CCESK: A Chinese Character Educational System Based on Kinect

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Abstract—In this paper, a Chinese character educational system based on Kinect is proposed for guiding beginners to learn the basics of Chinese characters in a more intuitive way. It extracts 19 common components, denoted as alphabets, from Chinese characters. Nineteen postures were designed according to the shapes of these alphabets. Instead of memorizing Chinese characters through repetitive copying, students can first associate an alphabet with the corresponding designed posture. Then, they break down a Chinese character into a set of alphabets in order to perform the sequence of corresponding postures so that they can easily remember the whole character. Our proposed system contains two major functions: 1) the learning function that is responsible for delivering the courseware, and 2) the testing function that is used to let students acquire their learning progress through some tests. A rule-based algorithm is designed to recognize the students' input postures captured from the Kinect motion sensor so as to determine whether the students have performed the correct postures. We conducted a survey which involved 90 students to try our proposed system as well as two other learning modes for comparison. Moreover, we have interviewed those 30 students who had tried our proposed system with some open-ended questions. The positive results show that the proposed system can promote students' experiences in learning Chinese characters.

Index Terms—Computer-aided instruction, courseware, posture recognition, student experiments

1 Introduction

In view of globalization, many non-Chinese speakers choose to learn Chinese, resulted in an increasing popularity of the language. While many learners may find it easier to speak Chinese, reading and writing are often presented as much bigger challenges. This is because there are tens of thousands of Chinese characters and every character is different. Local Chinese students spend many years in learning different Chinese characters through repetitive copying and writing. By the end of their primary school, they often can read and write a few thousand Chinese characters. However, this learning method is time-consuming and ineffective, especially for non-Chinese learners in their beginning stages of learning. They easily get bored and frustrated, thus causing cognitive overload and disorientation.

In teaching Chinese characters, teachers usually break them down into combinations of 5 basic strokes, namely, dot stroke, horizontal stroke, vertical stroke, left-falling stroke, and right-falling stroke. However, since there are many Chinese characters and some characters contain many strokes, there are too many combinations if only 5 strokes are used. This will result in a large amount of information for the students to memorize. Such information typically includes the order of strokes and the relations between strokes, for example, "旧", "田" can be composed of the same set of strokes, namely, 3 "—" and 3 "|", but the orders of these strokes are different, for "旧", the order of strokes should be "|", "|", "—", "|", "—", "—", while for "田", the order should be "|", "—", "|", "—", "|", "—". As another example, "夫", "天" are composed of the same set of strokes in the exact same order, namely, "—", "—", "/", "\", but the relations between these strokes are different, for "夫", stroke "/" goes through both "—" strokes, while for "天", stroke "/" only goes through the second "—"stroke.

In order to help students to learn writing Chinese characters in a more intuitive and effective way, we propose an interactive Chinese character learning environment. Inspired by the work in [1], we extract 19 common components of Chinese characters and denote them as alphabets. The details of these 19 alphabets could be found in Supplementary, which can be found on the IEEE Xplore Digital Library at https://ieeexplore.ieee.org/document/7972968/. All Chinese characters can be composed of these alphabets. Since some of the stroke relations have already been considered while designing the alphabets, the students have less information to memorize when they are learning a Chinese character. [1] designed 19 postures according to the shapes of these alphabets and we redesigned 7 out of these 19 postures to avoid occlusion in front of the Kinect sensor, such that all postures can be detected automatically with our proposed system. Instead of learning to write the Chinese characters through repetitive copying, students can learn them by imitating the postures to memorize the corresponding alphabets, and combining these postures to associate them with the sequence of alphabets that form the whole character. The proposed system contains 2 major functions: 1) the learning function that is responsible for delivering the courseware, and 2) the testing function that helps students acquire their learning progress through some tests. The learning function demonstrates each Chinese character, its English meaning, composed alphabets as well as the corresponding postures to the students, so that the students can watch and rehearse the postures. With the testing function, the English meaning of a character is shown and then students need to perform the postures representing the Chinese equivalent in a limited time to receive a score. A rule-based algorithm is designed to recognize the students' input postures so as to determine whether or not the students have performed the correct postures.

