFIS networks (Jang, 1993) which are arranged in a parallel combination. The combination has been made since the original ANFIS is a single output network. Figure 3 shows an example of MANFIS network with 3 inputs, x_1, x_2, x_3, and 11 outputs, f_1, f_2, f_3....f_{11}. For recognition purpose, the number of input depends on the number of cameras multiply by the number of moment combination while the number of outputs depends on the number of objects to be recognized. A hybrid learning algorithm which combines gradient descent and least square estimator has been used for the learning procedure. In the recognition step, if any output node has the value greater than 0.5, that node is determined as 1. Otherwise, the node is considered as 0.

$$f_n = \begin{cases} 1 & if \quad |f_n| \geq 0.5 \\ 0 & if \quad |f_n''| < 0.5 \end{cases} \tag{10}$$

Details discussion on algorithm, learning method and designing parameters of ANFIS can be found in Jang (1993).

Results and Discussion

Two types of objects were chosen in order to analyze the system performance. Each type consisted of eleven 3D objects. The first type, Type 1 object, contained simple 3D shapes like cylinder, box, trapezoid, sphere etc. The second type, Type 2 object, contained free-form objects. Figure 4(a) and 4(b) show these types of objects. Figure 4 shows the recognition performance for types, Type I and Type II objects using Affine Moment Invariants.

