

# IDENTIFYING TABLE TENNIS BALLS FROM REAL MATCH SCENES USING IMAGE PROCESSING AND ARTIFICIAL INTELLIGENCE TECHNIQUES

Dr. K. C. P. WONG

Department of Communication and Systems  
Open University, Walton Hall  
Milton Keynes, UK  
Email: k.c.p.wong@open.ac.uk

**Abstract:** *Table tennis is a fast sport and it is very difficult for a normal human being to manage accurate umpiring, especially in services (serves), which usually take less than a second to complete. The umpire needs to make over 30 observations and makes a judgment before or soon after the service is complete. This is a complex task and the author believes the employment of image processing and artificial intelligence (AI) technologies could aid the umpire to evaluating services more accurately. The aim of this research is to develop an intelligent system which is able to identify and track the location of the ball from live video images and evaluate the service according to the service rules. In this paper, the discussion is focused on the development of techniques for identifying a table tennis ball from match scenes. These techniques formed the basis of the ball detection system. Artificial neural networks (ANN) have been designed and applied to further the accuracy of the detection system. The system has been tested on still images taken at real match scenes and the preliminary results are very promising. Almost all the balls from the images have been correctly identified. The system has been further tested on some video images and the preliminary result is also very encouraging. It shows the system could tolerate the poorer quality of video images. This paper also discusses the idea of employing multiple cameras for improving accuracy. A multi-agent system is proposed because it is known to be able to coordinate and manage the flow of information more effectively.*

**Keyword:** *Image processing, neural networks, multi-agent systems, table tennis umpiring*

## I. INTRODUCTION

This research proposes the development of a novel intelligent system which is aimed at assisting table tennis umpires to make accurate judgment about services, which involves a series of fast actions and its legitimacy is strictly governed by the Laws of Table Tennis stated in the International Table Tennis (ITTF) Handbook [1]. A service usually takes less than a few seconds to complete but there are 31 observations an umpire has to be aware of and make a decision of its legitimacy before or just after the service is complete [2]. To make the matter worse, one of the table tennis rules requires an umpire to visually measure the height of ball rise and check whether the ball rise is vertical. This is a very challenging task for a human being and often requires lots of professional judgments.

The author therefore proposes a computer system which incorporates image processing and artificial intelligent technologies in analyzing the service and suggesting a recommendation for the umpire to consider. The proposed system must be able to accomplish the following four main tasks:

- identifying the ball from match scene and tracking the location of the ball;
- taking the necessary measurement (e.g., ball rise and deviations)

- evaluating the service according to the service rules, which can be found from the International Table Tennis (ITTF) Handbook [1].
- making recommendations

The idea is very novel and a literature review did not reveal any previous attempt on this application. However, there are some papers on detecting small objects using image processing techniques. One paper in particular discussed a technique in detecting a table tennis (ping pong) ball. Desai et al [3] proposed a multiple filter bank approach in detecting a table tennis ball. Although Desai could demonstrate detecting and tracking a table tennis ball from a low contrast background, the setting was in a laboratory rather than real match scenes. Furthermore, the main purpose of their research was to detect objects rather than umpiring, so the time taken for the detection was not as critical.

To be able to aid an umpire in making an accurate decision, the proposed system has to be able to make a recommendation rapidly. This means the algorithm employed must be highly efficient. Details of the proposed algorithm are shown in Section 3.

The overall goal of this research project is to develop an intelligent system which is able to evaluate table tennis services from one or more live video feeds at different angles. A multi-agent system is to be developed to coordinate the processes. The prototype system is being developed using Matlab and its Image Process [4] and Neural Networks Toolboxes [5].

In this paper however the focus is on the identification of the table tennis ball from real match scenes. Other developments will be published in future papers.

## II. TABLE TENNIS RULES – SERVICES

The chapter entitled Laws of Table Tennis stated in the International Table Tennis (ITTF) Handbook [1] specifies the rules for table tennis matches. Seven rules are directly related to services. For the benefit of those who are not familiar with table tennis rules, the seven rules regarding the service are reproduced and listed in Table 1.

