Determining Golf Swing Patterns Using Motion Sensors for Injury Prevention

Wisan Tangwongcharoen and Wisut Titiroongruang

Abstract— **Golf is a popular sport for exercise or socializing. It affects an increasing number of patients. Because of these reasons the researchers decided to focus on this problem. We presented the analysis golf swing using sensors named Razor IMU to detect golf swing motions. The rotation and acceleration data were gathered by sensors attached on the upper and lower back. These data were clustered by K-Mean Clustering. The data clusters were calculated boundaries by Z-Score. The normal and abnormal data were compared for the Back Swing-Half Swing to Top Swing position and Top Swing to impact position. From the experimental results, this algorithm can classify normal and abnormal data due to the significant differences. This paper can help to improve and correct swings and thus avoid injuries.**

***Index Terms*—Golf Swing Pattern, Injury Prevention, Gyroscope, Accelerometer, Polar Coordinate System, K-Mean Clustering, Standard Score**

I. INTRODUCTION

Presently, many people around the world like to play golf. The person who plays is at risk of many kinds of injury such as at the back, waist, spine, wrists and elbow. Records from Vibhavadi hospital [1]-[4] showed that 80% of golfers, both professional and amateurs, who paid a visit to the hospital, had painful injuries from playing golf, and the main cause was improper swing. The 8 basic stages of a swing are as shown in Fig.1

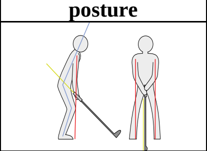
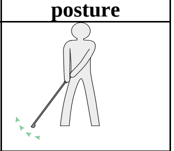
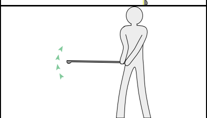
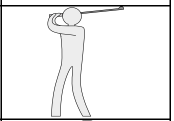
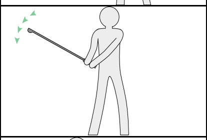
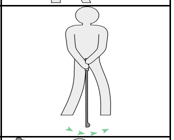
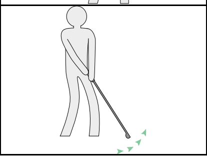
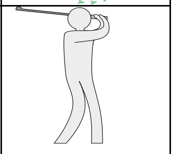
name	posture	name	posture
1.Set up		2.Back Swing – Takeaway	
3. Back Swing – Half Swing		4. Top Swing	
5. Down Swing		6. Impact	
7. Follow Through		8. Finish	

Fig.1. The 8 golf swing stages

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Because of the popularity of golf, there have been many research papers on detection of golf swing motion. A search of the literature showed us that swing motion detection were done mainly with 2 types of devices: using camera to capture the posture of golfer while he or she is swinging and using sensors attached to the golfer's body parts. Using only one camera[5]-[6] may not capture all of the important body parts; adding more cameras at different locations around the golfer can fix this problem but it is very costly to do so. On the other hand, reliable results can be obtained using sensors[7]-[8] and the cost is much lower. This study investigated golf swing motion by using sensors with a new algorithm to classify proper and improper swings. Sensors were attached to 2 parts of the body where injuries have been most found at: upper back and lower back. Raw data were transformed into angular degree graphs. The graphs were then clustered by K-Mean Clustering in order to easily classify proper and improper swing. Subgroups of data processed by K-mean clustered were determined of their corresponding density by Z-Score.

II. RELATED THEORIES

A. Gyroscope

A gyroscope [9] is a spinning wheel in which the axis of rotation is free to assume any orientation by itself. When rotating, the orientation of this axis is unaffected by tilting or rotation of the mounting, according to the conservation of angular momentum. Because of this, gyroscopes are useful for measuring or maintaining orientation. The rotation around X axis called "Pitch". The rotation around Y axis called "Yaw" and Z axis called "Roll". For Razor IMU tilt and swivel values are ±180.

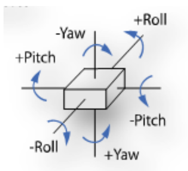

Fig. 2. The rotation around Yaw, Pitch, and Roll

B. Accelerometer

An accelerometer [10] is a device that measures proper acceleration in 3 dimension: x,y, and z. In this case proper acceleration is not the same as coordinate acceleration (rate of change of velocity). For Razor IMU acceleration values are ±16g.

