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MOBILE LEARNING AND RESOURCE SHARING MODE OF HIGHER EDUCATION BASED ON 5G MOBILE COMMUNICATION TECHNOLOGY

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Abstract. Currently, the development of mobile learning and resource sharing models for higher education, along with the application of 5G and other mobile communication technologies to education, hold significant scientific value. These models will help improve the speed and efficiency of retrieving learning resources for higher education while also organizing and managing learning resources more effectively. The complementarity and growth of mobile learning technology for traditional online learning technology are the major features that this research combines. This research builds a mobile learning and resource sharing mode for higher education based on 5G mobile communication technology, utilizing the Moodle online teaching platform. It also designs and implements a mobile learning model, as well as the system architecture, functional modules, learning mode, and learning process. Ultimately, the system model's primary functional modules are put into practice and put through testing. encouraging mobile learning to assist in a variety of ways in the teaching field. The test probability value P (siq)=0.00, which is significantly less than the significant level of 0.05, and the overall accuracy rate of 74.7% indicate that the AKAZE algorithm is utilized to optimize the model, according to the experimental results. As a result, we think that using a mobile learning instructional design mode will benefit students' academic achievement.

Key words: 5G mobile communication technology; Higher Education; Mobile learning; resource sharing

1. Introduction. The widespread application of mobile devices in education can personalize learning, enrich classroom content, and improve student performance [1]. Building an effective learning resource management platform is crucial for efficient mobile teaching [2]. However, current platforms face issues such as resource redundancy, low retrieval precision, outdated content, and simplistic storage formats [3, 4]. Additionally, traditional concepts and technologies hinder effective resource usage and sharing, impacting the effectiveness of education informatization.

With increasing international competition, lifelong learning has been embraced globally, forming a systematic approach to continuous education from childhood through old age, including school education and in-service training [5]. In China, rapid economic transformation necessitates continual skill improvement among workers, making both formal education and in-service training essential [6]. Mobile learning supports lifelong learning by promoting independent and collaborative learning, reducing resistance to formal learning models, and encouraging continuous engagement and self-improvement [7]. However, maximizing the benefits of mobile learning requires a robust foundational system for mobile learning and resource sharing. Teachers, burdened with heavy teaching loads, often lack the time and programming knowledge needed to develop custom learning systems [8, 9]. Existing commercially developed systems are often costly, inflexible, and unsuitable for open and independent learning management. Thus, constructing a mobile learning and resource sharing model based on 5G technology for higher education has significant practical value. It can free teachers from complex platform operations, allowing them to design mobile learning courses tailored to their teaching methods and experiences, thereby promoting mobile learning in education [10, 11].

2. Model of Mobile Learning and Resource Sharing in Higher Education. The teaching process is complex, and each link is crucial, so any factor in the teaching design process cannot be ignored. From the overall perspective, the teaching design model consists of four basic elements: teaching objects, teaching objectives, teaching strategies and teaching evaluation. Its simplified model is shown in Fig. 2.1.

In fact, the learning mode of mobile learning is "personal, seamless, spontaneous, anytime, anywhere"[12].

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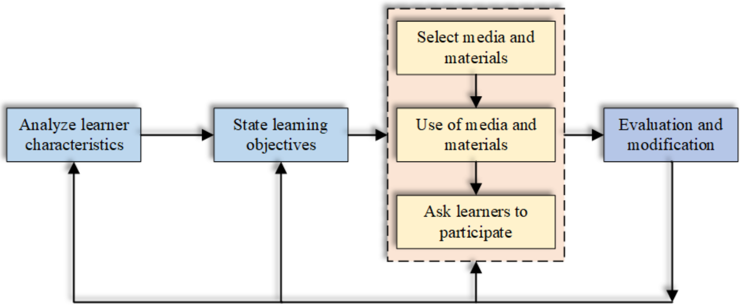

Fig. 2.1: Simple Design Model of ASSURE Mobile Teaching.