TABLE I. TABLE TENNIS RULES REGARDING THE SERVICE

Index	Description
2.06.01	Service shall start with the ball resting freely on the open palm of the server's stationary free hand.
2.06.02	The server shall then project the ball near vertically upwards, without imparting spin, so that it rises at least 16cm after leaving the palm of the free hand and then falls without touching anything before being struck.
2.06.03	As the ball is falling the server shall strike it so that it touches first his court and then, after passing over or around the net assembly, touches directly the receiver's court; in doubles, the ball shall touch successively the right half court of server and receiver.
2.06.04	From the start of service until it is struck, the ball shall be above the level of the playing surface and behind the server's end line, and it shall not be hidden from the receiver by the server or his doubles partner or by anything they wear or carry.
2.06.05	As soon as the ball has been projected, the server's free arm shall be removed from the space between the ball and the net. Note: The space between the ball and the net is defined by the ball, the net and its indefinite upward extension.
2.06.06	It is the responsibility of the player to serve so that the umpire or the assistant umpire can see that he complies with the requirements for a good service.
2.06.06.01	If the umpire is doubtful of the legality of a service he may, on the first occasion in a match, declare a let and warn the server.
2.06.06.02	Any subsequent service of doubtful legality of that player or his doubles partner will result in a point to the receiver.
2.06.06.03	Whenever there is a clear failure to comply with the requirements for a good service, no warning shall be given and the receiver shall score a point.
2.06.07	Exceptionally, the umpire may relax the requirements for a good service where he is satisfied that compliance is prevented by physical disability.

Rule 2.06.02 is notoriously difficult for human umpires to judge. Firstly, it is hard to visually determine whether the ball is projected near vertically upward. Furthermore, the wording of "near vertically upward" is ambiguous. It does not state what degree of deviation is acceptable. The second difficulty of interpreting this rule is that it is sometimes quite hard for a human being to

determine whether the ball rises 16 cm or more after leaving the palm. Moreover, a service usually takes a few seconds to complete and this means the umpire has to make the observations and make a decision within a few second. This is a challenging task and even the experienced umpires could make mistakes sometimes.

The computer system proposed by the author is aimed to tackle these difficulties by identifying the ball from live video images and measure the height and angle deviation of the ball rise.

## III. IMAGE PROCESSING

In this section, image processing techniques employed for identifying table tennis balls are to be discussed. Initially, still images which were taken at real match scenes (Source: ITTF Photos Gallery [6]) were used for testing the proposed system. Subsequently, sequences of video images of services, produced by the ITTF Umpire Committee [7] were also used.

In these still images, a real ball as well as objects whose appearance similar to a ball can be found. The location of the ball can be either situated on the palm of the player or in mid-air. The ball is more difficult to be detected when it is rested on the palm because the bottom part of the ball is often hidden by the player's palm. However, the proposed system must be able to detect the ball at this situation because it signifies the start of a service. Further discussion on this point can be found in the Discussion Section.

### A. Threshold based object detection

Initially, a basic threshold based object detection algorithm, which was based on the algorithm described by the Matlab Image Processing Toolbox [4], was constructed. The algorithm was the first attempt and is now mainly used as a benchmark for performance comparison in this paper. The algorithm conducts the following tasks:

- Binarisation: Convert pixels that have similar colour of the ball to white and other pixels to black. This yields a binary image.
- Object forming: Connect the neighbouring white pixels together to form objects.
- Clean up: Remove irrelevant small objects and fill in holes in detected objects.
- Evaluation: Examine the properties (e.g., size and roundness) of these objects and check if they are similar to a ball.
- Classification: Classify whether it is an irrelevant object, a ball on the player's palm or a ball in mid air.

Figure 1 gives an example of the above process.