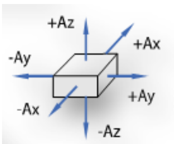

Fig. 3. The acceleration in X, Y and Z.

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C. Polar Coordinate System

In mathematics, the polar coordinate system is a two-dimensional coordinate system in which each point on a plane is determined by a distance from a reference point and an angle from a reference direction. The reference point (analogous to the origin of a Cartesian system) is called the pole, and the ray from the pole in the reference direction is the polar axis. The distance from the pole is called the radial coordinate or radius, and the angle is called the angular coordinate, polar angle, or azimuth.[11] as shown in Fig. 4.

D. The relation between Cartesian coordinate system and Polar coordinate system

Both systems are related in trigonometry. The Polar Coordinate System will convert between r and φ to Cartesian System x and y using Sin and Cos as shown in (1) and (2)

$$\mathrm{x} = \mathrm{r}\cos\theta \tag{1}$$

$$\mathrm{y} = \mathrm{r}\sin\theta \tag{2}$$

Both equations illustrated in Fig.5

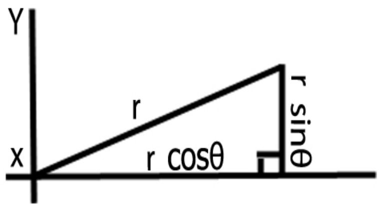

Fig. 4. The relation between Cartesian System and Polar Coordinate System [11]

E. K-Mean Clustering

K-Mean Clustering[12] is the easiest unsupervised clustering. This clustering will cut partitions. The data is separated to K groups. Each cluster is represented by mean. Means are used centroid in the clusters and used for calculating distance between data in same group. The distance between data is less when the data is in the same group. If the distance is big, the data is in a different group. The distances were calculated by Euclidean distance. Each data is only one group. The properly data used K-Mean Clustering is quantitative variable, interval scale or ration scale. Start clustering by equation (3)

$$\mathrm{SSE} = \sum_{i=1}^{K} \sum_{x \in C_i} dist(\mathbf{c_i}, \mathbf{x})^2 \tag{3}$$

Where **x** is the data wanted to clustering
C_i is the cluster order i
$\mathbf{c_i}$ is centroid of cluster order i
K is number of cluster

Using equation (4) for adjusting new centroid

$$\mathbf{c_i} = \frac{1}{m_i} \sum_{\mathbf{x} \in C_i} \mathbf{x} \tag{4}$$

Where m_i is number of data in cluster order i

Equations (4) and (5) explains the algorithm as in Fig. 5.

Algorithm	Basic K-means algorithm.
1:	Select *K* points as initial centroids.
2:	**repeat**
3:	Form *K* clusters by assigning each point to its closest centroid.
4:	Recompute the centroid of each cluster.
5:	**until** Centroids do not change.

Fig. 5. K Means algorithm[12]

From Fig.4, the nonclustered data were random centroid and calculate distance between each data and centroid by Euclidean distance as in equation (5)

$$dist(\mathbf{c_i}, \mathbf{x}) = \sqrt{(x_i - c_i)^2 + (x_i - c_j)^2} \tag{5}$$

Distance was checked for all data. When check was finished, the new centroid was generated by equation (5) until convergence.

F. Standard Score

Standard score [13] is the value using for comparing between 2 data sets. When the data sets were compared, there were problems, i.e. either the mean or SD were not equal. The data cannot be compared if there is no standard. The main idea of Standard value is to change the data to the same standard. The most commonly used standard scores are Z-scores, T-scores, and stanines. The Z score was used in this paper because the data was not calculated in percentage and only changed for calculating boundaries. The basic Z-Score calculation as shown in equation (6)

$$z = \frac{\mathrm{X} - \overline{\mathrm{X}}}{\mathrm{SD}/\sqrt{n}} \tag{6}$$

Where Z is the clusters in X which are classified
X is the raw data
$\overline{\mathrm{X}}$ is the mean of the example data
SD is the standard deviation of the example data
n is number of data

When Z-Scores were calculated, the data was changed to the normal curves to cut the boundaries. The boundaries were calculated by the critical value (α) divided by 2 for equality of upper bound and lower bound. The boundaries were calculated by equation (7)

$$P\left\{\bar{x} - Z_{\alpha/2} * {}^{SD}/_{\sqrt{n}} \le \mu \le \bar{x} + Z_{\alpha/2} * {}^{SD}/_{\sqrt{n}}\right\} = 100(1-\alpha)\% \tag{7}$$

