

Farmer skill training system based on motion sensing technology and user behavior analysis

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Abstract: The difficulty in receiving and understanding agricultural technology knowledge has always been a bottleneck restricting the effect of agricultural information service. However, most multimedia teaching system for farmers is lack of man-machine interaction. Rural intelligent experiential information service is an effective way to solve the problem. The farmer skill training system has been designed based on user behavior analysis and motion sensing technology. The system includes body movement interactive module, resource acquisition processing module, multimedia player module, and user behavior analysis module. Based on motion sensing technology and DTW algorithm, users can control the completion of the system through the motion sensing interaction. The system can provide users with training video data while reducing operational complexity. The accuracy of the action can provide users with a convenient experience. Using the fuzzy evaluation algorithm model, by way of making statistics and analyzing the farmers' action in the use of the operation process, rules of the user and accurate positioning of user preferences can be found. The interested training content can be recommended for users according to user preferences and tendencies. Based on motion sensing technology and user behavior analysis method, the multimedia training system provided farmer users with strong interaction and deep sense of immersion. It can realize the new learning mode of multi-dimensional interactive experience and multimedia teaching, and reduce the dependency and complexity operation of traditional mouse and keyboard, and provide an effective method for training the farmers.

Keywords: motion sensing technology, farmer skill training, user behavior analysis, multimedia teaching

Citation: Cai, Y. F., Q. Ma, Q. Wang, H. Chen, Y. Lu, T. W. Feng, and Y. Zhang. 2017. Farmer skill training system based on motion sensing technology and user behavior analysis. *International Agricultural Engineering Journal*, 26(3): 349–355.

1 Introduction

The difficulty of accepting and understanding the agricultural science and technology information has always been the bottleneck, restricting the effect of rural information service. It is also an important factor affecting the enthusiasm of farmers to use the training information. Rural intelligent experiential information service is an effective way to solve this problem. Agricultural and rural technical information is always more complex, the farmers low educational characteristics make them difficult to understand the highly conceptualized scientific and technological

information. The professional science and technology information is hardly accepted by less educated farmers while the information simply pushed to the front of farmers' faces.

The typical training modes and effects of the new professional farmers and the various factors influencing the training effect have become the hotspot of the current domestic and foreign scholars. Research pointed out that the popularization and application of modern distance education in rural areas can avoid the control of the audience's quality level, so that rural informatization can benefit more farmers (Gong et al., 2009). Based on the web, Zhao J. C. (2016) has developed a platform for farmers' personalized learning and education based on neural network, so that farmers can use the network to obtain the knowledge of what they are concerned. Niu J.B. et al. (2010) developed a comprehensive training system

Received date: 2017-06-29 Accepted date: 2017-08-17

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for farmers based on virtual reality. After analyzing the characteristics of farmer training, this system built a comprehensive training system by virtual reality technology embedding virtual animal and plant model, but the individual training for farmers still lacks. Yoo H. S. et al. (2014) has developed an agricultural training game containing simulators such as crops, livestock, weather, pests, fertilizers and so on, through the historical simulation combined with the game elements, to achieve the purpose of modern agricultural training and entertainment functions. Chen H. et al. (2011) developed a virtual experiential pig disease training system, and farmers have a more intuitive way to understand the pig in the breeding process of common diseases. Torrens F. et al. (2017) developed a welding technology lab based on virtual reality, the trainees can improve the welding method according to the advice made by the system and reduce the damage caused by improper operation.

1.1 User behavior analysis and recommendation system

In the context of big data, a new information filtering technology - personalized behavior based on user behavior has become a popular research direction in recent years (Zhu et al., 2017). It is through the record and analysis of the user's historical behavior data to obtain the user's interest preferences, and then learning the level of information users interested in, the relevant information will be presented in front of the customers. At present, there are many examples of user-based recommendation system at home and abroad. In China, Chen H. C. et al. (2005) proposed a music recommendation system based on music and users' grouping, which builds a method based on content, collaboration and statistics through the user's favorite degree of music group and their group of users. Cheng S. et al. (1977) proposed a document recommendation model based on the integration of time perception and user interest importance. It not only summarizes the user's interest based on behavior analysis, but also assigns the time decay function to allocate a higher time weight for the most recent browsing document, accurately lock user interest and recommended information. While abroad, Abdullah N. et al. (2011) proposed a recommendation

system which shows occasionally-purchasing products based on user behavior and opinions in e-commerce sites, and better satisfying the needs of buyers. Out of the traditional way of recommendation, more and more scholars are committed to seeking more innovative, more accurate and more efficient recommendation methods.