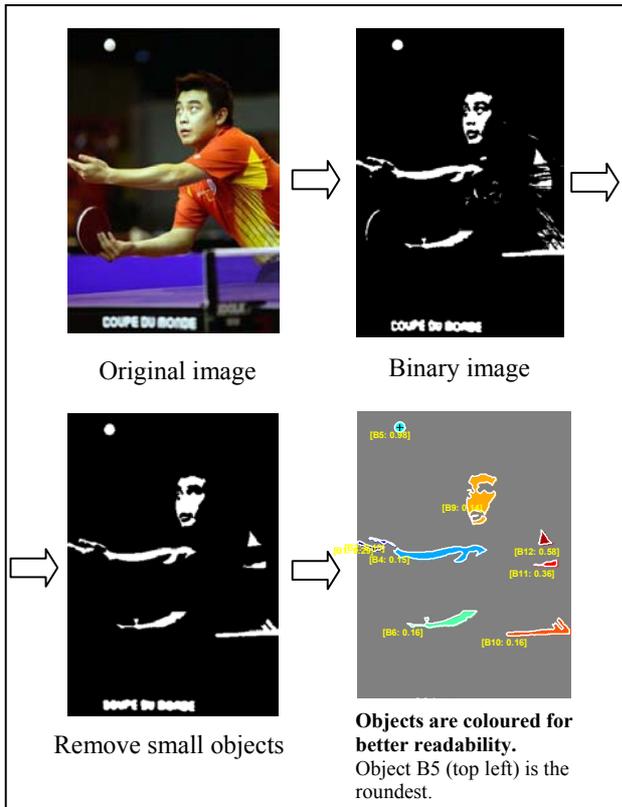


Figure 1. Identifying the ball from the scene

Binarisation is a process aimed at turning pixels with similar colours of the ball to white and other pixels to black. A threshold is employed to control the minimum acceptable degree of similarity. The threshold can be quite sensitive and difficult to be set appropriately. A too low threshold may result in too many irrelevant objects left in the binary image. Otherwise, part of or the whole ball may disappear from the binary image. Figure 2 illustrates an example which shows that a small change in the threshold value may result in different numbers of objects remaining in the binary image. The shape of objects may be affected significantly too.

Because of the sensitivity of the threshold value, it is impossible to find a single threshold value that suits all match scenes. To combat this, a heuristic is needed to estimate an appropriate threshold for each image. One standard way is to use a histogram- or other statistics-based algorithm to analyse the input image and estimate an appropriate threshold value. However, this method did not perform very well in this application because the size of the ball is very small and its colour distribution is insignificant. The author thus proposed an alternative method, namely Two-pass threshold method. Details of the technique will be described in Section 3.2.

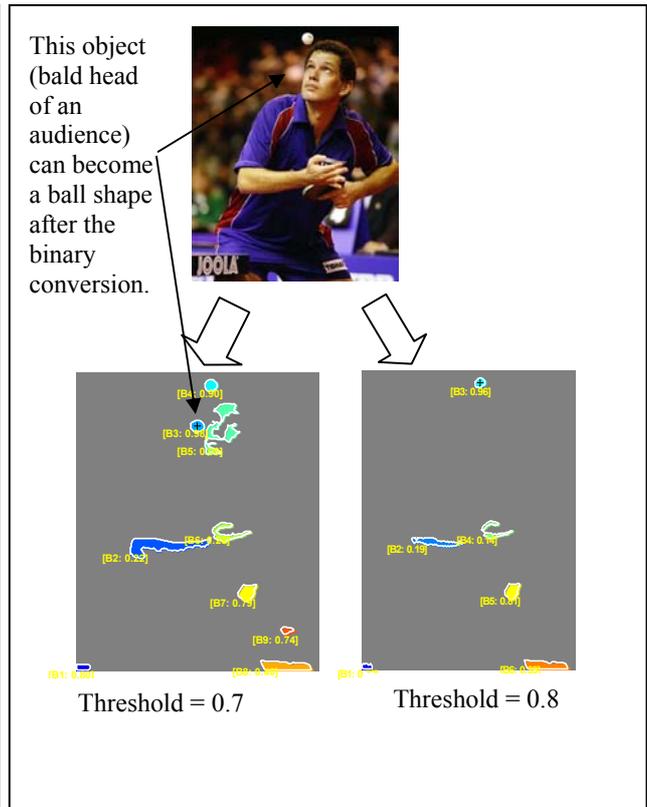


Figure 2. An example showing how the threshold can affect converted binary image.

### B. Two-Pass Threshold Method

The main reason that the standard threshold method failed in this application was believed to be that the colour of the ball was not uniform, i.e., some parts were brighter and other parts were darker. The threshold had to be "lenient" enough so that the whole ball was allowed to be included. At the same time, the threshold needed to be "harsh" enough so that pixels of different colour would be filtered out. It is often difficult to find a balance point. Furthermore, the brightness and contrast of the ball varies as the ball moves to different locations.

Experiments on detecting the ball using colour based and k-mean clustering techniques [4] were conducted, but the results were not encouraging. As the still images are composed of a large number of different colours, it is difficult to set the appropriate number clusters. Setting too many clusters may break the object (including the ball) into more than one cluster; otherwise, irrelevant objects are clustered together.

The proposed two-pass threshold method, however, was designed to reduce the above mentioned effects suffered by the standard threshold and clustering techniques. In the first pass, a harsh threshold is applied so that all but those areas which have a very similar colour to the ball are eliminated. This significantly narrows down the number of objects the system has to

be evaluated. However, the ball often cannot be identified from these objects because the shape and size of the objects is heavily eroded by the harsh threshold. Nevertheless, the locations of these objects give clues on where the areas of interests are. In the second pass, a lenient threshold is used but only applied to the areas of interests detected in the first pass and their neighbouring areas. The lenient threshold allows the binarization to only remove pixels that have colours significantly different from the ball. This ensures the interested objects will not be heavily eroded. As the lenient threshold only applies to areas of interests, objects elsewhere will still be removed.

