

GOLF SKILL AND SWING MOTION

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Abstract: Golfers always want to score well, and here we investigate the factors in golf club swing motions that are most related to improving the score. In experimental studies, we found that average score of a golfer is accurately estimated from the artificial neural network by the conventional factors and the factors involved in body-twist motion. From a sensitivity analysis of the linear function, we found that factors most related to improving the score are (1) faster ball velocity, (2) less standard deviation of twist angle, (3) less standard deviation of ball velocity, (4) faster body-twist angular velocity, and (5) faster body-twist acceleration in relation to impact time.

Keywords: Golf driver swing, body-twist motion, score improvement.

1 INTRODUCTION

Golf is one of the most popular sports, and the golf population is gradually increasing. Most golfers practice hard and/or pay for good clubs to improve their average score, but their scores stabilize unless they can improve their skill level. To improve their scores, two basic strategies are considered: (1) the employment of scientific training by measuring and analyzing the golf swing motion and (2) employment of training that adjusts the golf club swing motions that are effective in improving the score and/or sensitive in relation to the score.

For the first strategy, we found many studies of bio-mechanics that treat the golf swing as a mechanical motion. Image processing is also among the most powerful technologies to be applied to sports measurement.

In the golf swing, the body-twist motion or the rotation around the body axis is considered an important motion. However, only a few experimental investigations that treat this motion can be found.

This paper describes a new body-twist motion and rotation sensing system that uses a small gyro. By using the system sensing body-twist motion as well as the conventional image-processing system, we measure the various motion variables in the golf club swing and estimate accurate linear equations that relate the average score to some of the variables. Sensitivity of these variables to the average score identifies the most effective variables (or motion in the golf swing) for improving the score.

2 PROBLEM DESCRIPTION

2.1 Golf Driver Swing

Figure 1, a and b, show the driver movement, ball flight, and body-twist motion in a driver swing. In the figure, we define the variables as v_h : head velocity; v_b : initial ball velocity; w_u : ball flight angular velocity of backspin; w_s : ball flight angular velocity of side spin; q_u : upper angle; q_s : side angle; c : estimated carry; q : twist angle; w_{\max} : maximum body-twist angular velocity; a_{\max} : maximum body-twist angular acceleration; $t_{w \max}$: time when the body-twist angular velocity is maximum; $t_{a \max}$: time when the body-twist angular acceleration is maximum; $w(t_i)$: twist angular velocity at impact time; $a(t_i)$: twist angular acceleration at impact time; s : the average score of the golfer.

2.2 Assumptions and Problem Description

Assume for golfers and the average scores declared by them:

(A1) Advanced golfers swing a driver in an advanced manner.

(A2) The declared average score is reliable.

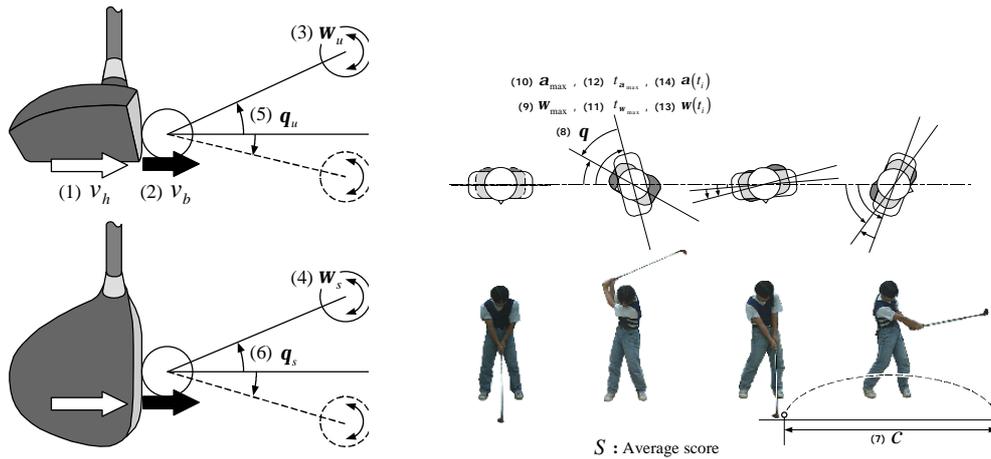


Figure 1 (a) Driver movement and ball flight **Figure 1 (b)** Body-twist motion

(A3) The average score is given by a nonlinear equation of some of the variables that have been defined.

