Advance Journal of Food Science and Technology 12(2): 93-96, 2016
DOI:10.19026/ajfst.12.2846
ISSN: 2042-4868; e-ISSN: 2042-4876

Submitted: September 14, 2015 Accepted: November 4, 2015 Published: September 15, 2016

Research Article

Research on the Experiment of Dynamic Analysis in the College Sports Nutrition Food Courses

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Abstract: The study had practiced the experiment of the dynamic analysis to teach to the general lesson of college sports nutrition food courses, our purpose lied in better proceeding teach according to there ability of students and increasing the teaching quantity of general sports nutrition food lesson. With the development of educational reform in our country, for further cultivate, the modern talented person who be required for the society and push the development of the character education, many athletic experts that regarded modern teaching theories as the leading and based on the advanced teaching thoughts and methods from abroad to begin to proceed college sports nutrition food reform in education research and obtained good result according to the foundation of past.

Keywords: Food courses, sports nutrition, teaching quantity

INTRODUCTION

Because of reasons of many factors, such as hereditary, geography, family, educated and social, the students are very different in development and foundational level of sports nutrition food which cause that the good students feel easy but the bad students feel hard in the sports nutrition food elective course and not settle for the students (Sun and Luo, 2008). For this question, the paper brings up a now teaching model, that is dynamic grouping which asks to take the diffidence of students into consideration, separate the students into diffident group and meet their needs (Wen and Ren, 2011). While there was no obvious difference in the The findings indicated that, sic fitness score. The dynamic grouping teaching design completely conforms to the education for all-around development requirement, has the superiority compared to the traditional teaching; dynamic grouping teaching is advantageous comprehensively grasps the sports nutrition food technology to the student, enhances the teaching effect; dynamic grouping teaching is advantageous to stimulates student's study motive, raises the study interest and the enthusiasm; dynamic grouping teaching is advantageous to the establishment of good teacher and students relations.

MATERIALS AND METHODS

Teaching experiments takes the dynamic grouping in Xuchang University into the research. The author carries out a stochastic selection of six classes for a semester basketball experiment of public basketball in Xuchang University enrolled in the year 2006. And contrast three classes take traditional teaching method while contrast the other three classes take hierarchical teaching.

State equation of dynamic model: Take the system state vector $x = [q_\gamma \; \dot{q}_\gamma \; q_\lambda \; \dot{q}_\lambda]^T$, respectively representing inertia elevation LOS angle, inertia elevation LOS rate, inertial azimuth LOS and inertial azimuth LOS rate and then traditional 4-dimensional state equation is established as follows:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -\dfrac{2\dot{r}}{r}x_2 - x_4^2 \sin x_1 \cos x_1 - \dfrac{a_{yS}}{r} \\ \dot{x}_3 = x_4 \\ \dot{x}_4 = 2x_2 x_4 \tan x_1 - \dfrac{2\dot{r}}{r}x_4 + \dfrac{a_{zS}}{r\cos x_1} \end{cases} \tag{1}$$

where, a_{yS}, a_{zS} representing the missile acceleration relative to target are respectively the components in LOS coordinate axis oy_S, oz_S, r is the distance between missile and target, the equation can be obtained from the geometric relationship as follows:

$$r = \frac{y_m - y_t}{\sin q_\gamma} \tag{2}$$

In which, y_m is missile altitude, y_t is target altitude, regarded as 0 for target locating on the ground, then:

$$r = \frac{y_m}{\sin q_\gamma} \tag{3}$$

And $\dot{r}$ in Eq. (1) is the change rate of the distance between missile and target and can be obtained by taking the derivation of t from Eq. (3) on the either side as follows:

$$\dot{r} = \frac{\dot{y}_m}{\sin q_\gamma} - \frac{y_m \cos q_\gamma}{\sin^2 q_\gamma}\dot{q}_\gamma \tag{4}$$

Considering the missile navigation error in height y_m, larger errors will arise in calculating the distance between the missile and target directly from the Eq. (3) and (4), which will further have a greater impact on the state estimation accuracy, so the distance can be introduced into sate equation. The process is as follows:

The distance between missile and target is added to the state vector which is dynamic to $x = [q_\gamma\ \dot{q}_\gamma\ q_\lambda\ \dot{q}_\lambda\ r]^T$. The following equation is:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -\dfrac{2\dot{x}_5}{x_5}x_2 - x_4^2 \sin x_1 \cos x_1 - \dfrac{a_{y_S}}{x_5} \\ \dot{x}_3 = x_4 \\ \dot{x}_4 = 2x_2x_4 \tan x_1 - \dfrac{2\dot{x}_5}{x_5}x_4 + \dfrac{a_{z_S}}{x_5 \cos x_1} \\ \dot{x}_5 = \dfrac{\dot{y}_m}{\sin x_1} - \dfrac{y_m \cos x_1}{\sin^2 x_1}x_2 \end{cases} \tag{5}$$

By extending the distance as an estimated variable, the accuracy of r in the original 4-dimensional state equation is improved, thereby the accuracy of $\dot{r}$ enhanced, which will improve the estimation accuracy of the terminal elevation rate and azimuth rate. Meanwhile, increasing the dimension of state vector can take the maximum advantage of fifth-degree CKF in high-dimensional state vector estimation.