The two-pass threshold method does not only reduce the processing time required for analysing the image but also reduces the chance of having an object that has similar shape to the ball after the binarisation (see the annotation in Figure 2). The remaining objects can be thoroughly examined in the second pass as more details are revealed. Figure 3 shows an example of the two-pass conversion. The ball was on the player's palm, which was more difficult to be detected as part of the ball was hidden by the player's palm. The binarisation using a harsh threshold (first pass) was used to establish where the interested regions are. However, part of the ball was often eroded due to the harsh threshold. To regain the eroded part, a binarisation with a lenient threshold was applied to only the regions where interested areas were found in the first pass (yellow boxes in Figure 3).

### C. Object Evaluation

After the binarisation, there are often a number of objects left. To confirm whether one of these objects is the ball, each of the objects is to be evaluated and compared with features of a typical ball. In this study, seven features are looked at. The name and the definition of these features are shown in Table 2. In an ideal situation, the object that matches each feature of a typical ball can be considered as the ball. However, in most occasions some of the features do not perfectly match. These defects may be caused by factors such as poor lighting and interference by the ball-coloured background. Furthermore, when the ball is situated on a palm, it will not be round as the bottom part of it will be hidden by the player's palm. In order to detect (or more precisely classify) the objects, a point system has been devised. The system awards points to an object when it matches a particular feature. Some features such as roundness and rounded top are considered to be more important as they are key features of the ball and hence are given more points. The object which is awarded the highest points and has a rounded top is considered to be the ball. Table 3 shows the features and their associated points. Based on the point system, a classifier has been devised. It can classify the object into three categories: Not a ball, ball on the palm and ball in mid-air. To classify the objects, some rules were employed and the method is shown in Table 4.

