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Pattern Recognition of Overhead Forehand and Backhand in Badminton Based on the Sign of Local Euler Angle

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Abstract

Studying the badminton skill based on the arm movement is a challenge since the limitation of the sensor such as camera to record the movement parameter. This study proposed a new method to determine the pattern of arm movement for forehand and backhand strokes in badminton based on the sign of the local Euler angle gradient from four points of right arm segments. Each segments was identified by motion sensor attached to the dorsal surface of the hand (sensor 1), wrist (sensor 2), elbow (sensor 3) and shoulder (sensor 4). Three certified coaches participated in this research to determine the arm movement patterns for forehand and backhand strokes. Skills in forehand and backhand strokes from eight professional players and eight amateur players were observed to determine the pattern. The result showed that the local Euler angle can be used to recognize the arm movement pattern. Based on the observed patterns, the professional players had a higher similarity to the coaches' patterns than those amateur players to the coaches'.

Keywords*: badminton, local Euler angle, backhand, forehand*

1. Introduction

Indonesia has been reknown for producing world class badminton athletes. Badminton is a primary sport course in Indonesian elementary school curriculum. Almost every single Indonesian can play badminton well. Thus, an experimental study of sensor movement using motion in badminton is an interisting topic since it gives wider impact to Indonesian badminton hobbiest.

Today badminton is played all over the world. It was an exhibition sport in Olympic 1972 before it was officially played as the competitive sport for the first time in the Olympic 1992. Although it is a famous game, but browsing and searching cited references about this game take a relatively longer time than other racket sports such as tennis.

Many of the previous studies conducted camera to evaluate the badminton game. Wang, Liu and Moffit [1] recorded using cameras a number of students playing badminton to study the arm and trunk movement in overhead forehand strokes for some skill levels. They divided the sequences of arm movement into three steps; elbow flexion, elbow and humeral flexion, and upward flexion when someone performed the overhead stroke. Furthermoe, they tennis. Furthermore, they also had three segments of trunk movement for overhead forehand strokes, which comprise no trunk action, forward-backward movement and trunk action rotation. The result showed that the students at advanced skill performed a better action in this stroke compared to another level.

Meanwhile, Zhu [2] studied the string tension for fast swing and angled striking. In this research eight different level of string tensions were used. Some players were recorded using a camera while striking a shuttlecock with the rackets of eight level string tensions. The result showed that expert players could adjust the power belonging to the string tension to stroke the shuttlecock. The player with low level skill failed to perform fast swing and angled striking with various types of string tension.

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Nagasawa et al [3] analyzed the human motion based on the badminton smash image. The human motion in Space-*G* was mapped into Space-*V* using KL transform. This method classified the motion related to the center of the body into cloose loop, curve and line. In [4] the diffference of forehand overhead smash performed by male and female players was investigated. The arm was segmented into upper arm, forearm and wrist. Oqus camera systems recorded the motion starting from the position of the holding racket to the smashing motion. Qualisys Track Manager software was used to analyze the motion. The result showed that the male subject has higher racquet grip velocity that the female subjects. Using Qualysis-MCU500 high speed camera, the method to stabilize and balance the center gravity of body was studied since this plays an important role in badminton athletes to regulate the spiking action [5].

To tackle the limitations of camera such as workspace area and complexity of the numerical process, local sensors were developed. Using electrogoniometer, Teu et al [6] proposed dual Euler angles to analyse arm movement. The body was segmented into three sections. The relationship between segment velocity and the racket velocity was determined using kinematic equations. The racket velocity was also measured using an accelerometer as the comparison of the simulation result. In [7], the smash stroke in badminton was studied. Accelerometer and earthquake sensor attached to the badminton racquet. The Adaptive Neuro Fuzzy Inference System was developed to combine the information from the accoustic emission and acceleration information in order to determine the the ball speed.

Hastie et al [8] studied the development of skill and tactical knowledge of students after the badminton season. The result showed that after the season, students improved their ability to send the shuttlecock to their desired locations. Students were more aggresive in hitting the shuttlecock. Students could decide with the reasons and the tactics that they want to use in some given cases.

This research proposed the of the local Euler angle gradient to model the overhead forehand and backhand stroke in badminton. The patterns of overhead forehand and backhand strokes were determined from certified coaches. Some players from professional and amateur level participated in this research. The patterns were used to investigated the similarity of skill between players and the coaches.