Where Z is standard score
μ is the Confidence Interval
$\overline{\mathrm{X}}$ is the mean of the example data
SD is the standard deviation of the example data
n is number of cluster data

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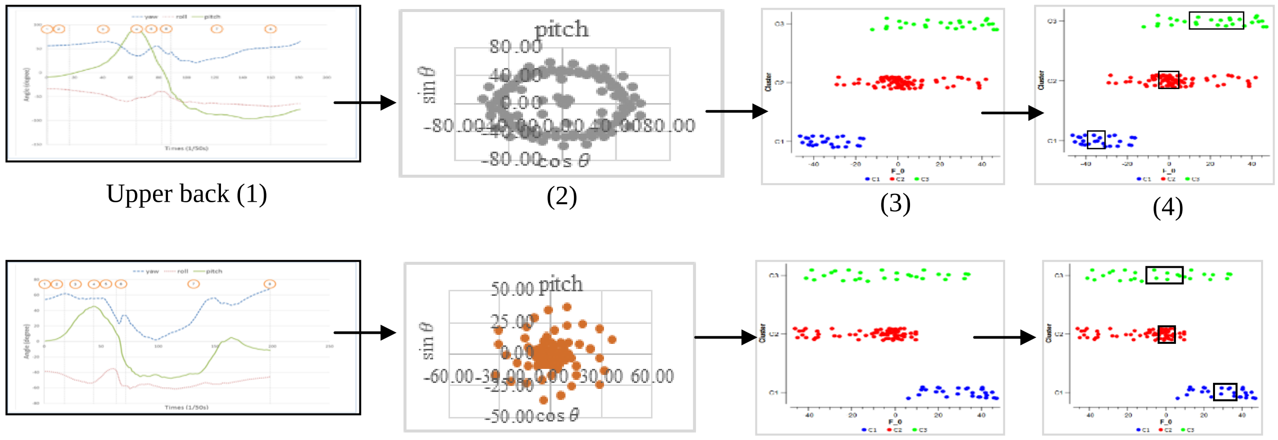
III. Methodologies

The algorithm is showed in Fig. 6.



Upper back (1) (2) (3) (4)

Lower back (1) (2) (3) (4)

Fig.6. The algorithm stages

From Fig.6, shows the raw data obtained from the Razor IMU sensor developed by Sparkfun Co. Ltd. These sensors were wireless, using Bluetooth for data transfer and battery usage. These sensors were contained in an acrylic box and there was a body suit for the tester to wear as shown Fig. 7(a) and (b). The motion sensors was attached to the upper and lower back as shown in Fig. 7(c)

(a) (b) (c)

Fig.6. The motion sensor and how-to attached sensors to the tester body [13]

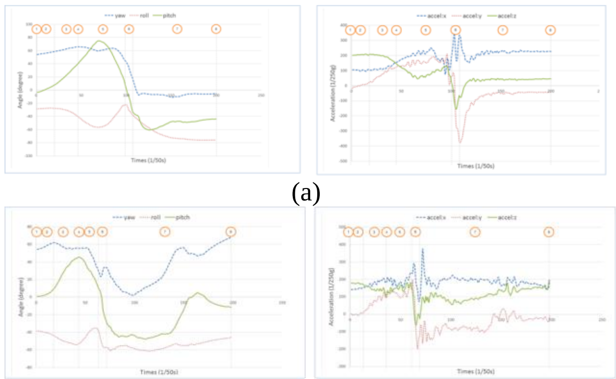
We tested with 10 testers: five were normal subjects and five were abnormal subjects. Each subject swung five times.

The raw data were transformed to linear graphs. Linear graphs were transformed to angular degree graphs (Euler's graphs) by equation (2) and (3) and time variables were represented by t1, t2 and t3 in second unit. Euler's graphs were classified by K-Mean Clustering to separate normal cases and abnormal cases by equation (4) and adjusting centroid by equation (5) From the K test, K=3 was suitable in this case. Each group had some sub data with obvious density. Standard deviations were calculated by Z-Score in equation (6) and boundaries of densities were calculated by equation (7) for bolded densities data.