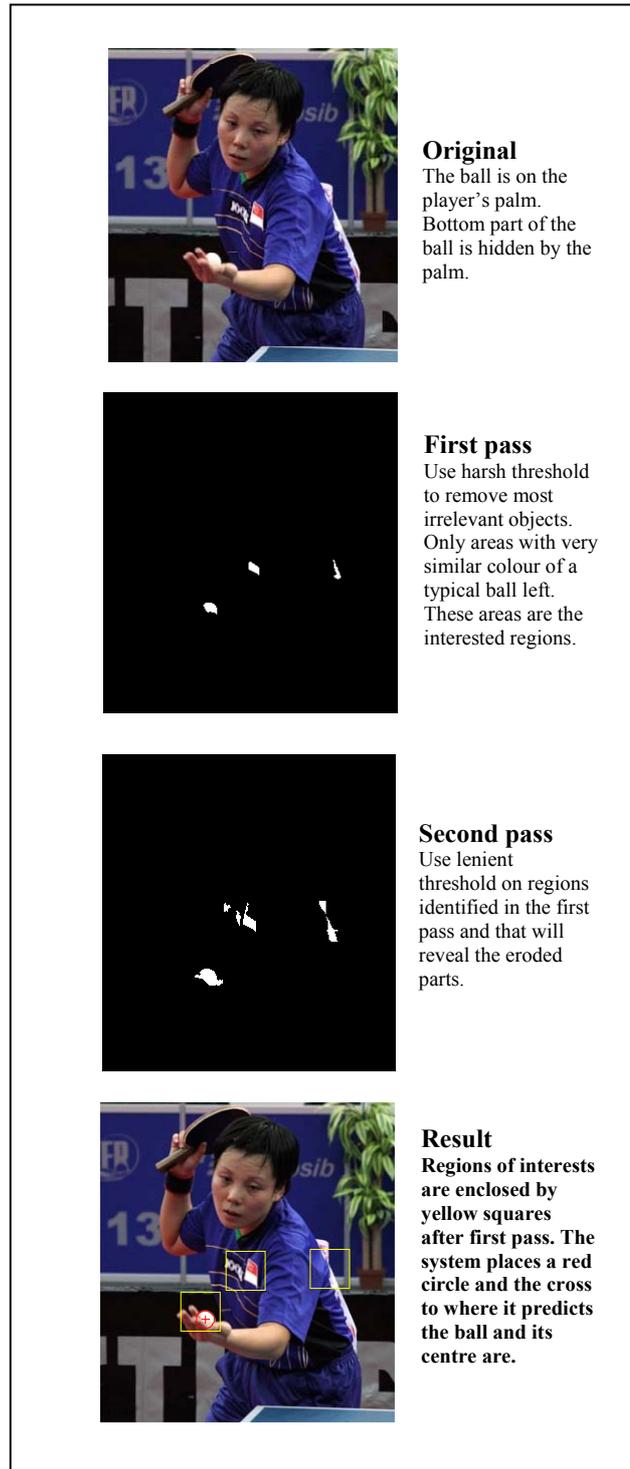


Figure 3. An example showing the two-pass conversion

TABLE II. NAME AND DEFINITION OF THE SEVEN FEATURES

Features	Description
Area (A)	Number of pixels the object possess
Maximum width	The distance between the leftmost and rightmost pixels of the object
Maximum height	The distance between the top and bottom pixels of the object
Perimeter (P)	The length of the object's boundary
Roundness	A metric is employed to estimate the roundness of an object: $m = \frac{4\pi A}{P^2}$  The roundness metric will be equal to 1 if the object appeared to be circle in the image because A will be $\pi r^2$ and P will be $2\pi r$ .
Rounded top	If the object is a ball, the top of it will be round. To check this, the pixels on the upper boundary of the object are to be used to estimate the radius and the centre of a circle by substituting their co-ordinates to the equation of a circle: $r^2 = (x - x_c)^2 + (y - y_c)^2$ Where r is the radius and (xc,yc) is the centre. Then 5 points selected randomly from the upper boundary are to be tested and checked whether they lie on the circle. If so, the object is considered to have a rounded top.

TABLE III. FEATURES AND POINTS

Features	Points
Area (A)	1
Maximum width (diameter)	1
Maximum height (diameter)	1
Perimeter (P)	1
Roundness	3
Rounded top	2

TABLE IV. CLASSIFICATION AND RULES

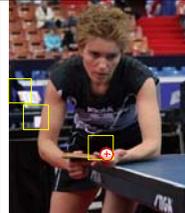
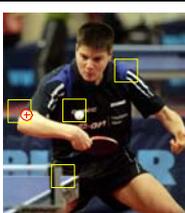
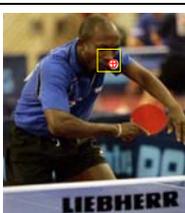
Class	Rule	Remark
Not a ball	Object does not have a rounded top and its size is much biggest or small than a typical ball	Most objects which are not a ball do not have a rounded top.
Ball on the palm	Object has a rounded top and has at least 2 points	Area, perimeter and roundness are unlikely to match as the bottom part of the ball is hidden
Ball in mid air	Object has a rounded top and has at least 7 points	Ideally all six features should match, but the system accepts a minor imperfection

D. Results

The ball identification system was put to test with 22 still images, which were captured in real match scenes and contain situations where the balls are on the palm and in mid-air. In these 22 still images, the system found 83 objects which have similar colour, shape and size of a typical ball after the binarisation process. The test

results are very encouraging. The system was able to correctly classify 80 out of 83 objects (two non-classifications (Image 15 and 22) and one misclassification (Image 6 in Table 5)). The system was also able to highlight the ball on the image by using the radius and centre information from the object that was identified as the ball. Out of 20 occasions where a ball is detected, 19 occasions the system can accurately draw a circle around the ball and estimate its size correctly. Table 5 shows the results in more details.

TABLE V. RESULTS OF THE TESTS

		
1. Correctly classified: Ball in mid air	2. Correctly classified: Ball on the palm	3. Correctly classified: Ball in mid air
		
4. Correctly classified: Ball in mid air	5. Correctly classified: Ball on the palm	6. Wrong object was identified
		
7. Correctly classified: Ball in mid air	8. Correctly classified: Ball in mid air	9. Correctly classified: Ball in mid air
		
10. Correctly classified: Ball in mid air	11. Correctly classified: Ball in mid air	12. Correctly classified: Ball on the palm



#### IV. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) are well known for their pattern recognition ability. Although the simple classification system described in Section 3.3 produced encouraging results, it was thought that it was worth investigating whether an ANN can improve the results. In brief, an ANN may be considered as a greatly simplified biological brain. An ANN is usually implemented using electronic components or simulated in software on a computer. The massively parallel distributed structure and the ability to learn and generalise makes it possible to solve complex problems that otherwise are currently difficult [8].

ANNs are particularly good at classifying patterns. In this study, they have been employed to determine whether a detected object is a ball and whether the ball is on the palm or in mid-air. More information about ANNs and their applications can be found in [8-11].

Two types of ANNs have been selected for this classification problem, namely the multi-layer perceptron (MLP) and the radial basis function network (RBF). They were selected because they have been used by the author and others [8-11] in solving many classification problems satisfactorily.