2. Motion Sensor

In this research, the motion was caculated in 3-dimesional space by an inertial measurement unit produced by Motionnode. This is a compact sensor designed for human motion tracking. This 10 gram sensor was easy to use The physical size is 35 mm x 35 mm x 15 mm, as shown by Figure 1. The sampling rate is 100 Hz and the error is about 0.5° to 2° RMS. Another research [9], used accelerometer as the motion sensor to detect road disease.

Figure 1. Inertial measurement unit by Motionnode

The motion was indicated by the Euler angles. Euler angles are the succesive rotation to the moving reference point. It was the sequence of rotations about x_1, y_2 and z_3 coordinate, as shown by Figure 2. The first rotation about the x-axis by an angle ψ produced the $x_1\, y_1\, z_1$-axis. The second rotation about the y_1-axis by an angle θ generated the $x_2y_2z_2$-axis. The last rotation is about the z_2-axis by an angle ϕ constructed the $x_3\, y_3\, z_3$-axis.

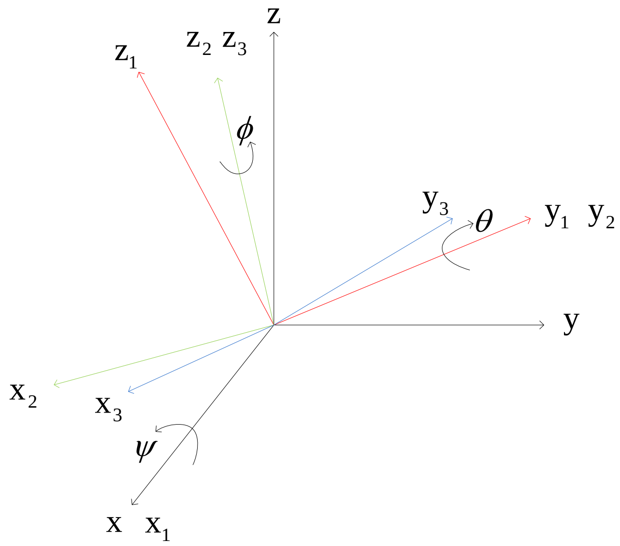

Figure 2. Three rotations of coordinate

3. Sign of Local Euler Angle

The signs of the local Euler angle are determined from the slop of the signals. There are three probabilities of the sign: positive (+), negative (-) and stationery (0). Two threshold values—positive threshold and negative threshold—were applied in this research. There were movements if the signal was bigger than the positive threshold or smaller than the negative threshold. If the sign was stationary, the players finished stroking the racket. The threshold values were always renewed if there was a new local maximum or local minimum point of the local Euler angle. The local minimum or local maximum was called as reference point. The new threshold value for positive and negative were calculated by (1) and (2). Rusydi et al., [10] used 3the threshold value of a biosginal to indicate a human activity. Figure 2 illustrates the process to determine the sign of local Euler angle.

Figure 3 gives an example of local Euler angle of arm movement. In this example, there are four areas of the local Euler angle: (a), (b), (c) and (d). There are four positive and four negative thresholds. Area a and c have a positive (+) signs of the gradient. They are different from area (b) which has a negative sign of the Euler angle gradient. Area (d) is the stationary area with its gradient is equal to zero. Based on this method, the pattern of local Euler angle in this example is “+-+0”. Rusydi et al., [11] briefly introduced this method for the pattern of the arm movement recognition system.

4. Method

In this study, the pattern of local Euler angle was established based on three coaches' techniques for forehand and backhand strokes. The coaches were certified by Badminton Association of Indonesia. Each coaches performed forehand and backhand strokes ten times. Eight professional players (from 14 to 17 years old) and six amateur players (about 20 years old) were evaluated based on the similarity in the pattern of the local Euler angle. All of the coaches and players were right-handed.