IV. Experimental Results

A. Sensor data

Two data sets were obtained from motion sensors as shown in Fig. 8



(a)

(b)

Fig.8. the tilt and acceleration graphs

From Fig. 8 shows the data obtained from the sensors on both the upper and lower back. Linear graphs are separated into 3 ranges followed by the basic stages of golf swing, which are Set up to Top Swing, Down Swing to Impact and Follow through to Finish. There are two types of data, which are the tilt and swivel data as shown in Fig. 8(a) left and acceleration data as shown in Fig. 8(a) right. Tilt and swivel data has 3 data types: yaw, roll, and pitch. Yaw and pitch data around range 4 to 6 shows extreme change, but roll data shows a steady graph. The acceleration has 3 data types: x, y, and z, changed from the end of range 5 to 6. In Fig.8 (b) the tilt and acceleration data of lower back shows change from range 3 to range 8.

B. Euler's Graphs

The raw data from sensors were transformed to Euler's graph as shown in Fig. 9

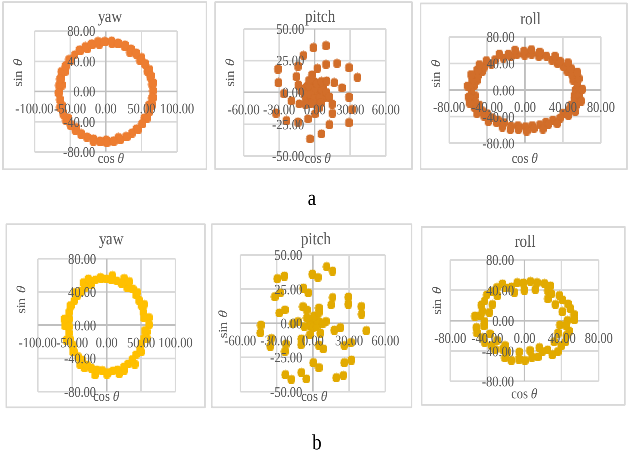


Fig.9. Tilt and swivel Euler's graphs comparison. The graph in normal case is shown in Fig. 8(a) and the graph in abnormal case is shown in Fig. 8(b)

From Fig.9 shows that the pitch and roll axis graphs for normal cases are different when compared to graphs for abnormal cases. The graph for normal cases in pitch axis has the density only center, but for the graph for abnormal cases in pitch axis, the data is distributed. The graph for normal cases in roll axis also has more density than the graph for abnormal cases.

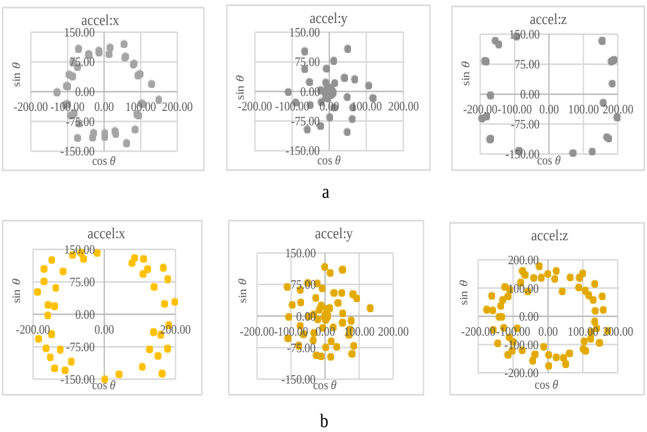


Fig.10. Acceleration Euler's graphs comparison. The graph for normal cases showed in Fig. 9(a) and the graph for abnormal cases showed in Fig. 9(b)

From Fig.9 the normal acceleration graphs in 3 axis can see difference clearly. The normal graph has pattern more than abnormal case.

C. K-Mean Clustering

The Euler's graphs were clustered by K-Mean Clustering. In this case, we use K = 3 because the number of data points in each range is small. K= 3 is optimal because number of data points is suitable and good results were obtained as shown is Fig.11.