A MLP is a multi-layer feedforward network that "learns" through supervised training, which is usually a gradient descent method such as backpropagation. Nonlinear functions such as sigmoid are used as the activation functions for the hidden and output neurons. It is the most popular network architecture and has been successfully deployed in solving many practical problems. Although it is known that it can sometimes suffer premature saturation and that it can be difficult to design the optimal structure, it is overall a flexible and robust type of network and easy to use and understand.

On the other hand, RBF is a network that employs both unsupervised and supervised training. It is also a feedforward network but always has 3 layers, namely input, prototype and output layers. Similar to MLP, the input neurons are not processing elements. They simply feed the input to the hidden layer. However, the prototype neurons work differently. Unlike a MLP's hidden neurons, which pass the weighted sum of the inputs to their activation functions, RBF's prototype neurons pass the Euclidean distance between the input and weight vectors to their activation functions, which are usually Gaussian functions. During unsupervised training, the network adjusts the weights between the input and prototype neurons in an attempt to minimise the Euclidean distance between input and weight vectors. When this is complete, a separate supervised training is conducted on the output neurons. The output neurons, which usually employ linear functions, are trained to associate each cluster with a particular class [9]. The advantage of a RBF is that it usually takes less time to design a workable network for a problem, especially when plenty of training patterns are available [5]. However, it usually requires more processing neurons than a MLP.

##### A. Classifying the balls using ANN

ANNs have been employed in classifying objects detected using the system described in Section 3.2 and 3.3. The 83 objects which have similar colour, shape and size to a typical ball were detected from the 22 still images by the system described in Section 3.2. The six features of these objects, listed in Table 2, form the basis of the input part of the training patterns. To be precise, the inputs are:

- Difference between the object's area and a typical ball's area;
- Difference between the object's maximum width and a typical ball's diameter;
- Difference between the object's maximum height and a typical ball's diameter;

- Difference between the object's perimeter and a typical ball's perimeter;
- Roundness value;
- Whether the object has a rounded top (Yes/No)

As for the desired outputs, they are binary bits that represent the class the training pattern belongs to. For example, when the desired outputs are "1 0 0", it represents the pattern belongs to class 1, which means the object is not a ball; "0 1 0" represents class 2 and so on. The full list is shown in Table 6.

TABLE VI. DESIRED OUTPUTS

Desired Outputs	Description
1 0 0	Object is not a ball
0 1 0	Ball is on the palm
0 0 1	Ball is in mid air

The whole data set consists of 83 patterns. 66 (80%) patterns were randomly selected as training patterns and the remaining 17 (20%) patterns were used as validating patterns during training. The training stopped when the network responses to the validating patterns were no longer improved. The ANNs were then tested with the whole data set. Table 7 shows an example training pattern.

TABLE VII. EXAMPLE TRAINING PATTERN – BALL IS IN MID AIR

Inputs						Desired output		
0.95	0.37	0.19	0.25	0.23	1	0	0	1

### B. Results from MLP and RBF Network

A number of MLP network structures were experimented and found that a MLP network with 6 inputs, 10 hidden and 3 output neurons classified the patterns most successfully. To reduce the chance of getting a bad result because of premature saturation, the same MLP was re-initialised, re-trained and re-tested more than 100 times. The best trained MLP can correctly classify 81 out 83 objects (two class 2 objects were misclassified as class 1).

Similar to the procedure described above, a number of RBF network structures were tried and found that a RBF network with 6 input, 67 prototype and 3 output neurons produced the best result. The best trained RBF can correctly classify 82 out 83 objects (one class 2 was misclassified as class 3). The results indicate that ANN has a superior classification ability and can detect balls that the point system described in Section 3.3 failed to detect.

## V. IDENTIFYING THE BALL FROM VIDEO

Section 3 and 4 discussed the techniques used to identify the ball from still images. This section looks at whether the same techniques can be applied in identifying the ball from video, which is a sequence of still images. Preliminary results and considerations of video quality parameters such as resolutions and frame

rate with respect to the effectiveness of the ball detection have also been studied and will be discussed below.

The video clips employed for this study were obtained from the web site of the ITTF Umpires and Referees committee in 2006 and the videos were designed for training purposes [7]. The video clips were captured at a frame rate of 30 frames per second and with a resolution of 352 x 240 pixels.