Measurement information provided by strapdown seeker is the body angle of LOS q_α, q_β, used as the observation variables. Observation equation can be written as:

$$\begin{cases} y_1 = \arcsin(R_{21}\cos x_1 \cos x_3 + R_{22}\sin x_1 - R_{23}\cos x_1 \sin x_3) + v_1 \\ y_2 = \arctan(\dfrac{R_{33}\sin x_3 - R_{31}\cos x_3 - R_{32}\tan x_1}{R_{11}\cos x_3 + R_{12}\tan x_1 - R_{13}\sin x_3}) + v_2 \end{cases} \tag{6}$$

where, R_{ij} is the element of matrix $L(\gamma, \vartheta, \psi)$, ϑ is pitch angle, ψ is yaw angle, γ is roll angle, v_1, v_2 is measurement noise.

Because of the strong nonlinear relations of the model state equation, known as a classic nonlinear system state estimation filtering algorithm, UKF will be introduced to do comparative analysis with the filtering method mentioned herein.

Unscented Kalman Filter (UKF) theory: Assume statistical characteristics of n-dimensional state vector X are: mean as $\bar{X}$, variance as P. Construct the matrix of $2n + 1$ sigma sample points as follows:

$$\begin{aligned} &X_{(0)} = \bar{x} \\ &X_{(i)} = \bar{x} + (\sqrt{(n+\lambda)P})_i^T,\ i = 1,\dots,n \\ &X_{(i+n)} = \bar{x} - (\sqrt{(n+\lambda)P})_i^T,\ i = 1,\dots,n \\ &w_0^m = \frac{\lambda}{n+\lambda} \\ &w_0^c = w_0^m + (1-\alpha^2+\beta) \\ &w_i^c = w_i^m = \frac{1}{2(n+\lambda)},\ i = 1,\dots,n \end{aligned} \tag{7}$$

In which, $\lambda = \alpha^2 (n+k)-n$ is the scaling factor, α determines the distribution of the sample points around $\hat{x}$. The impact of higher-order terms can be minimized by adjusting α, in general $\alpha \in [0, 1]$; although there is no definite limit to k, usually $(n+\lambda)P$ should be guaranteed as semi-definite matrix. For a Gaussian distribution, when the state variables are multi-dimensional, it is defined as $k = 3-n$; $k = 3-n$ is often chosen in parameter estimation; β is to be selected, $\beta \geq 0$. Variance estimation accuracy can be improved by adjusting β. For a Gaussian distribution, $\beta = 2$ is optimal; $(\sqrt{(n+\lambda)P})_i^T$ refers to the i column of the matrix $(n+\lambda)P$.

State vector X of sample point is obtained by nonlinear function $f(\square)$ and after UT transformation we get the sample points:

$$y_i = f(X_i),\ i = 0,\cdots,2n \tag{8}$$

UKF algorithm is described as follows:

Initialization: Statistical characteristics of the initial state are:

$$\begin{aligned} &\hat{x}_0 = E[x_0] \\ &P_0 = E\left[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T\right] \end{aligned} \tag{9}$$

Calculating sigma sample points:

$$\chi_{k-1} = \left[\hat{x}_{k-1}\quad \hat{x}_{k-1} + \sqrt{(n+\lambda)P_{k-1}}\quad \hat{x}_{k-1} - \sqrt{(n+\lambda)P_{k-1}}\right] \tag{10}$$

Time update:

$$\begin{aligned}
&\chi_{k|k-1} = f\left(\chi_{k-1} \quad u_{k-1}\right) \\
&\hat{x}_{k|k-1} = \sum_{i=0}^{2n} w_i^m \chi_{\mathrm{i},k|k-1} \\
&P_{k|k-1} = \sum_{i=0}^{2n} w_i^c \left[\chi_{\mathrm{i},k|k-1} - \hat{x}_{k|k-1}\right]\left[\chi_{\mathrm{i},k|k-1} - \hat{x}_{k|k-1}\right]^T \\
&z_{k|k-1} = h\left(\chi_{k|k-1}\right) \\
&\hat{z}_{k|k-1} = \sum_{i=0}^{2n} w_i^m z_{i,k|k-1}
\end{aligned} \tag{11}$$

where, $\hat{x}_{k|k-1}$ is the weighted sum of all particles one-step prediction.