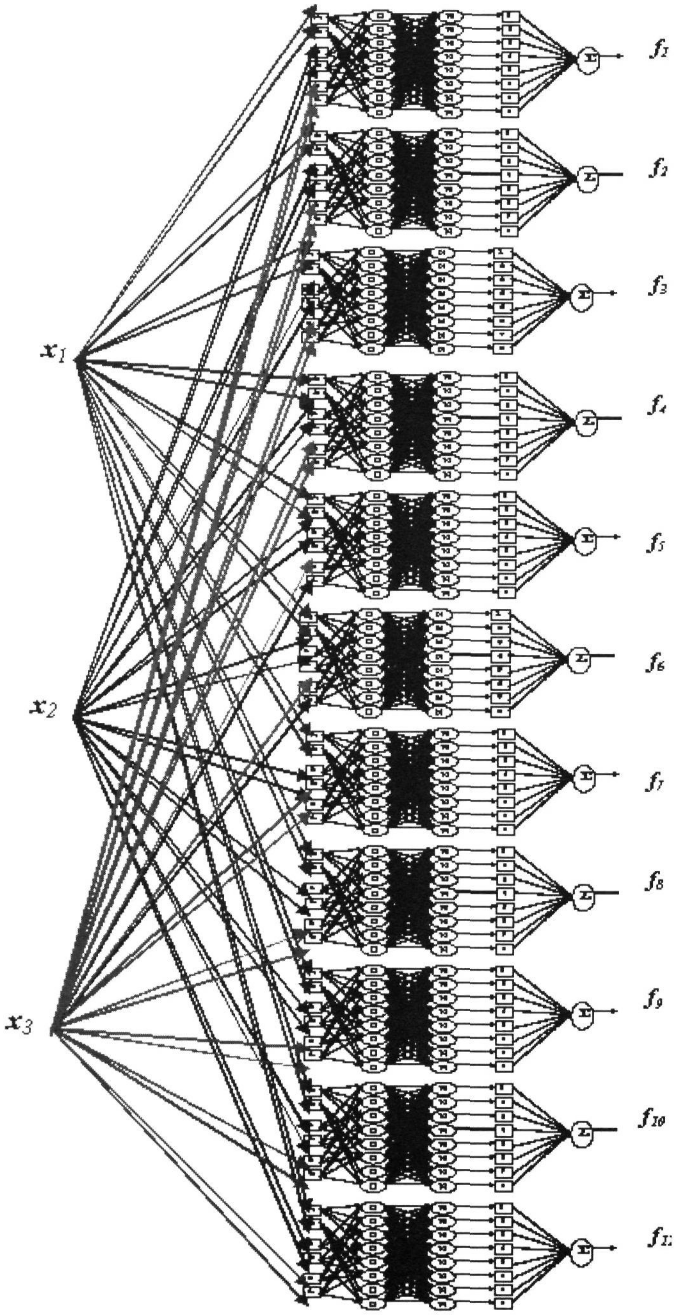

Figure 3: MANFIS Network with 3 Inputs and 11 Outputs

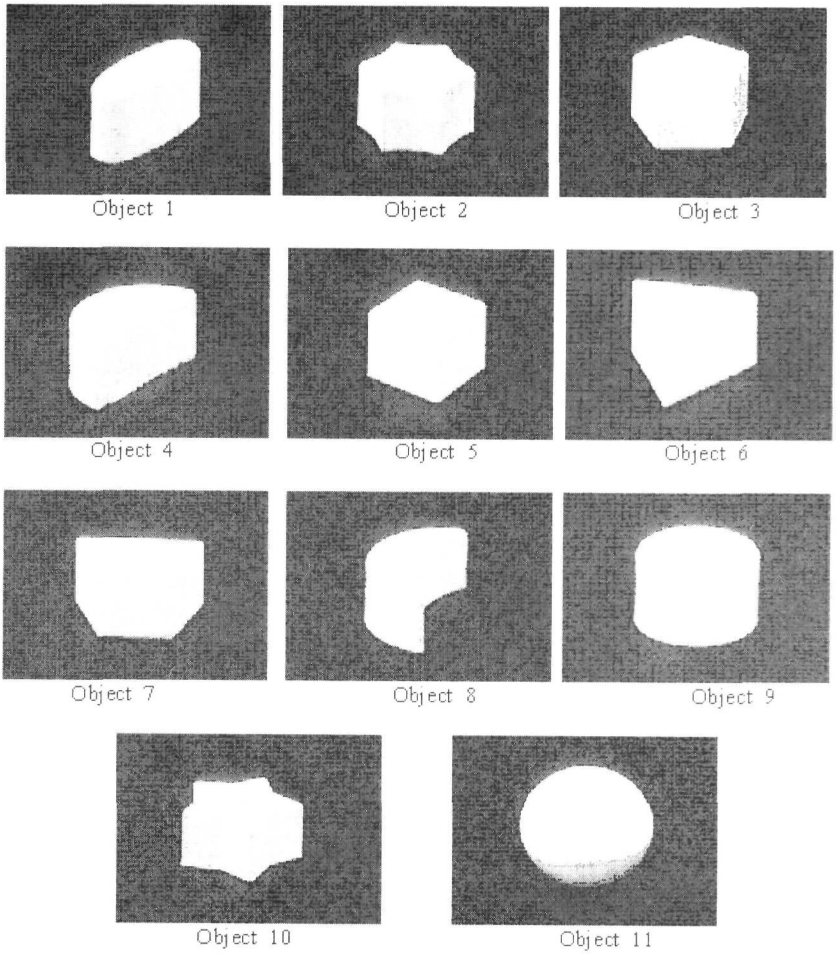

Figure 4(a): Type 1 Objects

With reference to Table 1, for Type 1 object, recognition rate using I_6 achieved the best performance with 100% for training and 98.48% for testing. Similarly, the recognition rate using I_1 and I_5 also produced acceptable results with 98.48% and 99.75% for training, and 98.23% and 96.72% for testing respectively. It is found that I_1, I_5 and I_6 changed slowly for each rotation and less sensitive to noise compared to I_2, I_3 and I_4. Consequently, the features stability would increase and improve the recognition rate.