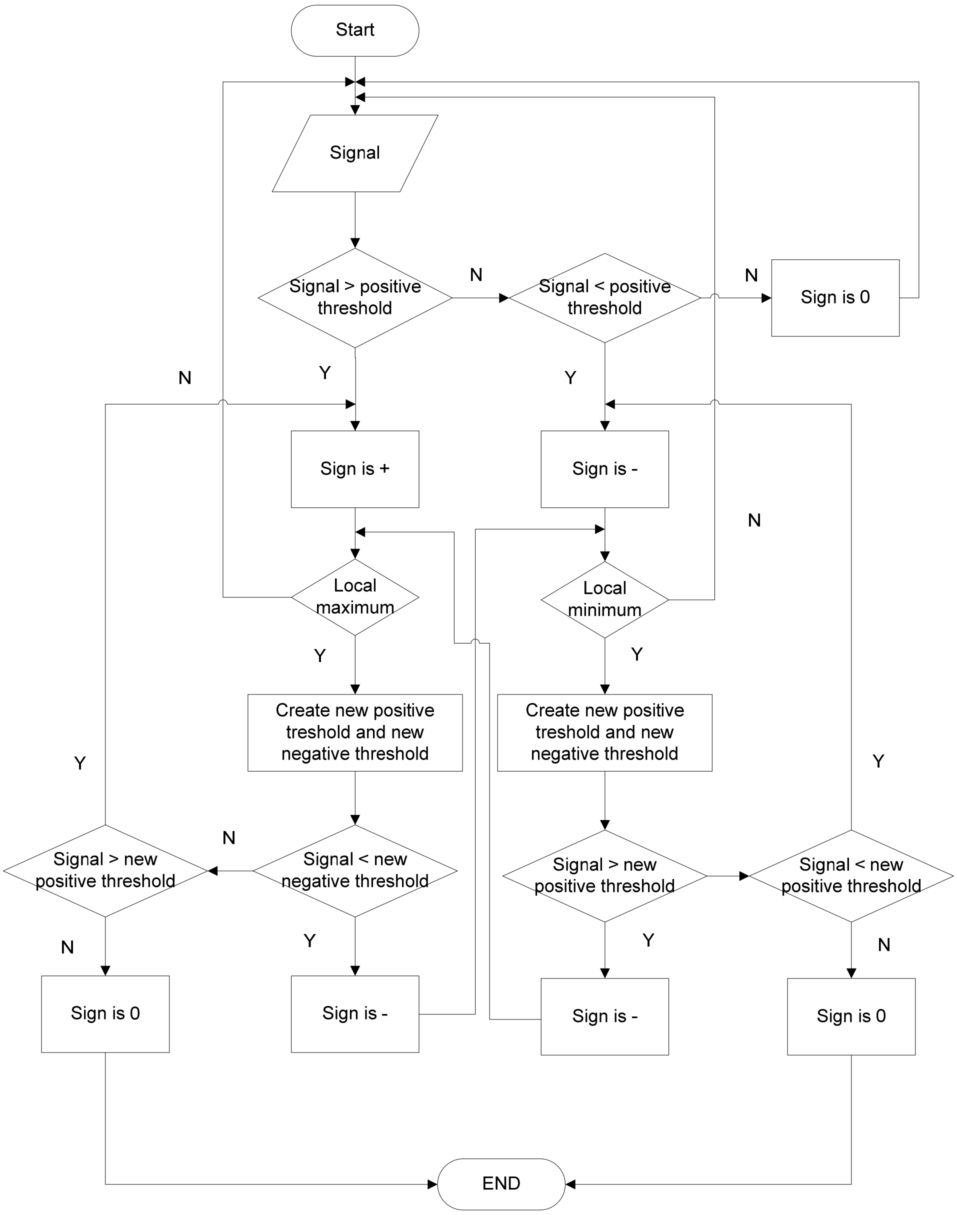

Figure 3. The process to determine the sign of local Euler angle

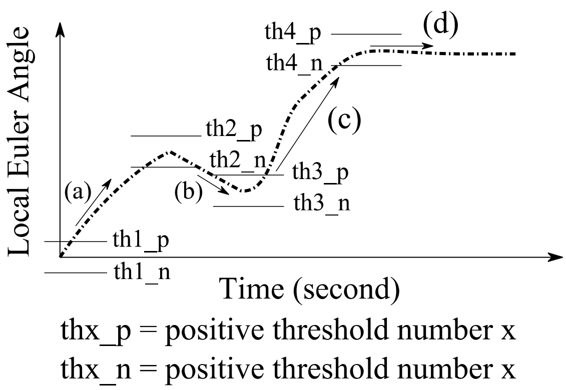

Figure 3. The local Euler angle wave

The right arms of coaches and players were segmented into four sections, which were determined based on the kinesiology of the human arm [12]. Four gyro sensors were attached each on the dorsal surface of hand (sensor 1), wrist (sensor 2), elbow (sensor 3) and shoulder (sensor 4) as shown in Figure 4. This sensor measured the 3-dimensional local Euler angle of each segment. Based on the previous research by Rusydi et al. [11], the initial condition of the sensor was very important in this study to improve the system performance. The initial position of the sensor relative to the world coordinate was set to standardize the result. These positions are given in Table 1. The relationship between the world coordinate to the sensor coordinate is illustrated by Figure 5. The symbol α is the angle about the x-axis, β is about y-axis, and γ is about z-axis.