The proposed system is named as the Chinese Character Educational System based on Kinect (CCESK). We carried out some user studies to evaluate our proposed system with both quantitative and qualitative approaches. This includes a survey which involved 90 students who were asked to try our proposed system and two other learning modes for comparison, as well as an interview with an open-ended question which involved those 30 students who had tried our proposed system. The learning experiences of the students were examined. The results suggest that our proposed system could enhance students' experiences in learning Chinese characters.

The rest of this paper is organized as follows. Section 2 reviews some related works. Section 3 covers the details about our proposed Chinese character educational system. In Section 4, the methodology for our experiment is given. Section 5 provides the experiment result. The limitation of our proposed system is discussed in Section 6. Section 7 concludes the paper.

2 Related Works

In this section, the works that are related to our proposed system will be reviewed. We will first review some works related to character education. Then, a literature review about various methods for recognizing human activities based on Kinect will be provided.

2.1 Character Education

Traditionally, human teachers teach Chinese characters by decomposing each character with 5 basic strokes. This restricts the learning

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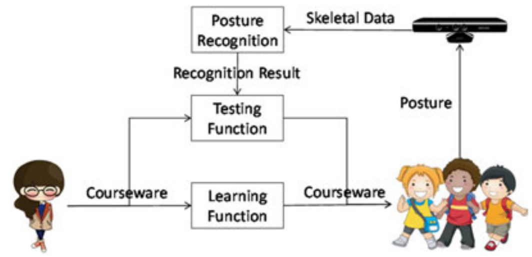

Fig. 1. Architecture of the proposed system.

activities in a specific time and place, and the students cannot control the pace of their learning in this instructor-centered learning environment. With the development of technology, some tools were developed to help students reinforce the learning of characters in the absence of the human instructor. [2] proposed an intelligent Chinese character educational system, which could demonstrate the characters for the student to learn, and detect different types of errors in the students' handwritings to help them improve. In the Chinese handwriting learning system presented in [3], the visual pictorial feedback about the handwriting error was provided to the students. For example, a crooked animal was shown according to the error. [4] combined the Chinese character learning with Dongba pictograph, and found that it improves the orthographic acquisition. [5] adopted rote memorization in teaching Chinese character, and concluded that it was more effective than handwriting exercises. The narration was explored in [6] for teaching Chinese characters, and it was claimed to be more effective than text depicting images. [7] identified 8 main factors in interface design, and implemented a web-based interface for teaching the writing of Chinese character. In the work of [8], Interactive Character Learning Model (ICLM) that was based on WhatsApp was proposed to help Malay L3 learners to learn Chinese characters. It was discovered that the system could promote the ability in recognizing, writing characters and sentences. [9] proposed Hanzi Lamp, which was an intelligent guide interface for learning Chinese characters. It could perceive the learner's writing process and provide animated guidance just in time. [10] proposed a multimedia lecture system for teaching Chinese, where the teacher could simulate stroke order of a character which will be then synthesized into animation in the presentation stage. In [11] and [12], a very interesting game-based mobile learning environment for learning Chinese character was presented. Each student was assigned with a component of a Chinese character, and was required to form groups to assemble eligible Chinese characters using the components the group members possess. [13] proposed to use embodied animations to teach Chinese characters, and discovered that the proposed method could improve the students' learning performances.

Most of the current works on Chinese character learning is based on repetitive copying and writing, while research in neuroimaging indicates that the Chinese character processing is strongly related to the human body movements [14]. In this paper, we propose an interactive Chinese character learning system, where the students can learn Chinese characters by imitating postures in a game-based manner.