Under these assumptions, we will consider the relation between the score(skill) and the variables associated with the driver swing motions. The problems are to

(P1) find the equations that relate the score s and the variables listed in **Table 1** in the driver swing motion shown in figure 1, a and b, and

(P2) determine the most effective factors for improving the score

Table 1 Reference Variable

No.	variable	Unit	Average	Standard Deviation
-	Score	-	\hat{S}	-
(1)	Head speed	m/s	\hat{V}_h	S_{V_h}
(2)	Ball speed	m/s	\hat{V}_b	S_{V_b}
(3)	Back spin	Rpm	\hat{w}_u	S_{w_u}
(4)	Side spin	Rpm	\hat{w}_s	S_{w_s}
(5)	Upper angle	Deg	\hat{q}_u	S_{q_u}
(6)	Side angle	Deg	\hat{q}_s	S_{q_s}
(7)	Carry	Y	\hat{c}	S_c
(8)	Twist angle	Deg	\hat{q}	S_q
(9)	Maximum twist velocity	deg/s	\hat{w}_{max}	$S_{V_{max}}$
(10)	Maximum twist acceleration	deg/s ²	\hat{a}_{max}	$S_{a_{max}}$
(11)	Time at maximum twist velocity	S	$\hat{t}_{w_{max}}$	$S_{t_{V_{max}}}$
(12)	Time at maximum twist acceleration	S	$\hat{t}_{a_{max}}$	$S_{t_{a_{max}}}$
(13)	Twist velocity at impact	deg/s	$\hat{w}(t_i)$	$S_{w(t_i)}$
(14)	Twist acceleration at impact	deg/s ²	$\hat{a}(t_i)$	$S_{a(t_i)}$

3 RELATION BETWEEN THE SCORE AND THE DRIVER SWING VARIABLES; SENSITIVITY OF THE VARIABLES TO THE SCORE

3.1 Estimation of the Relation Between the Score and the Driver Swing Variables

The movement of a driver swung by a human golfer always includes fluctuation. Thus the variables must be treated as stochastic variables (average, standard deviation) by repeated measurements.

Table 1 shows the average and standard deviations of the variables associated with the driver swing shown in **Figure 1**, a and b. The relation between the score and all 29 variables in table 1 is

meaningless. We would like to know the relation that explains the score with fewer variables. The cluster analysis method is applied to reduce the variables.

First, we select the proper variables $x_i (i=1,2,\dots,n)$ from table 1. Under assumption (A1), we estimated the score from the selected variables. Further, from assumption (A2), the declared score is accurate and the equation that relates the score and the variables is nonlinear.

3.2 Employment of Artificial Neural Network

From assumption (A3), the score S can be described by a nonlinear function by the selected variable and /or factors $x_i (i=1,2,\dots,n)$. Here we employ an artificial Neural Network method to estimate the relation. **Figure 2** shows the artificial Neural Network employed here. The estimation of the relation can be automatically carried out by the Back Propagation learning function of the artificial Neural Network, once the input n factors and the scores for many golfers form no to advanced.

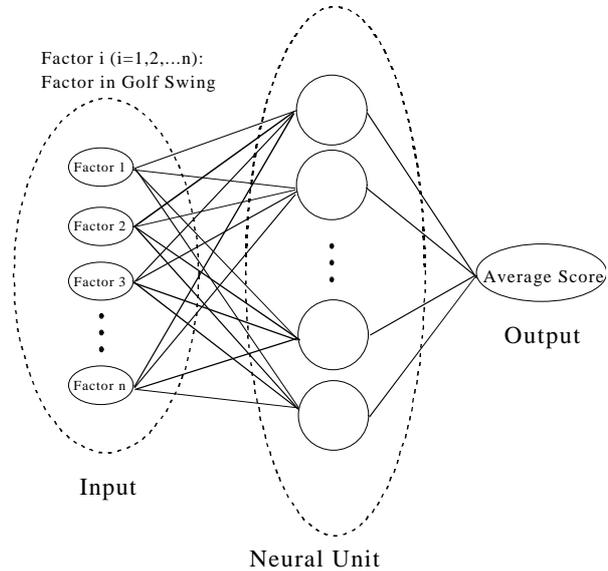


Figure 2 Neural Network

3.3 Sensitivity of the Variables to the Score

Supposing the estimated nonlinear model of the type of artificial neural network to be reasonable, the sensitivity of the variable to the score s can be calculated.

$$s_{xi} = \frac{\partial S}{\partial x_i} = \frac{\partial S}{\partial x} \frac{b_i x_i}{S} \quad (1)$$

We calculate the sensitivity of score for all the input factors in Figure 2. The variable with the maximum sensitivity most strongly influences the score.