Figure 4. Four sensors attached to the right hands

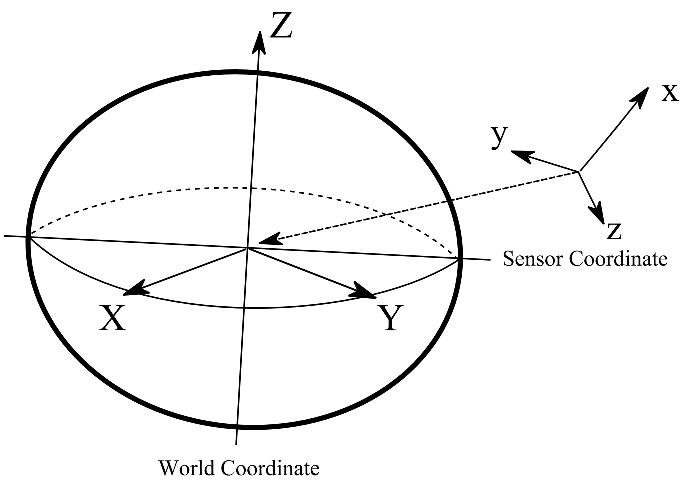

Figure 5. Sensor coordinate to the world coordinate

Table 1. The initial position of sensors

	α	β	γ
Sensor 1	150°	20°	85°
Sensor 2	110°	25°	120°
Sensor 3	-150°	30°	110°
Sensor 4	120°	25°	90°

Three coaches did the forehand and backhand strokes ten times for each skill. Each sensor had three local Euler angles, so there were totally 12 local Euler angles for four sensors. The data were analyzed to determine the pattern of local Euler angle based on the sign. The patterns produced by the coaches were called reference pattern.

The skills of eight professional players and six amateur players were compared based on their similarity to the coaches'. There were two methods to check the skill of the players'. First, determining the percentage of unknown arm movement was proposed. Unknown arm movement was the arm movement of players that dismiss the pattern produced by coaches'. The higher percentage of unknown arm movement is the worse of the players' skill. Second, the point produced by the players was calculated. The point depended on the percentage of players performed the patterns and the weight of those patterns. The weight of the patterns was determined by normalize the percentage the reference patterns from 0 to 1.

5. Result and Discussion

Table 2 shows the pattern of local Euler angle from three certified coaches for forehand strokes. The pattern was seen from the local Euler angle of 4 sensor locations. The result showed that there were three types of the pattern in the x-axis of all sensors. There were three types of the pattern on the y-axis for sensor 1, 2 and 3, yet there were only two types of sensor 2. The z-axis of sensor 1, 2 and 4 had also three patterns, except z-axis of sensor 4 which has 2 patterns only. Pattern 1 for each sensor suggested the coaches' mostly produced pattern. The average probability of all axes for the pattern 1 of the all sensors was almost 0.6. It has twice as many as pattern 2. Probability of pattern 3 was smaller than half of the pattern 2. The local Euler angles of the pattern 1 for forehand strokes are illustrated by Figure 6.

Table 3 shows the Euler angle patterns and the probability for backhand stroke. The average probability of the first pattern in backhand stroke, which was about 0.81, had a higher probability than the first pattern in forehand stroke. The average probability was only about 0.13 for pattern 2 and 0.06 for pattern 3. The x-axis on sensor 2, 3 and 4 had only 1 type of pattern. The y-axis on sensor 2 and 4 had only two patterns and also z-axis of sensor 3 which had only 2 patterns. Only sensor 1 had 3 types of pattern for all the axes. The local Euler angles of the pattern 1 for backhand strokes are illustrated by Figure 7.

Table 2. The pattern of forehand strokes

Pattern	Sensor 1			Sensor 2			Sensor 3			Sensor 4		
	x	y	z	x	y	z	x	y	z	x	y	z
1	-+0 (73%)	-+0 (47%)	-+0 (47%)	-+0 (67%)	-+0 (47%)	-+0 (67%)	+0 (67%)	-+0 (47%)	-0 (73%)	+-0 (40%)	-+0 (87%)	-0 (53%)
2	-+-0 (20%)	-+-0 (33%)	-+-0 (40%)	-+-+0 (20%)	-+-0 (40%)	-+-+0 (20%)	+-+0 (20%)	-+-+0 (40%)	-+0 (27%)	-+-+0 (33%)	-0 (13%)	-+0 (33%)
3	-+-+0 (7%)	-+-+0 (20%)	-+-+0 (13%)	-+-0 (13%)	-+-0 (13%)	-+-+0 (13%)	-+-0 (13%)	+-0 (13%)		-+-0 (27%)		-+-0 (13%)