2.2 Activity Recognition

In recent years, much research has been dedicated to the activity recognition from the RGBD signal captured by Kinect. [15] proposed features based on spatial distances between different joints as well as the temporal distances of joints for activity recognition. It combined action information including static posture and motion, thus making it a simple but efficient descriptor. [16] proposed a feature called histogram of 3D joints. It was claimed that this feature is robust against the change of camera view. However, features based on joint distance or angles may not be accurate because of sensor errors, especially under occlusions. In order to overcome this, [17] proposed to learn the discriminative features directly from the RGBD video signal with a restricted graph-based genetic programming method (RGGP). The RGGP features outperformed the state-of-art features but a large amount of RGBD video data were required to train the system. Among the methods used in recognizing human activities, [18] explored a single-layer hidden Markov model (HMM) to encode the sequential changes of features. In order to improve the expressiveness of single-layer HMM, [19] utilized a two-layer hierarchical hidden Markov model so that the human activities can be naturally treated as sequences of sub-activities. [20] applied dynamic time warping (DTW) with automatic feature weighing on each joint for online recognition of human actions. This method was fast but the accuracy depended heavily on the distance metric to measure the similarity between frames. In addition, for repetitive actions, such as waving hands, DTW might cause large temporal misalignment. In [21], a multi-kernel learning method was applied to model human motions for recognition. Their results suggested that this method was robust to noise, as well as spatial and temporal misalignment.

Fig. 2. User interface for learning function.

Most of the current works on recognizing human motion are based on the idea of machine learning. However, training these complex models with a limited amount of training data will easily cause overfit. In our work, instead of exploring these complex models, we propose to apply a simple rule-based method that does not require any training data to recognize human motion. It aims to recognize static postures in real time with high accuracy.

3 Chinese Character Educational System

3.1 System Description

In this section, the detailed process to implement the proposed system is described. As we can see in Fig. 1, the system contains 2 functions, namely, learning function and testing function.

The learning function is responsible for delivering the courseware by presenting each Chinese character, the English meaning of the character, the alphabets decomposed from the character and the corresponding postures to the students. As shown in Fig. 2, the student is learning the character "王", where the English meaning is "King", and the current alphabet is "Horizontal line" which is highlighted in pink. In order to learn the whole character, the students need to memorize the alphabets by mimicking the corresponding postures. Then, they need to memorize the orders and relations among these alphabets to construct the whole character. The students can browse these alphabets and characters by clicking the "Next" and "Prev" buttons. After the students finish learning, they can quit the learning by clicking the "Back" button.

The testing function is used to conduct the test so that the students will be able to acquire the status of their learning process. The testing function only displays the English meaning of a character to the students so they need to figure out which character is associated with the displayed English meaning. Furthermore, the students need to decompose the character into its alphabets in the correct order and perform the sequence of the corresponding postures. For each test, the students need to recall the desired alphabet and perform the corresponding posture in 10 seconds. The system recognizes the students' input posture and determine whether or not it matches with the posture associated with the correct alphabet. If the match lasts for 30 consecutive frames (1s), the students are considered to have correctly done the posture. Otherwise, the students are considered to have failed the test of this alphabet. As we can see in Fig. 3, the "Horizontal line" is highlighted in green indicating that the student has correctly done the posture

Fig. 3. User interface for testing function.

Fig. 4. The score report.

corresponding to this alphabet, whereas the “Plus” is highlighted in red indicating that the student has failed to do the posture for “Plus”. The students can also click the “Pause” button to pause the test, and click “Back” button to quit the test.

When the test is finished, a score report about the performance is shown to the students, as shown in Fig. 4. In addition to the overall score, the score report provides feedback about which alphabets the students have done wrongly, so the students could focus on these alphabets. The score in the score report can be calculated from the percentage of postures that are correctly done. A student should get an overall score of at least 60 in order to be considered as passing the test.

All the controls in the system can be remotely provided by the hand movements. For example, the students can control the position of the cursor by moving their hands or press a button by pushing their hands forward. So it was convenient for students to interact with the system.