In the training system introduced in this paper, the user behavior analysis module is included. It can judge the user's interest based on the user's click history and click frequency in the system. The same type of training video is automatically recommended in the search interface, and it can be recommended to users by video with the same interest. It greatly improved the user experience of the system.

1.2 Motion sensing technology and Kinect

Motion sensing technology can capture the physical movement of objects and change in the environment. It can interact with motion sensing hardware through body movement. When the motion sensing hardware reads the user's actions and translates them into commands, the user can achieve the motion sensing manipulation. In 2014, Microsoft Corp released the Kinect v2 somatosensory device, which is equipped with a depth sensor. Based on the infrared technology, Kinect's infrared lens can diffuse the infrared light. The infrared receiver can be used to capture the reflected light and calculate the distance of objects. The somatosensory technology provided by Kinect has a wide range of applications in many fields such as plant growth measurement (Yu et al., 2016), animal growth monitoring (Stavarakakis et al., 2015), training and education. At present, some studies and achievements have been made on the application of Kinect somatosensory technology in teaching. Based on Kinect v2, Scherer M. et al. (2016) developed residential rehabilitation training system. The system consists of two components, one is for the therapist of the clinical institution and the other is for the patient at home. The application algorithm saves the patient's reference data. The personal motion algorithm compares the current motion data with the recorded motion data, and provides real-time feedback, showing the correctness of the implementation. Palacios-Navarro G. et al. (2015) used Kinect for limb recovery in patients

treated with Parkinson's disease. Wang et al. (2017) has developed an interactive display system of cultural relics by using Kinect. Sasaki Y. and his partners realized the farmer daily operation record system by Kinect (Sasaki et al., 2013). Jamie I. M. et al. (2011) bind Kinect to the electronic whiteboard to realize the application of Kinect in university chemistry education, materialized the abstract molecules to improve the immersion of learning, and to make students more receptive to knowledge. Trajkova M. et al. (2015) used Kinect in ballet teaching to enable students to learn more intuitively and to adjust their actions based on the scores, so that each user can receive top-level training.

In the multimedia teaching for the farmers, the effect of the traditional listening mode, which is dominated by the teachers in the traditional video form, and the learner passively listens to the class, is not satisfactory. But with the emergence of Kinect, we can use its somatosensory technology to analyze the operator's action and understand the intention of the operator based on user behavior analysis. By the farmer skill training system based on motion sensing technology and user behavior analysis, we not only improve the interactive and fun learning, but also enhance the intuition of learning.

2 Construction of user behavior analysis and recommendation model

2.1 Training video scoring model based on fuzzy evaluation

In this paper, the fuzzy evaluation comprehensive evaluation method was used to establish the preference index model for evaluating the farmer skill training video resources.

S1: Establish the evaluation indicators of the farmer skill training video.

$$U = \{U_1, U_2\} = \{\text{video information, user operation}\};$$

$$U_1 = \{U_{11}, U_{12}, U_{13}, U_{14}\} = \{\text{users, classification, degree of difficulty, time}\};$$

$$U_2 = \{U_{21}, U_{22}, U_{23}\} = \{\text{classification of highest viewing frequency, difficulty level of highest viewing frequency, time of highest viewing frequency}\}.$$

S2: Establish the preference evaluation effect set.

$$V = \{V_1, V_2, V_3, V_4, V_5\} = \{\text{very strong, strong,}$$

general, poor, very poor}\};

$$V_1 = 100, V_2 = 75, V_3 = 50, V_4 = 25, V_5 = 0.$$

S3: Set the weight value for the video resource preferences by collecting user actions.

Take the user operation as an example:

- a. Determine user occupation U_{21} , classification of highest viewing frequency U_{22} , difficulty level of highest viewing frequency U_{23} , and time of highest viewing frequency U_{24} .
- b. By recording the user operation process, score the above four indicators. For example, operate n_i on $U_{1j}S_j(i)$, $i = 1, 2, \dots, n, j = 1, 2, 3, 4$. Constitute the matrix S:

$$\begin{bmatrix} S_1(1) & \dots & S_1(i) \\ S_2(1) & \dots & S_2(i) \\ \dots & \dots & \dots \\ S_j(1) & \dots & S_j(i) \end{bmatrix}$$

- c. Determine the weight matrix M for each scoring.
- d. Calculate the weight of the evaluation index $N = S M$.
- e. N is normalized to obtain the weight value of the evaluation index.