Table 3. The pattern of Backhand strokes

Pattern	Sensor 1			Sensor 2			Sensor 3			Sensor 4		
	X	y	z	X	y	z	x	Y	z	x	y	z
1	-+-0 (67%)	+-+-0 (60%)	-+-0 (60%)	-+0 (100%)	+-+0 (73%)	-+0 (100%)	-+0 (100%)	+-+0 (67%)	+0 (80%)	-+0 (100%)	+-0 (67%)	-+0 (100%)
2	-+0 (20%)	+-+0 (20%)	-+-+0 (20%)		+-0 (27%)			+-0 (20%)	-+-0 (20%)		+-+0 (33%)	
3	-+-+-0 (13%)	+-+-+0 (20%)	-+0 (20%)					+-+-0 (13%)				

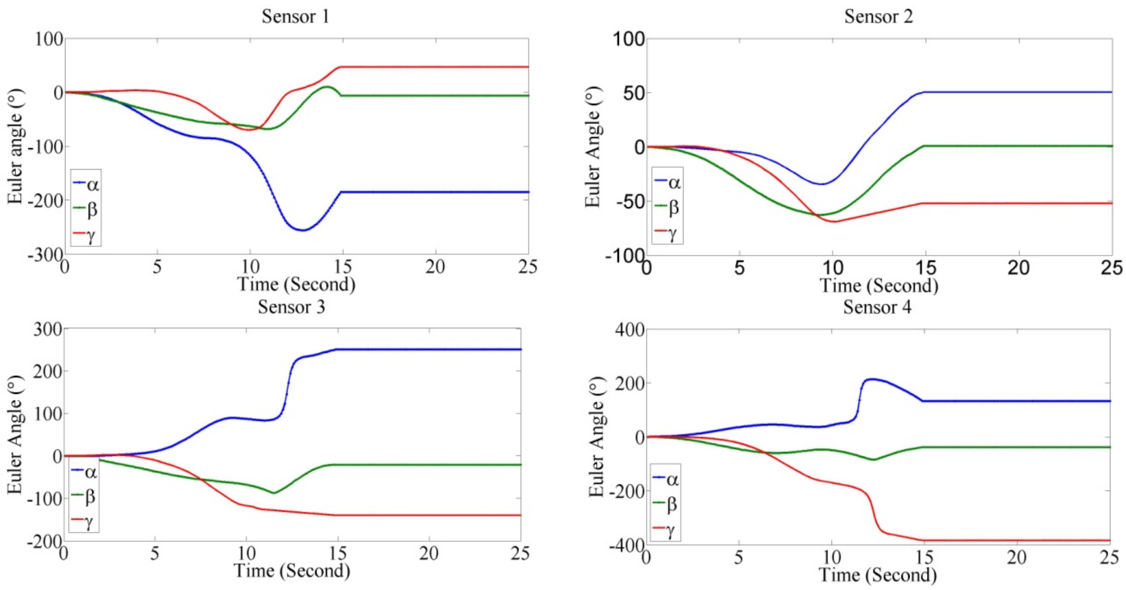

Figure 6. Local Euler angle from four sensors for first pattern of forehand strokes