4 EXPERIMENTS

An arbitrary group of 22 amateur golfers whose average score ranges from 80(T21) to 150(T1) were selected as the subjects of our experiments.

4.1 Measurement System

Figure 3 shows the measurement system, which is composed of three elements: (1) impact timing-detecting optical sensor, (2) camera set to measure the driver movement and ball flight, (3) body-twist motion-detecting jacket-type sensor.

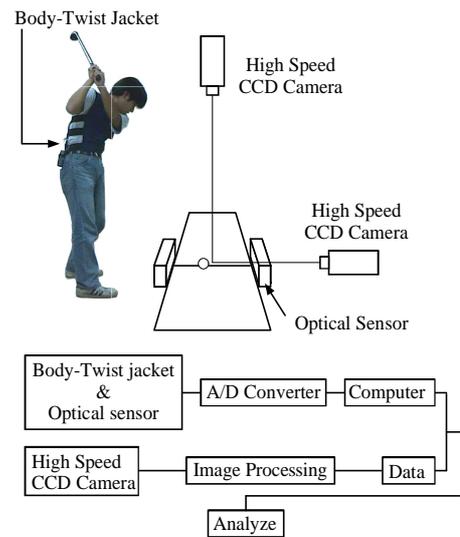


Figure 3 Measurement system

4.2 Measurements of Variables of the Ball Flight, Driver Movement, and Body-Twist Motion

Table 2 shows the variables measured for the subject T1 (the worst golfer, with average score of 150) and T21 (one of the best golfers with average score of 82). The variables correspond to those in table1.

5 RELATION BETWEEN THE SCORE AND DRIVER SWING VARIABLES

5.1 Score and Driver Movement, Ball Flight, and Body-Twist Motion

We estimate the score by the variables of driver movement, ball flight, and body-twist motion. The score is estimated by the following eight variables: $s_{v_h}, \hat{v}_b, s_{v_b}, s_{w_s}, s_q, \hat{w}_{max}, \hat{a}_{max}, s_{t_{a_{max}}}$. The

variables are selected by the cluster analysis. Note, among the selected factors, there are six standard deviation factors. It means the stability in the golf motion is important

The score estimated neural network is shown in **Figure4**.The input numbers of the network is eight, which is same as that of the selected factor. The number of neurons in the hidden layer was 17 and the out put is the estimated score. The data used to let the neural network learn is shown in **Table 3**.The data 8 players ranging from novice to advanced were employed.

Table 2 Reference Variables for T1 and T21

No.	Variable	Unit	T1		T21	
			Average	Standard Deviation	Average	Standard deviation
-	Score	-	150	-	82	-
(1)	Head speed	m/s	40.17	1.347	43.61	0.563
(2)	Ball speed	m/s	53.30	9.291	60.78	1.483
(3)	Back spin	Rpm	2946	1149	3475	670.0
(4)	Side spin	Rpm	-30.90	325.1	134.4	264.0
(5)	Upper angle	Deg	15.31	13.26	16.22	3.964
(6)	Side angle	Deg	1.370	10.22	-0.140	1.820
(7)	Carry	Y	160.9	39.96	212.5	5.416
(8)	Twist angle	Deg	49.88	4.495	75.14	4.774
(9)	Maximum twist velocity	deg/s	295.8	33.94	630.6	23.88
(10)	Maximum twist acceleration	deg/s ²	4184	1384	10457	875.2
(11)	Time at maximum twist velocity	S	0.110	0.020	0.061	0.03
(12)	Time at maximum twist acceleration	S	0.039	0.085	0.032	0.002
(13)	Twist velocity at impact	deg/s	121.1	17.78	225.3	32.36
(14)	Twist acceleration at impact	deg/s ²	1078	613.0	3095	913.1