The weight value of the indicator can reflect the final preference for all operations.

2.2 Training video priority ordering method based on fuzzy evaluation

The training video priority ordering method is as follows, the steps are shown in Figure 1.

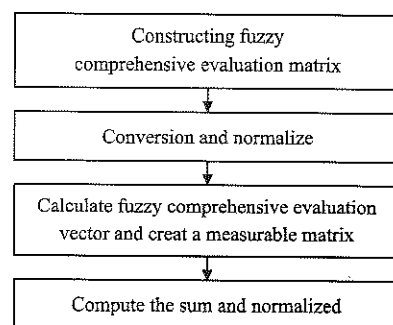


Figure 1 Steps of fuzzy evaluation

S1: $U = \{u_1, u_2, \dots, u_n\}$ is the index set of program measures and $\omega = \{\omega_1, \omega_2, \dots, \omega_n\}$ is the weight vector. For program X, in accordance with the j-th u_j indices measure, obtain measure value $r_{ij} = [r_{ij-}, r_{ij+}]$ from X_i obtained on the u_j , and form a row vector $R_i = (r_{i1}, r_{i2}, \dots, r_{in})$, which constituting the fuzzy comprehensive evaluation matrix:

$$R = [R_1, R_2, \dots, R_m]^T = \begin{bmatrix} r_{11} & \dots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \dots & r_{mn} \end{bmatrix} \quad (1)$$

$$= \begin{bmatrix} [r_{11}^-, r_{11}^+] & \dots & [r_{1n}^-, r_{1n}^+] \\ \vdots & \ddots & \vdots \\ [r_{m1}^-, r_{m1}^+] & \dots & [r_{mn}^-, r_{mn}^+] \end{bmatrix}$$

where, R is the interval number decision matrix.

S2: Through the following conversion:

$$a_{ij} = \frac{r_{ij}}{\max r_{ij}}, i \in I_1, j \in N \quad (2)$$

$$a_{ij} = \frac{r_{ij}}{\min r_{ij}}, i \in I_2, j \in N \quad (3)$$

Mentioned above,

$$\min r_{ij} = [\min_{ij}^-, \min_{ij}^+], \max r_{ij} = [\max_{ij}^-, \max_{ij}^+] \quad (4)$$

The above decision matrix is normalized to obtain a normalized decision matrix.

Among,

$$a_{ij} = [a_{ij}^-, a_{ij}^+] \quad (5)$$

S3: Calculate the fuzzy comprehensive evaluation vector and compare the interval number $b_i (i = 1, 2, \dots, n)$ to create a measurable matrix.

$$b = \omega * A = (b_1, b_2, b_3, \dots, b_n) \quad (6)$$

$$P = \begin{bmatrix} p_{11} & \dots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{m1} & \dots & p_{mn} \end{bmatrix} \quad (7)$$

S4: Compute the sum of each row of matrix p , and normalize the sum to obtain the order of decision making.

We proposed a new method of ranking the decision-making scheme based on fuzzy evaluation, gave

a concrete way to standardize the decision matrix, and provided a reasonable way to get the order of the scheme from the probability matrix. So that the sorting results are more objective and stable, the evaluation results are more comprehensive, more truly reflect the farmer users tend to the actual situation of video resources, and to achieve human video priority ranking recommended.

3 Farmer skill training system architecture based on motion sensing technology

The system is mainly composed of body movement interactive module, resource acquisition processing module, multimedia player module, and user behavior analysis module, as shown in Figure 2. The user can complete the somatosensory interaction through the simple movement under the control of the system, and achieve providing video data while reducing the complexity of the operation, and providing the users with a convenient experience. The body movement processing and interaction module, the resource acquisition processing module, the multimedia module and the user behavior analysis module are integrated in the host. It is connected to the tracking device, the display and the audio equipment respectively. The resource acquisition and processing module are used to asynchronously acquire information of a video resource and provide it to the system. With the aid of body sensor, complex operation can be simplified into simple body movements, lowering the use threshold, and improving the participation and motivation of farmers users.