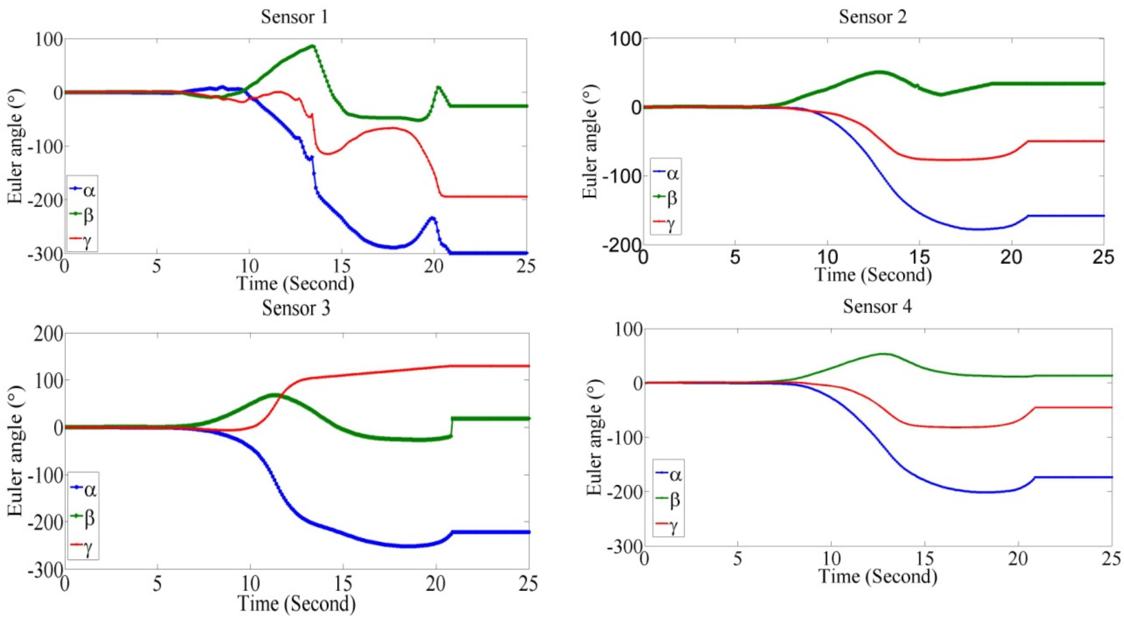

Figure 7. Local Euler angle from four sensors for first pattern of backhand strokes

Table 4 suggests the similarity between professional players and coaches for forehand skill. The athletes were asked to strike the shuttlecock using the forehand skill ten times. Their recorded arm movement patterns were compared to those of the coaches. Around 37% of their movements were recognized as pattern 1. In addition, the table of figures showed that 27% of the movements were found for pattern 2, while 21% for pattern 3. It demonstrated that about 16% of their movements were not associated with any types of the coaches'.

Table 5 shows the similarity between amateur players and coaches for forehand strokes. The distribution of the pattern for the amateur players while performing forehand strokes is the same between pattern 1 and pattern 2, which is 27.5% in average. It is slightly higher than pattern 3 which is only 20%. The overall even chance for pattern 1, 2 and 3 is about

76% for amateur players, while around 24% of their movements are unrecognized by the system derived from the coaches' pattern.

Table 4. Professional players' arm'movement for forehand stroke

Pattern	Sensor 1			Sensor 2			Sensor 3			Sensor 4		
	x	y	z	x	y	z	X	Y	z	x	y	z
1	57.5%	10%	12.5%	40%	45%	30%	40%	57.5%	7.5%	57.5%	70%	25%
2	17.5%	52.5%	30%	17.5%	15%	17.5%	25%	20%	52.5%	5%	5%	62.5%
3	15%	17.5%	22.5%	32.5%	32.5%	35%	35%	17.5%		32.5%		10%

Table 5. Amateur players' arm movement for forehand strokes

Pattern	Sensor 1			Sensor 2			Sensor 3			Sensor 4		
	x	y	z	x	y	z	x	Y	z	x	y	z
1	20%	17%	10%	40%	30%	27%	17%	40	23	43%	53%	10%
2	37%	20%	17%	3%	27%	17%	27%	13	37	30%	17%	87%
3	10%	27%	13%	40%	30%	27%	57%	20		27%		0

Table 6 displays the similarity between professional players and coaches for backhand strokes. The professional players approximately produce 48% of pattern 1. It is four times than pattern 2 and about 12 times than pattern 3. The probability of unrecognized strokes, while the professional players hit the shuttlecock with forehand skill, is about one-third.

Table 7 presents the percentage of amateur players' arm movements, which is the same as the coaches' movement for backhand skill. It points out that about 55% of arm movement is identified by the system, while 45% unrecognized arm movement. Furthermore, Pattern 1 is around 39% and pattern 2 about 11%.