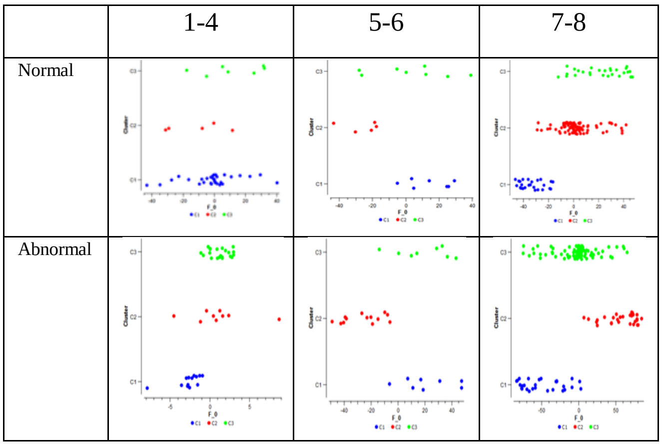


Fig.11 The K-Mean Clustering comparison

From Fig.11 the data in pitch axis were the best result obtained which are separated by the golf swing basic step in Fig.1. In range 1-6 there was not much difference in the result because the number of data points in this range is lesser. In range 7-8 data C2 for normal cases has obvious density. On the other hand, data for abnormal cases has obvious density in C3.

D. Boundaries Calculation

When we obtained clusters from data processed in the previous stage, the clusters were calculate for Z-score to determine the highest density of data by the boundaries. Clusters were arranged to the normal curve graph in which the area under the graph is equal 1. The normal curve graphs showed the highest density range.

The clusters were cut by range from normal curves used reliability percentage as 95% to find the boundaries.

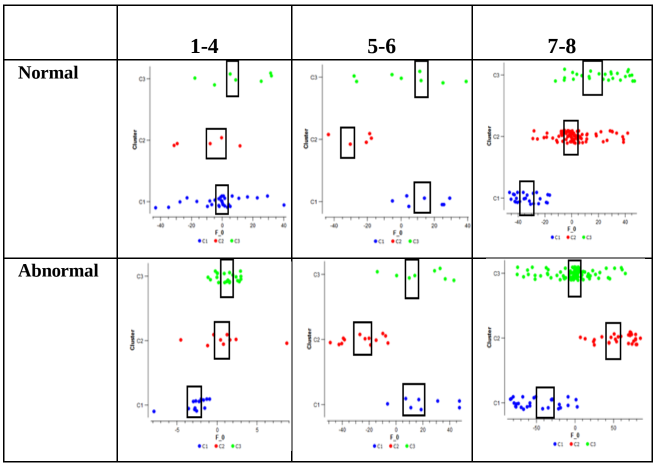


Fig.12. the pitch processed K-Mean clustering were cut boundaries.

From Fig.12. shows that each data set has a big difference range especially in the 7-8 range. In this range it can see that the normal case C2 and C1 have higher density than the abnormal case. The range 7-8 in Fig. 12 can be represented in numerical form as shown in Table I.

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TABLE I
BOUNDARIES COMPARISON

Pitch range 1-4	Normal	Abnormal
1	-1.36,[-2.41,0]	-2.7,[-5.4,0]
2	-11.54,[-23.07,0]	0.99,[0,1.98]
3	11.28,[0,22.56]	1.19,[0,2.39]
Pitch range 5-6	**Normal**	**Abnormal**
1	13.66,[0,27.32]	21.47,[0,42.94]
2	-26.25,[-52.49,0]	-26.04,[-52.08,0]
3	3.35,[0,6.70]	18.78,[0,37.56]
Pitch range 7-8	**Normal**	**Abnormal**
1	-33.19,[-66.37,0]	-48.62,[-97.25,0]
2	18.44,[-26.52,0]	56.73,[0,113.46]
3	21.71,[0,43.43]	-2.41,[-4.82,0]

From Table I. Due to the clusters having 3 groups: C1, C2, and C3, the range shows mean, upper and lower bound values in the bracket. We show only the range 7-8 because we can see the difference more easily in this range than the pitch 1-4 and 5-6. The number in each range can represent both the normal and abnormal case. Table I. can classify between normal and abnormal cases.

V. CONCLUSION

This paper is about golf swing analysis using motion sensors to detect golf swing motions for classifying normal and abnormal cases. Our work used 2 sensors attached on the upper back and lower back for gathering data from 10 testers. The raw data from sensors were transformed to Euler's graph. The Euler's graphs were classified by K-Mean Clustering and data was arranged to normal curves to find the highest density part in the sub data. From the experimental results, it is clear that this algorithm can classify between normal and abnormal. This paper can improve the golf swing in new players and avoid further injuries.

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