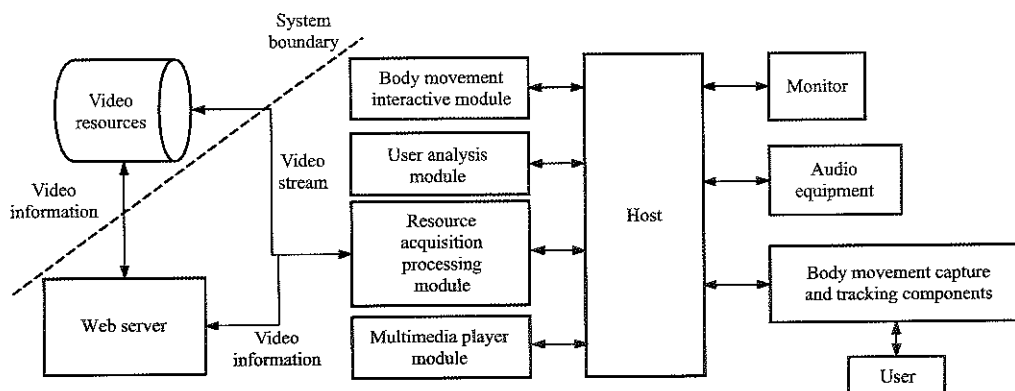


Figure 2 System structure diagram

3.1 Depth image and bone node acquisition

Kinect v2 has the 1920×1080 color camera, and

512×424 depth camera. The depth sensor is loaded, and the depth information is obtained by returning time from

the projected infrared reflection. With a depth camera, the Kinect allows the depth values of everywhere to be sorted into a depth matrix, and the current depth image can be obtained through proper transformation. The depth image captured by the Kinect can be represented by the coordinates (x, y, z), where (x, y) represent the coordinates of the pixel points in the image, and z represents the vertical distance between the coordinate point and the depth camera. The user's bone node data also can be obtained through the depth image, and refresh at 30 frames per second. The acquired 20 bone node data contains three attributes, including the skeletal point type, the position information and the tracking status capturing bone nodes, as shown in Figure 3.



Figure 3 Capture of human skeletal nodes

After the system identifying, the user will see the hand cursor in the screen, which corresponds to the user's hand movement. The user will press the screen to trigger the click effect, or move the cursor through moving hand and move the cursor to achieve drag and drop. The corresponding mapping relationships between specific body movement and operation refer to the Table 1.

Table 1 Mapping table of motion sensing

Operation	The result of motion sensing
Move hand right	The cursor moves to the right in the screen
Move hand left	The cursor moves to the left in the screen
Move hand up	The cursor moves to the up in the screen
Move hand down	The cursor moves to the down in the screen
Hand push	Select
Fisting drag	Drag and move the content as the hand's movements

However, Kinect cannot directly identify more complex actions, such as the user makes waving action or draws circular, Kinect cannot capture the complete action. So, we introduced the Dynamic Time Warping algorithm to solve such problems.

3.2 Dynamic Time Warping algorithm

Dynamic Time Warping (Berndt et al., 1994) refers to the use of Dynamic Time Warping to calculate the two unequal time actions, to not completely equal time sequence of the optimal matching, thus the influence of the time can be ignored, and two sequences of distance measurement can be defined. It is a better way to solve the problem that Kinect cannot accurately identify continuous action. The concrete implementation is: given two time sequences (the movement of the bone nodes) $A=a_1, a_2, a_3, \dots, a_n$ and $B=b_1, b_2, b_3, \dots, b_m$, find its best match: $\varphi=(\varphi_A, \varphi_B)$, then

$$\varphi_A = (\varphi_A^1, \varphi_A^2, \varphi_A^3, \dots, \varphi_A^K) \quad (1 \leq \varphi_A^i \leq n, 1 \leq i \leq K) \quad (8)$$

$$\varphi_B = (\varphi_B^1, \varphi_B^2, \varphi_B^3, \dots, \varphi_B^K) \quad (1 \leq \varphi_B^i \leq m, 1 \leq i \leq K) \quad (9)$$

The time series A and B are defined as follows Dynamic Time Warping

$$DTW(A, B) = \min_{\varphi} \{ \sum_{i=1}^K dtw(\varphi_A^i, \varphi_B^i) \} \quad (10)$$

$dtw(\varphi_A^i, \varphi_B^j)$ equals to the distance between the i -th element in A and the j -th element in B .

In this paper, $dtw(i, j) = |a_i - b_j|$.