Table 3 Learning data

Play /er	Average Score	s_{vh}	v	s_{vb}	s_{qs}	s_q	w_{max}	a_{max}	$s_{ta_{max}}$
T1	150	0.64	0.81	0.79	0.97	0.39	0.47	0.38	0.62
T2	130	0.39	0.85	0.99	0.82	0.62	0.32	0.40	0.16
T4	115	0.62	0.84	0.29	0.64	0.37	0.57	0.54	0.03
T6	110	0.32	0.77	0.90	0.15	0.31	0.44	0.34	0.16
T7	110	1.00	0.81	0.50	0.88	0.99	0.39	0.42	0.53
T8	108	0.93	0.91	0.34	0.99	0.28	0.59	0.42	0.44
T9	105	0.82	0.85	0.34	0.81	0.36	0.30	0.71	0.58
T10	104	0.34	0.79	0.17	0.97	0.36	0.36	0.43	0.28
T11	102	0.87	0.82	0.67	0.97	0.32	0.38	0.39	0.54
T13	98	0.40	0.89	0.35	0.93	0.42	0.43	0.51	0.02
T14	96	0.45	0.79	0.36	0.73	0.41	0.48	0.44	0.08
T15	95	0.44	0.98	0.17	0.77	0.46	0.56	0.76	0.34
T16	95	0.53	1.00	0.31	1.00	0.40	0.60	0.56	0.13
T17	92	0.61	0.87	0.10	0.71	0.32	0.51	0.67	0.04
T18	90	0.58	0.99	0.32	0.34	0.35	0.53	0.68	0.04
T19	87	0.47	0.95	0.17	0.71	0.23	0.45	0.31	1.00
T21	82	0.27	0.92	0.13	0.79	0.41	1.00	0.94	0.02
T22	82	0.65	0.97	0.11	0.83	0.45	0.58	0.87	0.04

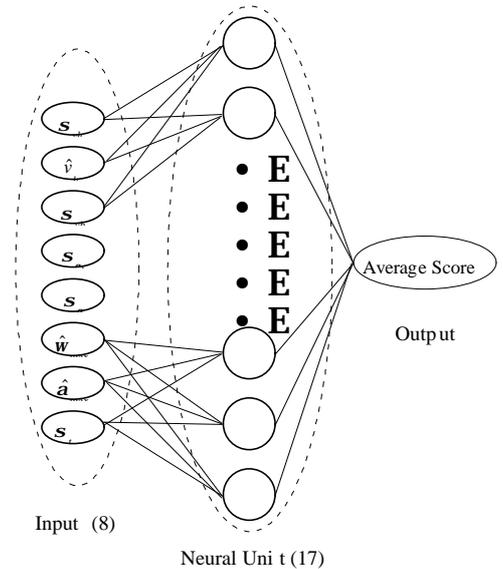


Figure 4 Artificial neural network

Figure5(a),(b),(c) shows the learning results for the allowable errors $l_t, l_t = 0.01$ and $l_t = 0.001$, respectively. the learning errors change in inversely proportional to the allowable error as usual. But for either case, the data were well learned by the neural network.

To compare the result by the linear regression mode, **Figure 6** shows the estimation result by the linear regression method. The result includes his errors in comparison with those by the neural network.

The neural network learned under the various allowable errors were evaluated by the test data in **Table 4**. The results are shown in **Table5**. The neural network learned under $l_t = 0.01$ is best. That under $l_t = 0.1$ is worst due to us learning and those under $l_t = 0.001$ and $l_t = 0.0001$ is worse due to the over learning.

The neural network learned under $l_t = 0.01$ shows the good estimate for golf player arbitrary selected.

5.2 Influence of the Variables on the Score

Here we investigate how each variable influences the score by the sensitivity of the neural network learned under $l_t = 0.01$ Figure7 shows the sensitivity of variables to the score. From **figure7**, that is from the model of body-twist motion, the score can be improved decrease by changing the following motions:

1. Initial ball
2. Standard deviation of twist angle (down)
3. Standard deviation of ball velocity (down)

That is, In order to improve the score, increase the velocity of the ball velocity keeping the body twist and ball velocity stable(from2,3)

Table 4 Test data

No	Average Score	s_{vh}	\hat{v}	s_{vb}	s_{qs}	s_q	\hat{w}_{max}	\hat{a}_{max}	$s_{ta_{max}}$
T3	130	0.37	0.88	0.45	0.89	0.47	0.49	0.55	0.0.8
T5	110	0.89	0.90	0.37	0.83	0.28	0.59	0.62	0.03
T12	100	0.39	0.86	0.22	0.84	0.50	0.49	0.34	0.17
T20	86	0.44	0.99	0.12	0.97	0.25	0.76	1.00	0.53

Table 5 Evaluation

$l_t = 0.1$			$l_t = 0.001$		
Score		Error	Score		Error
Real	Estimated		Real	Estimated	
130	127	2.3	130	136.65	-5.11
110	99.34	9.69	110	111.03	-0.93
100	111.54	-11.54	100	99.90	0.10
86	86.85	-0.98	86	92.80	-791

$l_t = 0.01$			$l_t = 0.0001$		
Score		Error	Score		Error
Real	Estimated		Real	Estimated	
130	134.26	-3.27	130	134.45	-3.42
110	110.29	-3.10	110	110.29	-0.26
100	103.10	-3.10	100	105.89	-5.89
86	85.87	0.26	86	90.07	-4.73