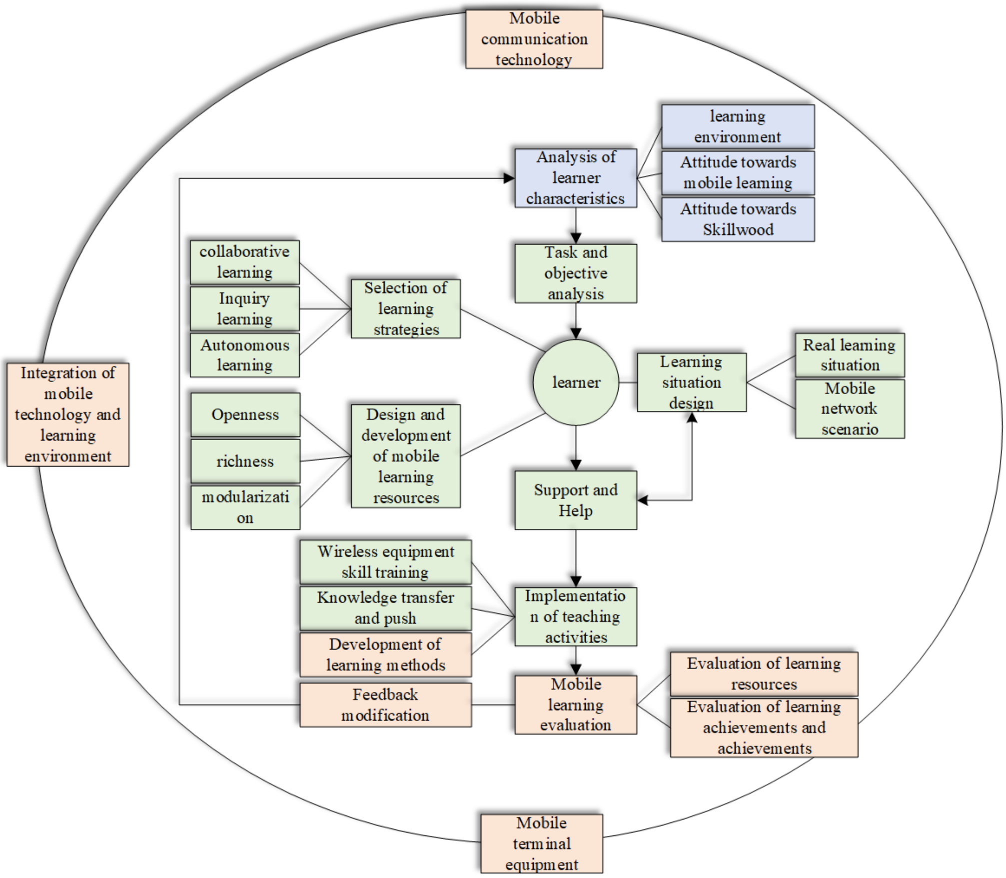

Fig. 2.2: Teaching Design Mode of Mobile Learning.

It focuses on interaction with external learning environment. It is applied to traditional education, online learning, enterprise training and other aspects. To better play a role in mobile learning, improve teaching efficiency and quality, and ultimately achieve good learning results, good teaching design is essential, as shown in Fig. 2.2.

In the process of mobile teaching, the process of resource sharing design and development is generally from front to back: preliminary analysis, resource design, resource development, resource implementation and

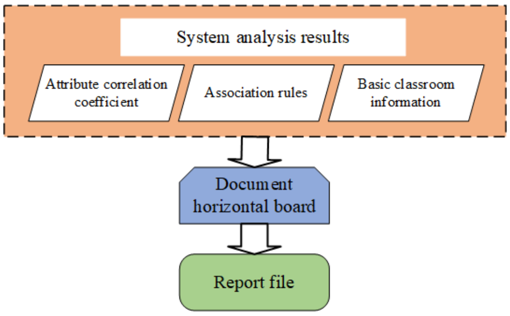

Fig. 2.3: Resource sharing design mode in mobile learning process.

resource evaluation, as shown in Fig. 2.3.

In mobile learning, time (t), space (S), content (C), technology (LE), mental factors (MM), and learning methods (M) all play crucial roles. Traditional learning time is often discontinuous, whereas mobile learning time is continuous. Traditional learning space is generally fixed, while mobile learning space is flexible and can include both physical and virtual environments. Mobile learning can structure courses to fit personal learning needs.