3.2 Motion Tracking

To recognize the students' input postures to provide useful feedback, it is necessary to track and capture the students' movements. The Microsoft Kinect sensor [22] is used as the motion capture device in our proposed system. Compared with marker-based motion capture systems that require users to wear markers, Kinect, as a markerless solution, is more affordable and convenient for people to use. As illustrated in Fig. 5a, Kinect is placed in front of the users who are ready to perform various motions. Kinect records the scene as Red Green Blue Depth (RGBD) signals, and by analyzing these RGBD signals, the human silhouette can then be segmented from the background. Afterwards, the body joint positions are determined according to a skeleton model with 20 joints as shown in Fig. 5b, with respect to the coordinate system shown in Fig. 5a.

3.3 Pose Recognition

We have followed the proposed scheme in [1] to extract 19 common alphabets from Chinese characters. [1] also proposed a posture for each alphabet. However, since some of the postures proposed in [1] will cause severe occlusions if performed in front of the Kinect sensor, we have redesigned 7 out of the 19 postures according to the shapes of these alphabets so that all postures can be detected automatically with our proposed system. The list of all the alphabets and corresponding postures used in this paper are shown in Supplementary, available online, with P2, P3, P4, P5, P6, P7 and P10 being our redesigned postures.

Since most of the postures are designed to be discriminative, instead of exploring machine learning methods that require a huge amount of training data, we explore a rule-based method to recognize those postures. The detailed rules for recognizing the designed postures are also listed in Supplementary, available online.

Note that the last 3 postures (P17, P18, P19) correspond to pointing postures associated with the meaning of the alphabets. For the alphabet “口” which means the mouth, the posture P17 is pointing towards the mouth. For the alphabet “目” which means the eye, the posture P18 is pointing towards the eye. For the alphabet “日” which means the sun, the posture P19 is pointing towards an imaginary sun above.

In order to reduce the error which is caused by occlusion, the users are required to perform the postures while facing Kinect. Moreover, except for the posture of “dot”, all joints in the other postures need to be approximately on the same plane.

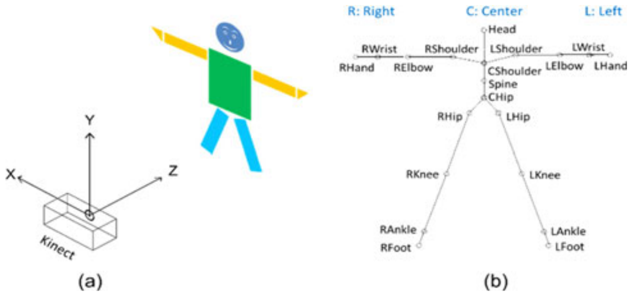

Fig. 5. Motion capture scenario.

TABLE 1
Detailed Arrangement for the Three Lessons

Lesson	Content	Learning time
Lesson 1	“王, 上, 下, 人, 水, 火, 刀, 山, 义, 木, 大, 小, 左, 右, 中”	12 minutes
Lesson 2	“及, 色, 母, 失, 子, 空, 月, 广, 成, 心, 习, 旬, 旧, 盯, 看”	18 minutes
Lesson 3	“书, 风, 回, 今, 合, 千, 可, 贝, 女, 白, 文, 直, 盲, 昌, 张”	25 minutes

4 Evaluation Methodology

4.1 Procedure

A total of 90 college students were involved in this study, and they were first given 55 minutes to learn 3 lessons with 45 Chinese characters in 3 learning modes. The detailed arrangement for the 3 lessons is shown in Table 1, ordered with increasing complexity level from Lesson 1 to Lesson 3. After learning each of the lessons, a human teacher was invited to evaluate their learning performances.