Table 6. Professional players' arm movement for backhand strokes

Pattern	Sensor 1			Sensor 2			Sensor 3			Sensor 4		
	x	y	z	X	y	z	x	Y	z	X	y	z
1	50%	60%	25%	27.5%	55%	52.5%	65%	20%	57.5%	62.5%	40%	65%
2	20%	10%	25%		17.5%			37.5%	25%		32.5%	
3	0%	5%	45%		-			32.5%			-	

Table 7. Amateur players' arm movement for backhand strokes

Pattern	Sensor 1			Sensor 2			Sensor 3			Sensor 4		
	x	y	z	X	y	Z	x	Y	z	x	y	z
1	37%	50%	25%	27%	33%	53%	65%	23%	47%		43%	37%
2	7%	13%	23%		13%			37%	30%		13%	
3	13%	13%	27%		-			0%			-	

Figure 8 shows the avarege percentage of unknown arm movement from professional players and amateur players. Unknown arm movement indicated any arm movement that produced dissimilar pattern with coaches' pattern. The blue bar is the unknown arm movement for the professional players and the red bar indicates the unknown arm movement for the amateur players. In a glance, the figure indicates that professional players had higher recognized arm movement than amateur players for both stroke types. The unknown movement for forehand is less than the backhand for both types of players. This data illustrated that professional and amateur players faced more challenges to learn backhand than forehand.

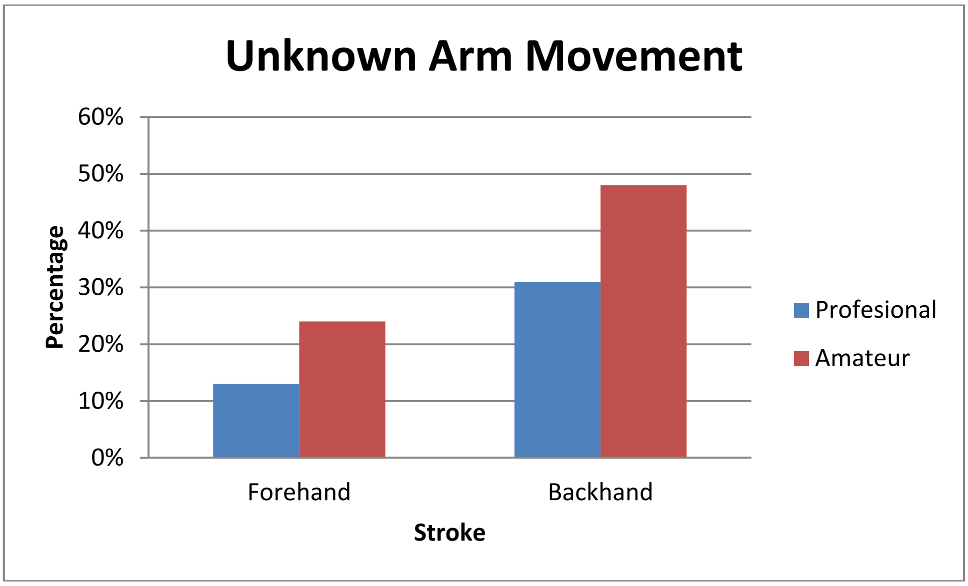

Figure 8. The percentage of unknown arm movement for forehand and backhand stroke

Hastie et al. [8] said that the skill of players increased after training. The skill of players in this research correlated to the similarity of their skill to the coaches'. To evaluate the similarity of the players' technique, the pattern probability produced by the coaches were weighted using normalization. Table 8 and Table 9 showed the weight for all the patterns. The players got the point by multipling their pattern probability to the weight value of the pattern. Figure 9 shows the points for forehand stroke and Figure 10 indicates the points for backhand stroke. The blue bar is the the point for profesional players and the red bar is the point for amateur players. The points evaluated for the entire axis at four sensors. The maximum possible point was 1.00 and the minimum was 0.00. The better players are the higher point. The result showed that in average professional players got higher point than amateur players for both stroke types.

Table 8. The weight of pattern for forehand strokes.

Pattern	Sensor 1			Sensor 2			Sensor 3			Sensor 4		
	x	y	z	x	y	z	x	Y	z	X	Y	z
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	0.27	0.70	0.85	0.30	0.85	0.30	0.30	0.85	0.37	0.83	0.15	0.62
3	0.10	0.43	0.28	0.19	0.28	0.19	0.19	0.28		0.68	0.00	0.25

Table 9. The weighting of pattern for backhand strokes

Pattern	Sensor 1			Sensor 2			Sensor 3			Sensor 4		
	x	y	z	x	y	z	x	Y	z	X	Y	z
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	0.30	0.33	0.33		0.37			0.30	0.25		0.49	
3	0.19	0.33	0.33					0.19				