Measurement update:

$$\begin{aligned}
&P_{zz,k-1} = \sum_{i=0}^{2n} w_i^c \left[\left(z_{i,k|k-1} - \hat{z}_{k|k-1}\right)\right]\left[\left(z_{i,k|k-1} - \hat{z}_{k|k-1}\right)\right]^T \\
&P_{xz,k|k-1} = \sum_{i=0}^{2n} w_i^c \left[\chi_{i,k|k-1} - \hat{x}_{k|k-1}\right]\left[z_{i,k|k-1} - \hat{z}_{k|k-1}\right]^T \\
&K_k = P_{xz,k|k-1} P_{zz,k-1}^{-1} \\
&\hat{x}_k = \hat{x}_{k-1} + K_k\left(z_k - \hat{z}_{k|k-1}\right) \\
&P_k = P_{k|k-1} + K_k P_{zz,k-1} K_k^T
\end{aligned}$$

UT transformation is different from general sample methods (such as Monte Carlo method). It does not require a huge number of sample points to approach the statistical nature of the state vector. In the Gaussian white noise, for general nonlinear systems, UT can achieve three-order filtering estimation accuracy.

Indicators data processing: When conducting unification of indicators data, M_{51} and M_{81} are respectively valued 1.40 million and 100%. Then based on the unification result, the efficacy coefficient method is applied to unify the indicators dimensions (Lv, 2009). The processing result is shown in Table 1.

RESULTS AND DISCUSSIO

Determining the indicators weights:

Indicators weights by eigenvalue method: According to the eigenvalue method, the indicators scores tables of relative importance and weighting result are shown from Table 2 to 3. And the weight of each indicator relative to the first class indicator is calculated, as Table 4 shows.

Table 1: Processing result of indicators data

	Unification			Non-dimensions		
Indicators	P1	P2	P3	P1	P2	P3
B_{11}	76	87	84	60	100	89.0909
B_{12}	31	40	26	74.2857	100	60
B_{21}	3.8	4.3	3.2	81.8182	100	60
B_{22}	3.1	3.4	4.2	60	70.9091	100
B_{31}	2.1	3.3	4	60	85.2632	100
B_{32}	3.8	4.2	3.6	73.3333	100	60
B_{41}	90	87	72	100	93.3333	60
B_{42}	81	89	76	75.3846	100	60
B_{43}	87	85	79	100	90	60
B_{51}	82	91	84	60	100	68.8889
B_{52}	75	86	88	60	93.8462	100
B_{61}	80	91	84	60	100	74.5455
B_{62}	90	95	87	75	100	60
B_{71}	95	92	90	100	76	60
B_{72}	93	97	85	86.6667	100	60
B_{81}	0.16	0.43	0.05	71.5790	100	60
B_{82}	0.72	0.88	0.9	60	95.5556	100

Table 2: Indicator weights of layer O-A

O-A	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	Weight
A_1	1	1.5	0.8	0.8	0.5	0.4	0.6	0.8	0.0902
A_2	0.6667	1	0.7	0.6	0.4	0.5	0.8	0.9	0.0813
A_3	1.25	1.4286	1	1.25	1	1.5	2	1.25	0.1585
A_4	1.25	1.6667	0.8	1	0.8	1.25	1.5	0.5	0.1249
A_5	2	2.5	1	1.25	1	1.5	1.25	1	0.1653
A_6	2.5	2	0.6667	0.8	0.6667	1	0.8	0.5	0.1164
A_7	1.6667	1.25	0.5	0.6667	0.8	1.25	1	0.8	0.1129
A_8	1.25	1.1111	0.8	2	1	2	1.25	1	0.1505

Table 3: Indicators weights of layer A_1-B

A_1	B_{11}	B_{12}	Weight	λ_{max}	test
B_{11}	1	0.8	0.4444	2	CI = 0; satisfied
B_{12}	1.25	1	0.5556		

Table 4: Indicators weights of layer A2-B

A_2	B_{21}	B_{22}	Weight	λ_{max}	test
B_{21}	1	0.85	0.4595	2	CI = 0; satisfied
B_{22}	1.1764	1	0.5405		

The maximum eigenvalue $\lambda_{\max}$ of judgment matrix is 8.2641, the value of Consistency indicator *CI* 0.0377, the value of random consistency *RI* 0.0267 and the matrix has satisfied consistency.

CONCLUSION

When the experiment was ended, we had the statistic analysis to the score of the physic fitness and technique to experimental group and controllable group, discovered that technique score of the experimental controllable group, there was distinct difference between group was the two groups better than ups (Ou and Fang, 2014; Song and Yang, 2004). The findings indicated that, the dynamic grouping teaching design completely conforms to the education for all-around development requirement, has the superiority compared to the traditional teaching; dynamic grouping teaching is advantageous comprehensively grasps the sports technology to the student, enhances the teaching effect; dynamic grouping teaching is advantageous to stimulates student's study motive, raises the study interest and the enthusiasm; dynamic grouping teaching is advantageous to the establishment of good teacher and students relations.

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