In this context, technology (LE) encompasses the network and technical devices enabling mobile learning. Psychological factors (MM) include learners' interests, motivation, and abilities. Learning methods (M) integrate all parameters related to the transmission of learning content, such as technology and pedagogy.Thus, the factors representing mobile learning under 5G communication technology can be summarized as follows:

$$Mlearn = f\{t, s, LE, c, IT, MM, m\} \tag{2.1}$$

where: t is the time (continuous in mobile learning), S is the space (unrestricted), C is the content (structured for personal learning), LE is the learning environment/technology, MM are the mental factors (interests, motivation, abilities), M are the learning methods.

From this, the representation factors of mobile learning under 5G communication technology can be formulated as:

$$c = f\{MM, soc, edu\} \tag{2.2}$$

where: MM are the mental factors (learners' interests, motivation, and background), Soc are the socially responsible factors, Edu is the educational relevance.

To further characterize the model flow of mobile learning and resource sharing, we use the anisotropy of image brightness diffusion to build the scale space, which needs to be solved by partial differential equations. The nonlinear diffusion equation can usually be expressed as:

$$\partial L/\partial t = div(c(x, y, t).\nabla L) \tag{2.3}$$

where L is the image brightness matrix, time t is the scale parameter, div represents the image divergence, (x, y, t) represents the conduction function, and ∇ represents the gradient calculation. The conduction function structure can be expressed as Eq. 2.4:

$$c(x, y, t) = g(|\nabla L_\sigma(x, y, t)|) \tag{2.4}$$

Then, we use Gaussian smoothing to process the gradient value of the post image L_σ . The form of function g can be expressed as Eq. 2.5-Eq. 2.6:

$$g_1 = \exp(-\frac{|\nabla L_\sigma|^2}{\lambda^2}) \tag{2.5}$$

Table 3.1: User Registration Information.

Serial No	Field Name	data type	length	Primary key	Is it empty	Field Description
1	name	varchar	10	Yes	Nonempty	Student Name
2	password	varchar	20	No	Nonempty	Login password
3	number	varchar	20	No	Nonempty	Student ID
4	phone	varchar	13	No	Can be empty	phone number

$$g_3 = \begin{cases} 1, |\nabla L_\sigma|^2 = 0 \\ 1 - \exp\left[-\frac{3.315}{\left(\frac{|\nabla L_\sigma|}{\lambda}\right)^8}\right], |\nabla L_\sigma|^2 > 0 \end{cases} \tag{2.6}$$

Among them, λ is a contrast factor used to control the diffusion degree, which can determine the integrity of edge information retained in the sampling process. The larger λ is, the less edge information retained in the mobile learning model.

The basic idea of additive operator splitting diffusion is to decompose a complex multidimensional problem into several simple one-dimensional problems, and then solve them separately to take the average value[13]. Compared with the traditional explicit solution, this method can adopt a larger step size for iteration, with faster convergence and higher stability. First, the original equation is discretized into an implicit difference scheme, as shown in Eq. 2.7:

$$\frac{L^{i+1} - L^i}{\tau} = \sum_{l=1}^{m} A_l\left(L^i\right) L^{i+1} \tag{2.7}$$

where τ is the iteration step size, and A_l is the matrix of the diffusion degree of the feature image on the scale l. The solution of this equation can be expressed as Eq. 2.8:

$$L^{i+1} = \left(I - \tau \sum\nolimits_{l=1}^{m} A_l\left(L^i\right)\right)^{-1} L_i \tag{2.8}$$

This manuscript takes Eq. 2.8 as the basic mathematical model to build a mobile learning and resource sharing model for higher education based on 5G mobile communication technology.

3. Methods.

3.1. Database structure design. MySQL database provides encryption connection with other multiple databases, and can also perform data batch processing. In this study, five data tables of mobile learning and resource sharing models are created, and the Chinese description of each field is given:

The first part is the user registration information table. As shown in Table3.1. This form is used to store student registration information, including student name, login password, student ID and mobile phone number. The student's name and login password are used for daily login verification. To protect student privacy, mobile phone number can be left blank.