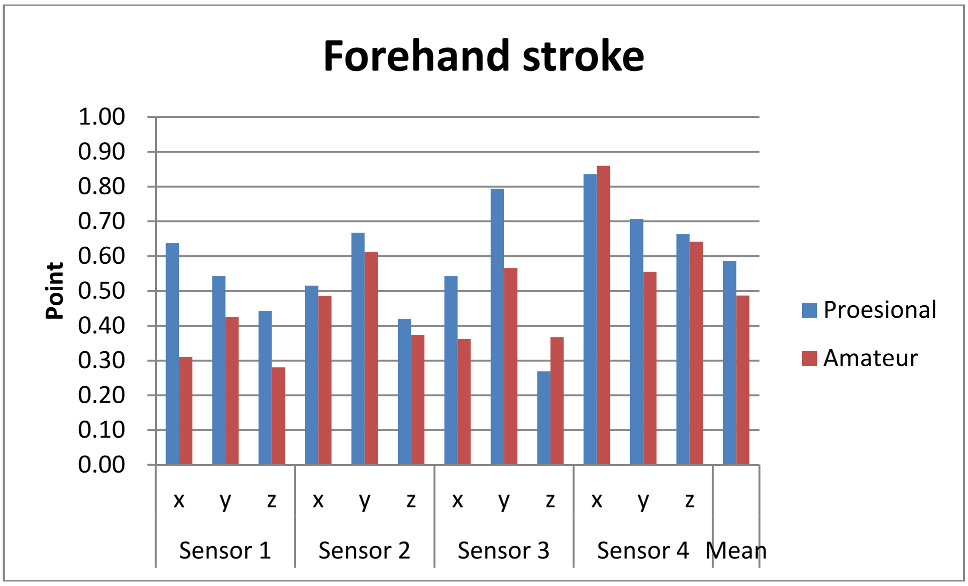

Figure 9. Point of players' arm movement for forehand stroke

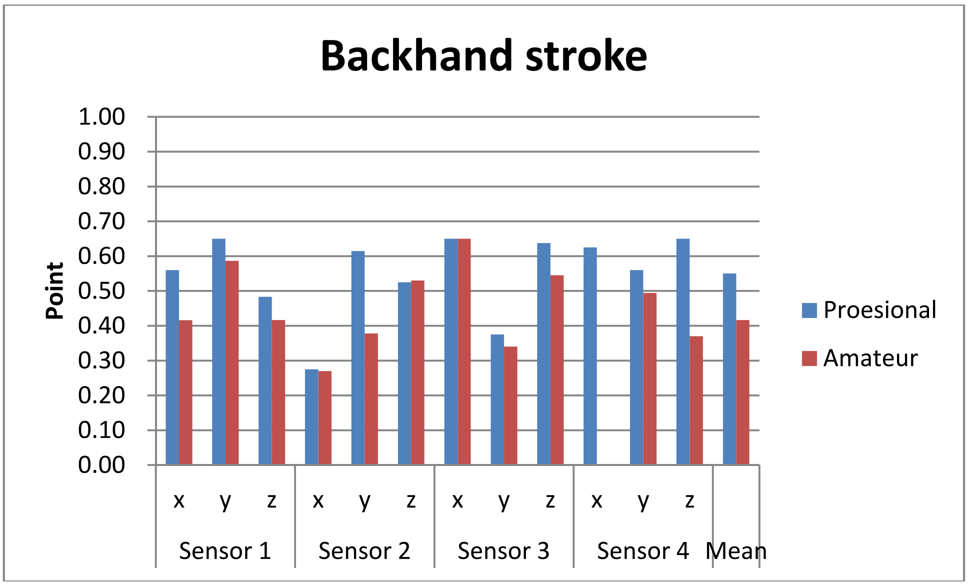

Figure 10. Point of players' arm movement for backhand stroke

6. Conclusion

There many methods were used in pattern recognition, such as fusion of local Gabor patterns [13] and fuzzy [14]. In this research the pattern of arm movement was determined by local Euler angle. The results indicated that the local Euler angle gradient could be used to construct the arm movement pattern while playing badminton for forehand and backhand sides. The initial sensor positions set the scene for three patterns of forehand strokes for all axes in sensor 1 and 2. However, z-axis in sensor 3 and y-axis in sensor 4 had only 2 patterns. Concerning backhand stroke, only sensor 1 had three types of arm motions. This condition showed that area of dorsal hand was the most preferable type of arm movement for forehand and backhand strokes. Pattern 1 had the highest average probability for forehand and backhand strokes. Cushioned by the similarity of skill, professional players had a higher similarity to the coaches than the amateur players. The professional players proved that they could imitate the skill of their coaches to hit the shuttlecock. This result is compatible with what Peter et al. (2009) said that there were skill and tactical development of players after badminton season.

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