After finishing all the lessons, the students were asked to rate the learning methods they had experienced by completing a questionnaire with 3 designated questions. The questionnaire adopts a five-point Likert scale [29] to evaluate each learning mode. The 3 questions are:

(1) I think the learning environment is helpful for learning Chinese characters.
(2) I am satisfied with the Chinese character learning environment.
(3) It is interesting to learn Chinese character with the learning environment.

The choices for these questions are: Strongly Disagree (SD); Disagree (D); Neutral (N); Agree (A); and Strongly Agree (SA). The ratings for the choices are 1, 2, 3, 4, 5 respectively.

In order to collect further feedback about how learners perceive our proposed system, those 30 students who had tried our proposed system were interviewed. They were presented with an open-ended question: ”which specific aspects do you like/dislike about the system?”. The interview gives students more freedom to talk about things they like/dislike about our proposed system, so that it may allow us to see perspectives that we did not consider.

The general aspects of the proposed system can be evaluated with a quantitative approach through the survey, while the specific aspects can be evaluated with a qualitative approach through the interview, our proposed system can then be studied comprehensively.

TABLE 2
Grouping Detail

Group	Learning mode	Number of students
Control1	Traditional method	30
Control2	Tablet-based method	30
Treatment	Our proposed method	30

4.2 Subjects and Grouping Information

The 90 college students consist of 38 females and 52 males. The subjects are all freshmen in Jiangsu University originally from non-Chinese-speaking countries, and their Chinese proficiencies were on a similar level. The students are randomly divided into three groups, namely, Control1, Control2, and Treatment group. The students in Control1 group learned from human instructor under the traditional method which is based on decomposing a character with five basic strokes. The students in Control2 group learned with the tablet-based Chinese character education system proposed in [2]. The students in Treatment group learned with our proposed method. They were required to learn the alphabets by mimicking the postures, and memorize the orders and relations among these alphabets to construct the whole character. The detailed arrangement can be found in Table 2.

4.3 Research Questions and Hypotheses

The research questions in this paper are:

Q1: What were the students' performances with the 3 learning environments involved in this study?
Q2: What were the students' perceived usefulness of the 3 learning environments?
Q3: What were the students' perceived satisfaction levels of the 3 learning environments?
Q4: What were the students' perceived learning interests of the 3 learning environments?
Q5: What specific aspects affected the students' attitudes toward our proposed system?

Accordingly, our research hypotheses are:

H1: Learning with our proposed system (Treatment) could result in better performance in written exams than learning with the tablet-based method (Control2), learning with tablet-based method (Control2) could result in better performance in written exams than learning with the traditional method (Control1).

H2: Learning with different modes has significant impact on the students' perceived usefulness of the system, i.e., our proposed system (Treatment) is more useful than the tablet-based method (Control2), the tablet-based method (Control2) is more useful than the traditional method (Control1),

H3: Learning with our proposed system (Treatment) provides more satisfying learning environment than learning with the tablet-based method (Control2), and learning with the tablet-based method (Control2) provides more satisfying learning environment than learning with traditional method (Control1).

H4: Learning with our proposed system (Treatment) is more interesting than learning with the tablet-based method (Control2), and learning with the tablet-based method (Control2) is more interesting than learning with traditional method (Control1).

Notice that for research question Q5, there is no hypothesis, because it is a qualitative research question, which aims to further study the factors affecting students' attitudes toward our proposed system.

4.4 Data Collection and Analysis

The students' learning performances are recorded to test H1. For quality assurance, all the students were required to write down the corresponding characters given the English meaning, and a human teacher was invited to evaluate and record their learning performances. Then for each lesson, the average learning performance is calculated as the number of characters the group of students have correctly written.

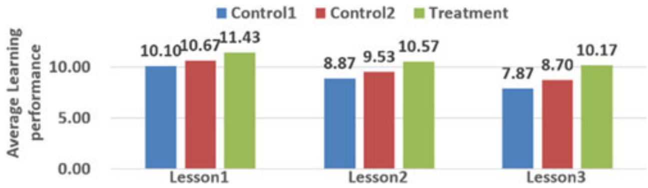

Fig. 6. Average learning performances (*ALPs*) for the students.