Compared to the still images described in Section 3, these video images have a much wider viewing angle and hence the objects including the ball appear to be much smaller (see Figure 4). In fact, the area of the ball is only approximately one quarter the size of that in the still images. The small size caused the system to be unable to detect the ball from the video images because the algorithm for detecting the rounded top of the ball requires the diameter of the object to be at least 10 pixels. Furthermore, the quality of the video images is not as sharp as the still images. Another main difference is that the ball used is orange rather than white in the still images.

To overcome the small ball size problem, the video images were magnified to double the original size, ie. to a resolution of 704 x 480. However, the sharpness of the images was worsened and the objects became slightly "blocky" (See Figure 4). Nevertheless, the system was able to detect the ball from the video frames where the shape of the ball is roughly circular. However, at frames where the ball is in high motion, the shape of the ball is distorted and become blurred. The system was not able to detect the ball from such frames. The distortion was caused by the video not being captured at a high enough frame rate.

Figure 4a - 4c shows example frames where the ball has remained roughly circular and the system was able to detect the ball (indicated by a red circle). Figure 4d illustrates the distortion of the ball when it is in high motion. The system could not detect the ball from that frame.

This result indicates that the system is robust enough to tolerate moderately poor quality of the image. However, when the shape of the ball is distorted, the current algorithm cannot cope. One simple solution is to capture videos at a higher frame rate such that the objects in high motion will not be distorted. However, the consequence is to have to process more frames. This is not desirable as the time taken for the process will be significantly longer.

Current research is focused on videos captured at 200 frames per second. At this rate, the ball remains circular even when it is in moderately high motion. To reduce the processing workload and time taken to detect and track the ball, an algorithm is being developed to predict the location of the ball at the next frame based on the information from previous frames. With the aid of the predicted location, only a small region of a frame is required to process and this will significantly improve the time taken to detect the ball.