To find the optimal matching of A and B can be converted to a two-dimensional matrix S of n by m , $S[i, j]$ is the DTW distance between submatrix $A'=a_1, a_2, a_3, \dots, a_i$ and submatrix $B'=b_1, b_2, b_3, \dots, b_j$, which can be remember to δ_{ij} . So, the algorithm can be converted to calculate the δ_{nm} , which are calculated from top to bottom, left to right all of the possible matches, by the principle of the Dynamic Time Warping

$$\delta_{ij} = dtw(i, j) + \min\{\delta_{i-1, j-1}, \delta_{i-1, j}, \delta_{i, j-1}\} \quad (11)$$

can reduce the complexity of the algorithm, which calculate the optimal matching results of the two-time series (Ding et al., 2016). Fifty groups of the experiments showed that the movement which have been processed by Dynamic Time Warping have better recognition rate than the unprocessed ones. The details are shown in Table 2.

Table 2 Matching rate of Dynamic Time Warping

Action	Normal matching rate	DTW matching rate
Move hand left or right	90%	96%
Push hand	90%	92%
Draw circle with hand	78%	92%
Continuous hand movement (such as wave hands)	28%	90%

3.3 Farmer skill training system implementation

Based on the somatosensory technology and user behavior analysis method, the system in this paper can capture the network training resources and provide a more comprehensive skills training system for farmers. The main interface as shown in Figure 4.

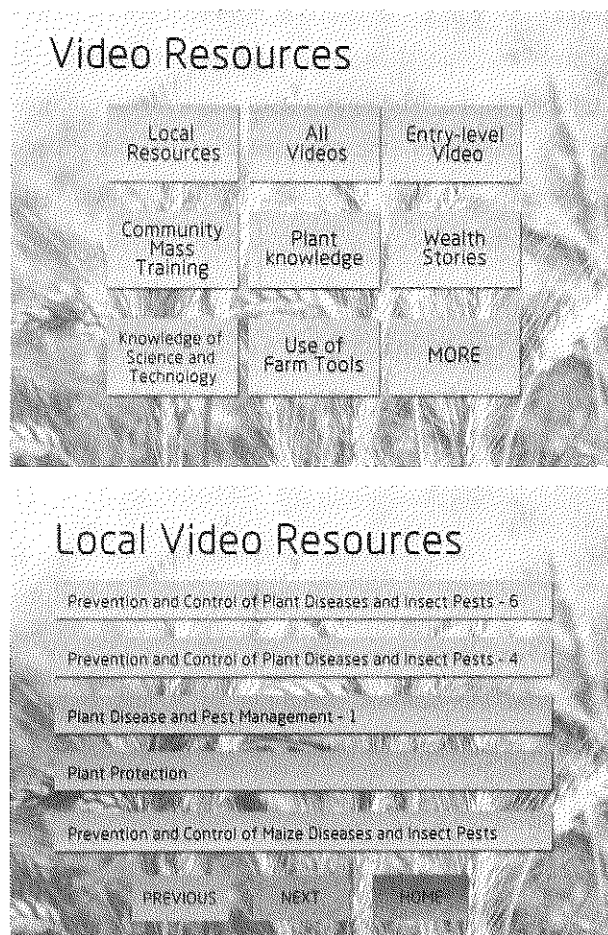


Figure 4 Interface of training system

Where the order of the training resources is rearranged according to the calculation and evaluation of the user behavior analysis and recommendation system, and it recommends higher quality, with more suitable resources for users. Users can learn the video resources through the corresponding motion sensing actions which is mentioned in the table above, through the control of the hand to complete the corresponding button click easily. The farmer training system can make the farmer easy to understand the highly conceptualized scientific and technological information.

4 Conclusion

Compared with the other training methods for farmers, the study based on motion sensing technology achieved

the multimedia training system and put forward the user behavior statistical analysis method. The system not only provided training video data for users through a very convenient way, but also made farmers use motion sensing action to control the system easily. The multi-dimensional interactive multimedia training and learning system provided a new way of learning and training for farmers. Specific conclusions are as follows:

- The system provides the farmers with video data. The resource acquisition and processing module can achieve video information asynchronously.
- The system uses the fuzzy evaluation comprehensive evaluation method to establish the preference index system for evaluating the video resources through building the evaluation index system, establishing the preference evaluation effect set, setting the preference weight value and matrix normalization.
- The system uses the motion sensing device to capture the user's skeletal node data with the depth image captured by Kinect, and uses the dynamic programming algorithm to handle the action, which greatly improves the action recognition rate.

Acknowledgements

We would like to thank to the reviewers for their helpful comments. This work was financially supported by the Special Fund from National Science and Technology Support Program (2015BAK04B04).

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