TABLE 3
Anova Test Results for the Learning Performance

Lesson	Source of Variation	Sum of Squares	*DOF*	Mean Squares	*F*	*ES*
Lesson 1	Between Groups	26.87	2	13.43	3.89	0.36
	Within Groups	300.73	87	3.46		
	Total	327.6	89			
Lesson 2	Between Groups	44.02	2	22.01	7.25	0.49
	Within Groups	264.3	87	3.04		
	Total	308.32	89			
Lesson 3	Between Groups	81.36	2	40.68	23.6	0.89
	Within Groups	149.93	87	1.72		
	Total	231.29	89			

The questionnaire is applied to test H2, H3, and H4, with all the questions printed on papers, and the students are required to provide their answers to each of the questions.

This work considers one-way ANOVA test to test H1, H2, H3 and H4, because there are 3 groups involved in this study, and ANOVA test can be applied to analyze the differences in cases where there are more than 2 groups.

Those 30 students who had experienced the proposed system participated in the interview. They can talk freely about the aspects they like/dislike about the proposed system and their feedbacks were recorded by the interviewer.

The recognition accuracy of the rule-based algorithm is also studied in this paper. The result can be found in Supplementary, available online.

5. Result

5.1 Learning Performance

Fig. 6 shows the average learning performances (*ALPs*) for all the groups. It is shown that for the 3 lessons, the *ALPs* of the Treatment group are better than that of the Control2 group ($11.43 > 10.67$; $10.57 > 9.53$; $10.17 > 8.7$); and the *ALPs* of the Control2 group are better than that of the Control1 group ($10.67 > 10.1$; $9.53 > 8.87$; $8.7 > 7.87$). The ANOVA test results shown in Table 3 indicate that these differences are significant (Lesson 1: $F = 3.89$, $P = 0.024 < 0.05$, $ES = 0.36$; Lesson 2: $F = 7.25$, $P = 0.0012 < 0.05$, $ES = 0.49$; Lesson 3: $F = 23.6$, $P = 0.0001 < 0.05$, $ES = 0.89$). These findings support hypothesis H1. Note that the effect size (ES) is calculated as Cohen's f, and $ES = \sqrt{F/n}$, where n is the number of subjects in each group.

5.2 Usefulness

Fig. 7 illustrates the students' responses to the question "I think the learning environment is helpful for learning Chinese characters" for the 3 groups. The students' ratings of this question are used to measure the usefulness of the system. It can be observed that the students in Control2 group hold more positive attitudes towards the usefulness of the learning environment than that of the Control1 group since the mean rating about the usefulness in the Control2 group is higher than that of the Control1 group ($3.37 > 2.83$), and the students in Treatment group hold more positive attitudes towards the usefulness than that of the Control2 group ($3.8 > 3.37$). The ANOVA test results shown in Table 4 indicate the differences are significant ($F = 5.67$, $P = 0.0048 < 0.05$, $ES = 0.43$). According to the above discussion, the findings support hypothesis H2.

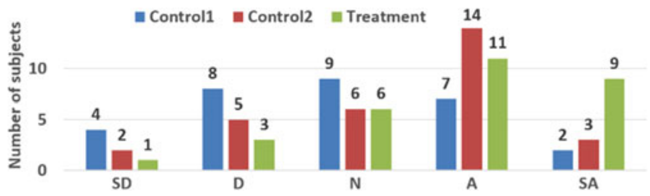

Fig. 7. Students' responses to the question "I think the learning environment is helpful for learning Chinese characters".