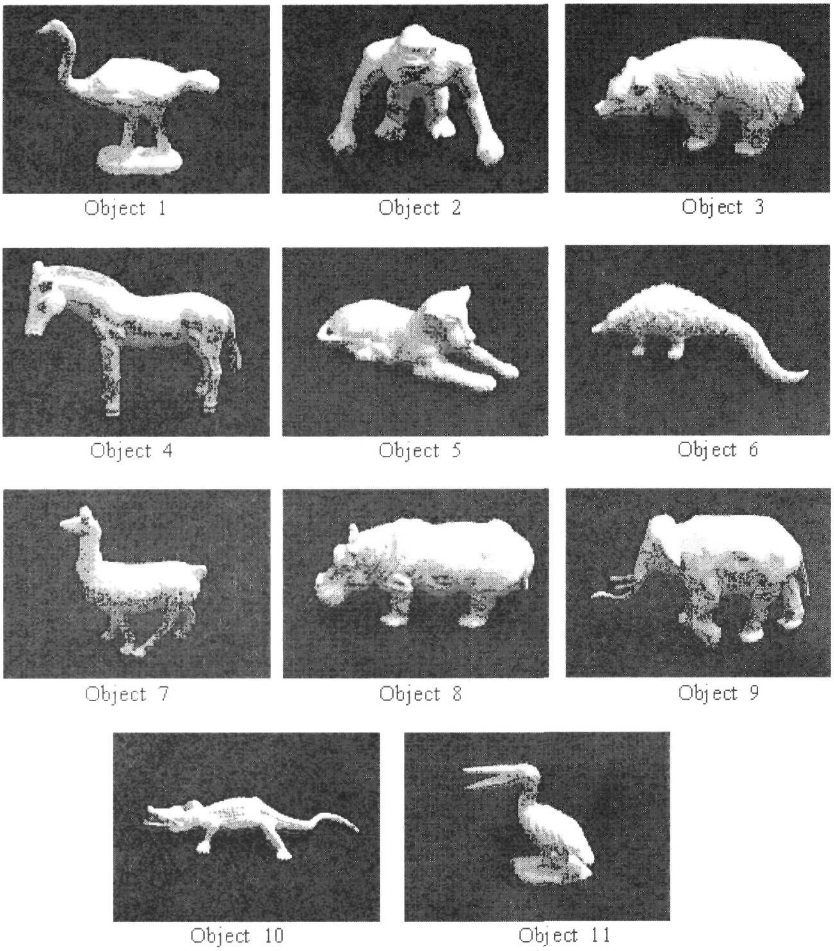

Figure 4(b): Type 2 Objects

Since I_1, I_5 and I_6 produced better results, further analyses attempted to investigate the effect of combining these moments. As illustrated in Table 1, it is shown that the combination of both I_1 and I_5 produced the best results. The recognition rate achieved 100% for both training and testing. However, the combination of I_1I_6 and I_5I_6 attempted to reduce the recognition rates. The combination of I_1I_6 and I_5I_6 seemed to confuse the MANFIS network and reduced the recognition rate.

For Type 2 object, recognition rate using I_1 achieved the best performance with 98.99% for training and 97.47% for testing. The recognition rate using I_3 and I_4 also produced acceptable results with 98.48% and 99.24% for training, and 90.91% and 96.72% for testing respectively. The combination of I_1 and I_4 helped to improve the recognition rate. The combination of both I_1 and I_4 achieved 100% for training and 98.74% for testing. However, the combination of I_1I_3 and I_3I_4 were unable to increase the recognition rates.

The overall results also show that different orders of Affine Moment Invariants are suitable for different types of objects. Among the six orders of Affine Moment Invariants, I_1 is the most suitable for both Type 1 and Type 2 objects. The recognition rate using I_1 for Type 1 produced acceptable results with 98.48% for training and 98.23% for testing, while for Type 2, the results were 98.99% for training and 97.47% for testing.

Conclusion

This paper investigates the performance of 3D object recognition system using 2D moments adapted with multiple views technique and MANFIS network. The proposed method shows that with some adaptation to multiple views technique, lower order 2D moments are able to model the 3D object well. The simplicity of moments calculation proved that the proposed system did not require complex features for 3D object representation, hence reducing processing time in feature extraction stage. In addition, since 2D moments are global features, it can be applied

Table 1: Recognition Performance Using Affine Moment Invariants for Type 1 Object

Affine Moment Invariants	Design parameter		Type 1	
	Membership function	Step size	Training accuracy (%)	Testing accuracy (%)
I_1	3	0.100	98.48	98.23
I_2	2	0.100	86.62	74.49
I_3	2	0.100	93.18	82.83
I_4	2	0.100	91.41	89.14
I_5	3	0.300	99.75	96.72
I_6	3	0.300	100.00	98.48
I_1 I_5	2	0.100	100.00	100.00
I_1 I_6	2	0.100	90.91	90.91
I_5 I_6	2	0.100	90.66	90.91

Table 2: Recognition Performance Using Affine Moment Invariants for Type 2 Object

Affine Moment Invariants	Design parameter		Type 2	
	Membership function	Step size	Training accuracy (%)	Testing accuracy (%)
I_1	3	0.200	98.99	97.47
I_2	2	0.100	83.08	78.28
I_3	3	0.300	98.48	90.91
I_4	3	0.300	99.24	96.72
I_5	2	0.100	67.17	63.64
I_6	2	0.100	81.82	80.30
$I_1\ I_3$	2	0.100	100.00	96.97
$I_1\ I_4$	2	0.100	100.00	98.74
$I_3\ I_4$	2	0.100	100.00	96.72

arbitrarily to any 3D objects. Overall results show that by using the proposed camera setup and MANFIS network, Affine Moment Invariants obtained great recognition rate. Throughout the analyses of two groups of object, polyhedral objects (Type 1) and free-form objects (Type 2), an accuracy of up to 98% was achieved using the proposed method.

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