The second part is the login information table, as shown in Table3.2. This table is used to record students' mobile learning application login. When students log in to the student client each time, they will automatically send the login time and student name to the database server.

The third part is the mobile learning progress record table, as shown in Table3.3. This table is used to record the learning progress of students at the mobile learning site, including student name, learning time, learning location, and learning duration. After the data information is stored, it is convenient for the teaching assistant to monitor the learning progress of each student in real time and supervise the learning externally.

The fourth part is the question information table, as shown in Table3.4. This table is used to record the information of students' questions, including their names, time and content.

Table 3.2: User Registration Information.

Serial No	Field Name	data type	length	Primary key	Is it empty	Field Description
1	login Time	varchar	20	no	Nonempty	login time
2	Login Name	varchar	10	Yes	Nonempty	Student Name
3	number	varchar	20	No	Nonempty	Student ID
4	phone	varchar	13	No	Can be empty	phone number

Table 3.3: Mobile Learning Progress Record.

Serial No	Field Name	data type	length	Primary key	Is it empty	Field Description
1	name	varchar	10	Yes	Nonempty	Student Name
2	time	varchar	20	No	Nonempty	Time of learning
3	title	varchar	100	No	Nonempty	Learning location
4	Study Time	int	10	No	Nonempty	Learning duration

Table 3.4: Mobile Learning Progress Record.

Serial No	Field Name	data type	length	Primary key	Is it empty	Field Description
1	name	varchar	10	Yes	Nonempty	Ask students' names
2	time	varchar	20	No	Nonempty	Question time
3	content	varchar	200	No	Nonempty Questions	
4	Study Time	int	10	No	Nonempty	Learning duration

Table 3.5: Reply to Questions.

Serial No	Field Name	data type	length	Primary key	Is it empty	Field Description
1	name	varchar	10	Yes	Nonempty	Ask students' names
2	Post time	varchar	20	No	Nonempty	Question time
3	time	varchar	20	No	Nonempty	Reply time
4	content	varchar	800	No	Nonempty	Reply content

The fifth part is the question reply information table, as shown in Table3.5. This table is used to record the information that the assistant teacher replies to the student's questions in the mobile learning situation. The assistant teacher makes targeted replies to the student's questions and stores them in the database server. The student client queries the database server's question reply to information table after each login. If the assistant teacher replies to the student's questions, download the reply to information.

Regarding data sources, the research object for this study was university mathematics class 1301 students. After a period of observation and consideration of the students' computer scores at the conclusion of the previous semester, the students were classified into two groups: Group A, which demonstrated strong computer acceptance ability and excellent computer performance, and Group B, which demonstrated moderate computer acceptance ability. To assess the simulation and development of the mobile learning model, however, and to guarantee the representativeness of the experimental results, 16 students from A and B, respectively, were chosen for the experimental group and the control group. Moreover, these students had not yet learned EXCEL2010 Chart Creation and Editing[14].

3.2. Model operation and optimization. SQLite, the underlying optimization algorithm of the model, is used in the application layer, application framework layer, system runtime, and Linux kernel layer of the mobile device operating system, as shown in Fig. 3.1. SQLite is integrated in the system runtime and runs on the Linux kernel layer.