TABLE 4
Anova Test Result for the Usefulness of the System

Source of Variation	Sum of Squares	*DOF*	Mean Squares	*F*	*ES*
Between Groups	14.07	2	7.03	5.67	0.43
Within Groups	107.93	87	1.24		
Total	122	89			

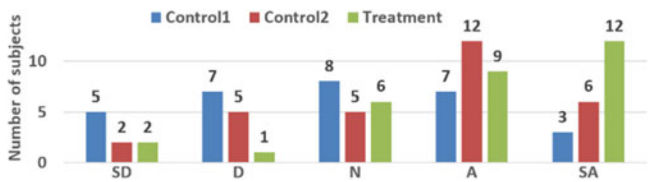

Fig. 8. Students' responses to the question "I am satisfied with the Chinese character learning environment".

TABLE 5
Anova Test Result for Satisfaction Level

Source of Variation	Sum of Squares	*DOF*	Mean Squares	*F*	*ES*
Between Groups	17.27	2	8.63	5.92	0.44
Within Groups	126.83	87	1.46		
Total	144.1	89			

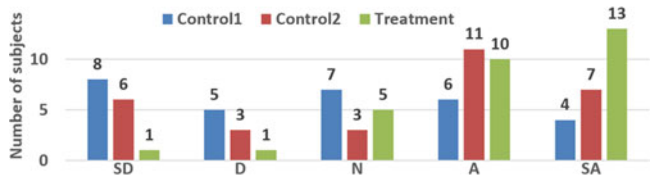

Fig. 9. Students' responses to the question "It is interesting to learn Chinese character with the learning environment."

TABLE 6
Anova Test Result for the Students' Interests

Source of Variation	Sum of Squares	*DOF*	Mean Squares	*F*	*ES*
Between Groups	26.87	2	13.43	7.75	0.51
Within Groups	150.73	87	1.73		
Total	177.6	89			

5.3 Satisfaction Level

Fig. 8 illustrates the students' responses to the question "I am satisfied with the Chinese character learning environment" for the 3 groups. The students' ratings of this question are used to measure their satisfaction levels. It can be observed that the students in Control2 group are more satisfied than the students in Control1 group since the mean rating about satisfaction in Control2 group is higher than that of Control1 group ($3.50 > 2.87$), the students in Treatment group are more satisfied than the students in Control2 group ($3.93 > 3.50$). The ANOVA test results shown in Table 5 indicate that the differences are significant ($F = 5.92$, $P = 0.0039 < 0.05$, $ES = 0.44$). According to the above discussion, the findings support hypothesis H3.

5.4 Learning Interest

Fig. 9 illustrates the students' responses to the question "It is interesting to learn Chinese character with the learning environment." for the 3 groups. The students' ratings of this question are used to measure their learning interests. It can be observed that the learning interests of students in Control2 group are higher than that of the students in Control1 group ($3.33 > 2.77$), the learning interests of the students in Treatment group are higher than that of the students in Control2 group ($4.10 > 3.33$). The ANOVA test results shown in Table 6 indicate the differences are significant ($F = 7.75$, $P = 0.0008 < 0.05$, $ES = 0.51$). Those findings support hypothesis H4.

5.5 Interview

Some important opinions made by the learners of our proposed system during the interview are described below:

One user stated that "It is quite cool to interact with the system using gestures", while another user commented "It is quite interesting to learn Chinese character with gestures" with similar comments presented by 6 other users. This suggests that the users think the interaction is an important feature in our system for helping them to learn Chinese characters.

Regarding the interface design, the positivie comments include "The interface of the system is clear", "The layout of the interface is neat" and "It is easy to understand how to use the interface". However, about 4 users thought that our interface design is inaesthetic."

Several users said that the functions provided by the system are simple and effective. However, one user stated "The system contains only the basic functions, which is too few to support the learning". This encourages us to add more functions to the existing ones to further support the learning of Chinese characters with our system.

Regarding the performance, one user commented "The system responds rapidly and correctly" and 5 other users made similar comments. On the other hand, some users pointed out these issues: "Interacting with gestures is less reliable and inefficient"; "Sometimes, it doesn't recognize my postures correctly"; "Sometimes, the system doesn't give me the correct feedback". These valuable comments help us identify further issues to improve the performance of the system in the future.