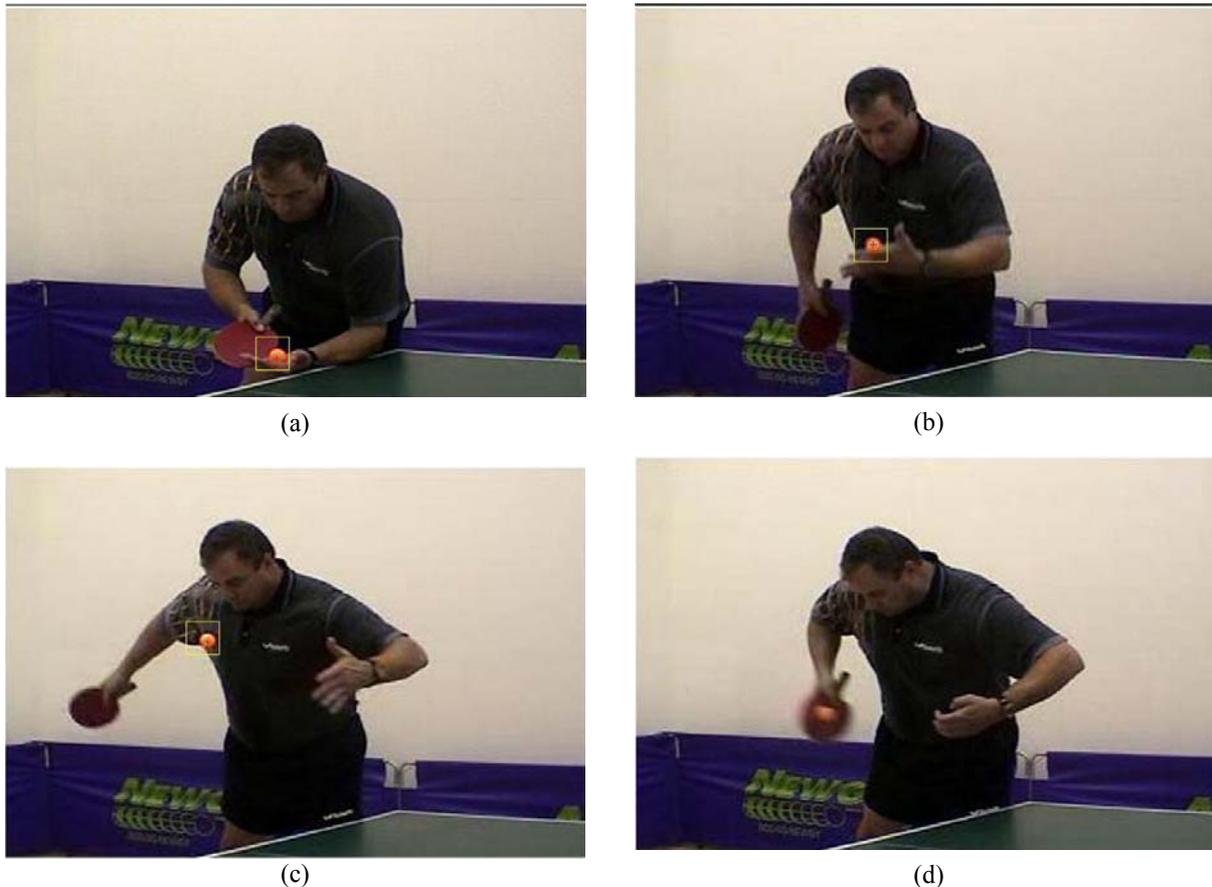


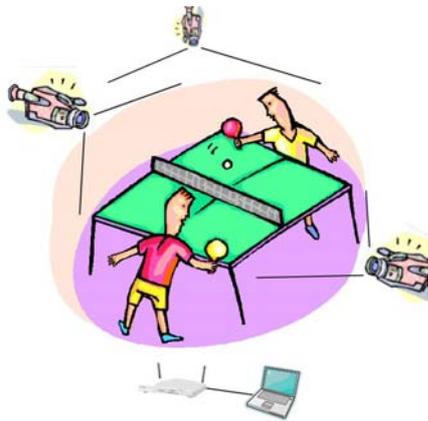
Figure 4. Example video frames showing detection of the ball (Video source: courtesy of ITTF Umpires and Referees Committee)

## VI. MULTI-AGENT SYSTEM (MAS)

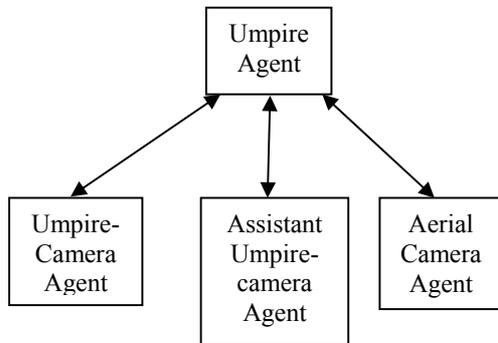
The point-based and neural networks approaches discussed in Section 3 and 4 are based on an image taken from a single angle. Although the preliminary results are encouraging, the ball is bound to be difficult to detected in situations where some or all of the ball are hidden by obstacles. The problem would be reduced if multiple cameras are employed. Two cameras could be fixed at positions where the umpire and assistant umpire are (opposite side of the table). Additional cameras may be fixed high above the table to take aerial views.

However, a higher amount of data feeding in from these cameras are now needed to be processed. The situation would be worse when conflicting results are produced from images capturing from different angles. To aid coordinating these complicated processes, a multi-agent system (MAS) is proposed. Each camera is associated with an agent that can make independent decision based on the image it receives.

These local decisions can then be fed into an agent at a higher level for consideration of the final decision. This higher-level agent should have the ability to evaluate the decisions made by the camera agents. Factors such as the position and angle of the camera, agreement among agents and prior experiences can form the basis of a heuristic that is applied to reason the final decision. This analogy is actually similar to what the real human umpiring system does, i.e. the umpire takes recommendations from the assistant umpire and makes the final decision based on both their judgments. Figure 5a illustrates setup and 5b shows the structure of the proposed MAS.



(a) Videos captured by the camera are sent to the system for processing



(b) Structure is the MAS. Umpire agent makes final decision based on the inputs from other agents.

Figure 5. MAS for table tennis umpiring.

### VII. CONCLUSION

An intelligent system has been developed to identify and track table tennis balls from match scenes. The preliminary results are very encouraging. The system can identify the ball, pin-point its location and estimate its size from still and video images with a good accuracy. ANNs have been employed in aiding classifications. The results are very promising. They have demonstrated that ANNs could identify the balls from images from which the point-system failed to detect the ball. The RBF network classified the data slightly better than MLP but it required over six times more hidden neurons. However, the time required to find a network structure that produced a satisfactory result was much shorter.

The immediate next stage of the research will focus on identifying and tracking the ball from video images. A technique for efficiently analysing consecutive frame of video images has been developed. Briefly, the principle of the technique is based on the fact that the location of the ball in next frame will be in the neighbourhood area of that in current frame if the video

is captured at a high enough rate. As a result, only the neighbourhood area of the subsequence frame needed to be analysed and hence the processing time and accuracy should be significantly improved.

### VIII. ACKNOWLEDGMENT

The author would like to thank Atlanta Georgia Table Tennis Association for providing video samples about table tennis services at the ITTF web site. Some frames of a video sample were extracted and referenced in the paper.

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