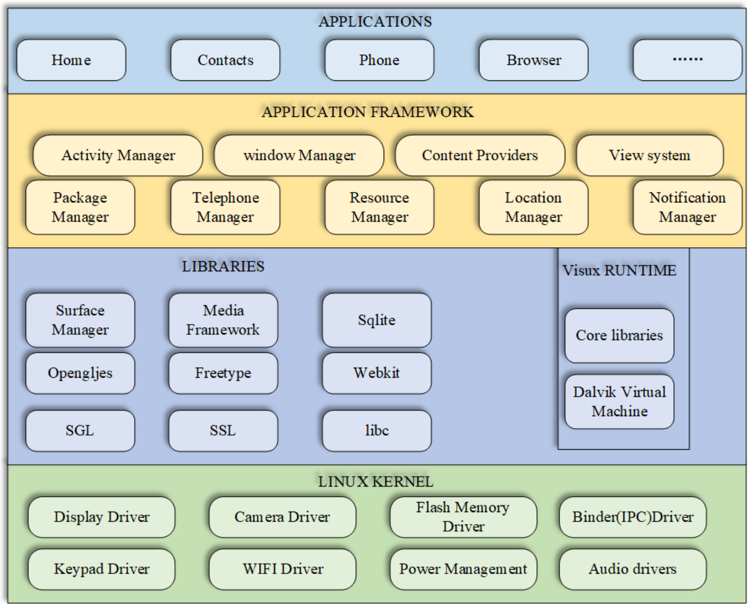

Fig. 3.1: Architecture of mobile device operating system.

Table 4.1: Reply to Questions.

-	Group	number	Average	standard deviation	Mean value of standard error
fraction	1	32	91.07	4.691	0.829
fraction	2	32	84.29	9.093	1.608

Since the data on the mobile learning mobile client needs not only to be uploaded to the database server but also stored in the local database, the tables existing on the database server also exist in the local database. The author will not repeat the structure of each table here. However, MySQL databases can create data tables through the Navi cat for MySQL visual interface without writing code. SQLite needs to use code to penetrate data tables.

4. Case study.

4.1. Empirical Results Output and Hypothesis Verification. Learners who choose mobile learning should complete the specified tasks within a specified class time (tasks must be submitted within the specified time), change the file name of the completed tasks to "student number name", and then submit the tasks to the server[15]. The author logs in to the server to download the task files submitted by all learners. After collecting the final learning task results of all learners, the author scores all the learners in turn according to the scoring rules and enters the learner's scores into the score sheet in turn, and finally collects the student scores of the experimental group and the control group. After the students in the experimental group finish their study, they should evaluate the recognition of the teaching design model constructed through the self-made questionnaire of this study. We compared the scores of the control group and the experimental group as samples and conducted independent sample T test through SPSS software. The test results are shown in Table4.1.

After students submit their homework, they use the mobile learning platform to send the teaching design model identification questionnaire shown in Table4.2 to the experimental object group, and the experimental object fills in the questionnaire and sends it back to the mobile learning platform. Collect, sort out and analyze the results fed back by the experimental subjects, as shown in Fig. 4.1: 68.75% of the experimental subjects are very interested in using WeChat to carry out "computer based" mobile learning activities; 56.26% of the

Table 4.2: Mobile Learning Model Recognition Questionnaire.

Title No	Sub item	strongly agree	agree with	uncertain	disagree	strongly disagree
1	I am very interested in using WeChat to carry out "Computer Foundation" mobile learning activities	-	-	-	-	-
2	Using WeChat to carry out "Computer Foundation" mobile learning activities has brought convenience to my study	-	-	-	-	-
3	I think the combination of mobile network situation and real situation in teaching design makes my computer learning easier, more convenient, and more effective	-	-	-	-	-
4	I think this teaching design mode has strengthened the communication between me and other learners	-	-	-	-	-
5	I think the activity design of teaching design strengthens the final learning effect	-	-	-	-	-

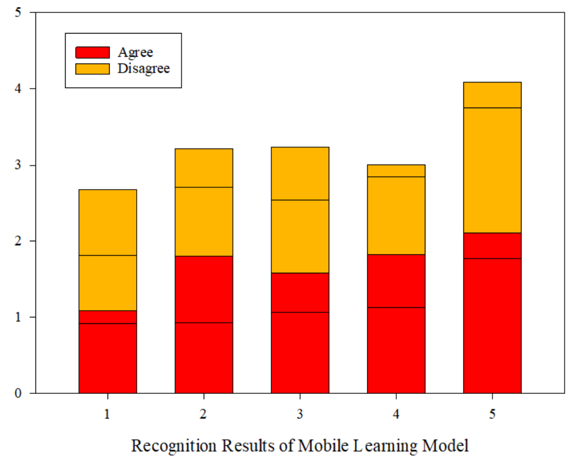

Fig. 4.1: Recognition Results of Mobile Learning Model.

subjects believed that mobile learning had brought convenience to learning; 72% of the subjects believed that instructional design made learning easier, more convenient and more effective; 85% of the subjects believed that the instructional design model strengthened the communication with other learners; 56.25% of the subjects believed that instructional design strengthened the final learning effect. The above data shows that the instructional design can effectively strengthen the communication between learners, make learning easier, more convenient, and effective, and strengthen the final learning effect.