One user stated "The demonstration is clear and expressive" and 4 other users made the similar comments. Some users gave more critical comments: "Some of the postures can not be associated with the alphabets"; "Just showing the Chinese character and its English meaning is boring"; "The learning material is disorganized"; "I think the way the system present the content is not good". This highlights the importance of content delivery in the system and gives us some ideas on improving the course plan of the system in the future.

Regarding students' perception about using our proposed system, these comments were received: "Learning Chinese character is not so difficult with the system"; "I feel confident in learning Chinese character with the system"; "I feel successful in learning the Chinese character with the system".

One user stated "The system is quite stable" whereas another user commented "The good aspect of the system is that I didn't see it crash once". On the other hand, a user expressed "It is rather complex to setup the environment", and another user said "The Kinect sensor may not be so convenient to access". This shows that the stability and the system deployment are important issues to pay attention if we try to promote the learning of Chinese characters using this technology.

6 Discussion

A Chinese character educational system which explores gesture-based interaction is proposed in this paper, the results suggest that the proposed system could promote the learning experience.

As reported in [24], the students who make gestures learn better than those who do not. The cognitive theory suggests that the mind is shaped from the body configuration, performing the posture may reduce the cost of storing information in our working memory, thus it will improve the efficiency of learning. In addition, the research in the field of neuroimaging indicates that incorporating gestures could enhance the learning of Chinese character as they discovered that the Chinese character processing is strongly related to the human body movements [14]. On the other hand, the novel gesture-based interaction could better motivate the students, stimulate their interests in learning Chinese character, and thus lead to the positive attitudes towards the proposed system.

The proposed system presents the Chinese characters to the students in an easy-to-complex manner. It is effective for simple characters, whereas for complex characters, a more sophisticated learning path should be planned. As stated in [25], it is effective for people to learn if an event is decomposed into a hierarchically organized parts. In our case, the complex Chinese characters can be decomposed into simpler characters, and the simplest characters can be decomposed into alphabets. This will lead us to a hierarchical structure, and by considering the prerequisite relations in the structure, an easy-to-complex learning path that simultaneously satisfies the constraint of prerequisite relations can be constructed.

The proposed system described in this work does not consider the students' different learning styles, while it is very important in designing an e-learning system. As described in [26], Different students have different learning styles, most people prefer specific ways to perceive and process information. Adapting the learning styles to the students could promote the learning experiences. More research can be done to extend the proposed system into a personalized learning environment.

Our proposed system is designed for students who do not have much prior knowledge about Chinese characters. It aims to teach the students to recognize and write Chinese characters. It would be an interesting research to teach students to write in a more artistic sense after they have grasped the basic concept.

7 Conclusion

In this work, we proposed a Chinese Character Educational System based on Kinect (CCESK) to help students learn to write Chinese characters. 19 alphabets were extracted from Chinese characters so that all Chinese characters can be composed of these alphabets. We have improved the set of postures proposed in [1] by redesigning 7 out of these 19 postures to avoid occlusion in front of the Kinect sensor such that all the postures can be correctly recognized. Instead of learning the Chinese characters through repetitive handwriting, students can learn Chinese character by breaking it down into a set of alphabets, imitating the corresponding postures to better memorize the alphabets, while combining them to learn the whole character.

The students' learning performances were recorded under 3 learning modes. After comparison, it was concluded that our proposed system could help students get better performances in written exams than the tablet-based method, and the tablet-based method could help students get better performances in written exams than traditional methods. We carried out a few user studies to evaluate our proposed system, both quantitative and qualitative approaches are explored to study the students' learning experiences. The results show that the students hold more positive attitudes towards our proposed system than the tablet-based system, and the students hold more positive attitudes towards tablet-based system than the traditional method.

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