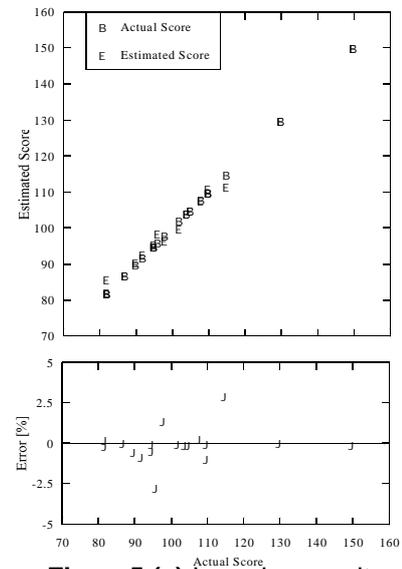


Figure5 (a) Learning result
(allowable=0.0001)

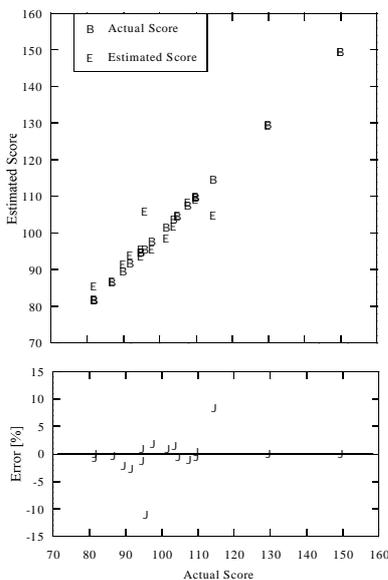


Figure5 (b) Learning result
(allowable error=0.01)

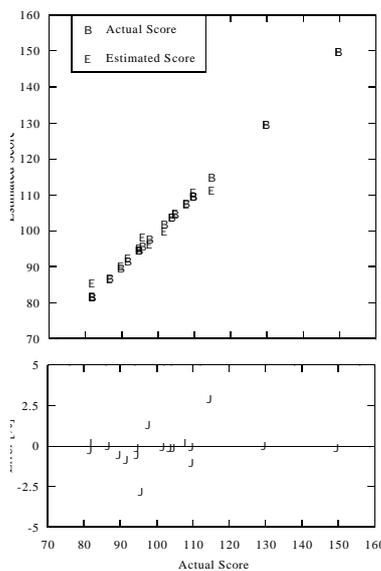


Figure5 (c) Learning result
(allowable error=0.001)

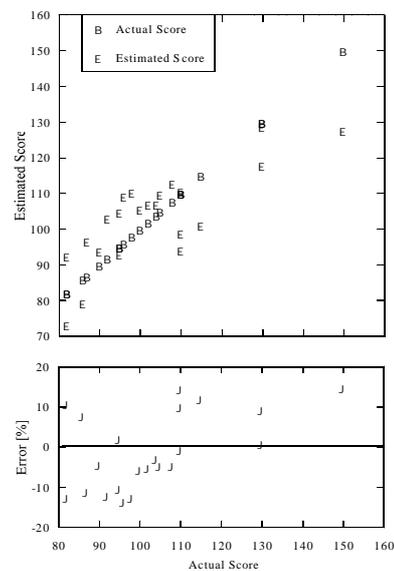


Figure6 Estimation by the
linear regression method

6 CONCLUSIONS

Here we investigated the relation between driver swing motions and golf skill (score) experimentally. First, we measured the variables related to driver movement, ball flight, and the body-twist motion of golfers whose scores range from 80 to 150. The models that relate the score and the measured variables are estimated by artificial neural network method. By apply sensitivity analysis to the estimated models, we determined the most effective motions for improving the score. Our results show these motions to be the following:

1. Increase the ball velocity at the time of impact
2. Stabilize the body-twist angle
3. Stabilize the ball initial velocity

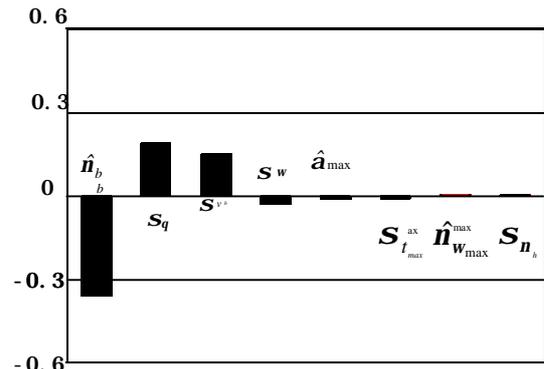


Figure7 Sensitive of factors to the score

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