4.2. Algorithm performance comparison. The AKAZE (Accelerated KAZE) algorithm is a powerful tool for identifying and describing features in images. It focuses on generating binary descriptors and multi-scale feature detection to optimize the image processing model.AKAZE finds feature spots in a picture by applying Nonlinear Diffusion Filtering. With the help of this filter, the image can be smoothed across many scales without losing important edge characteristics.

To better compare and analyze the performance difference between AKAZE optimization algorithm and other feature detection algorithms in the construction of mobile learning models, three algorithms are used to match the image features of models in the mobile learning and resource sharing experimental group and the control group. Mularczyk mobile learning database sets variables for factors affecting learning image features,

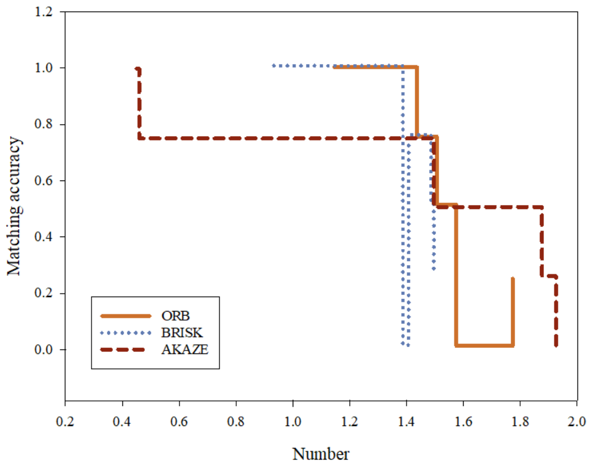

Fig. 4.2: Optimization Results of Mobile Learning Experimental Group.

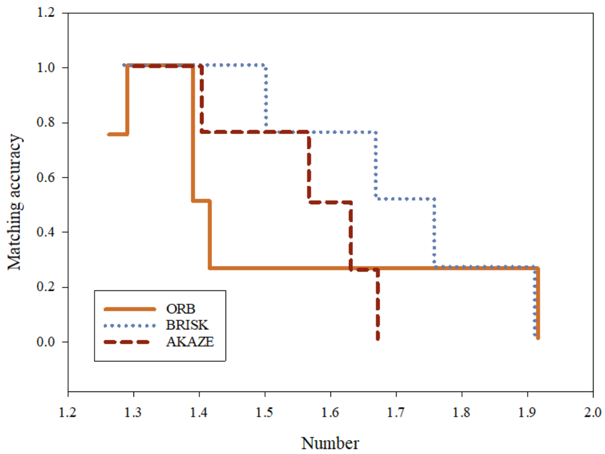

Fig. 4.3: Optimization results of mobile learning control group.

such as image blur, compression, illumination intensity, angle of view, rotation, and scaling. Five groups of images are selected, and each group of images takes 6 variable values for a certain influencing factor, keeping consistent with other factor variables. The first group, Boat learning group, is composed of six images with different rotation and scaling degrees; The second group, Leuven learning group, was composed of six images with different brightness; The third group, Ubc learning group, had six images with different compression levels; The fourth group, Bikes learning group, was composed of six images with different degrees of blur; The fifth group, Graf learning group, is composed of six images with different perspectives. The first image of each group of images is a preset image, and the other five images are matching images. The matching situation and preset situation are matched with three algorithms respectively, and the matching time and accuracy are compared. The learning situation matching process uses ratio ratio scheme for calculation and screening. Since ORB algorithm, BRISK algorithm descriptor and AKAZE algorithm M-LDB descriptor are all stored in binary form, hamming distance is used for rough matching during feature point matching, and possible feature point pairs are selected and filtered and eliminated by RANSAC algorithm, as shown in Fig. 4.2, Fig. 4.3, Fig. 4.4 and Fig. 4.5.

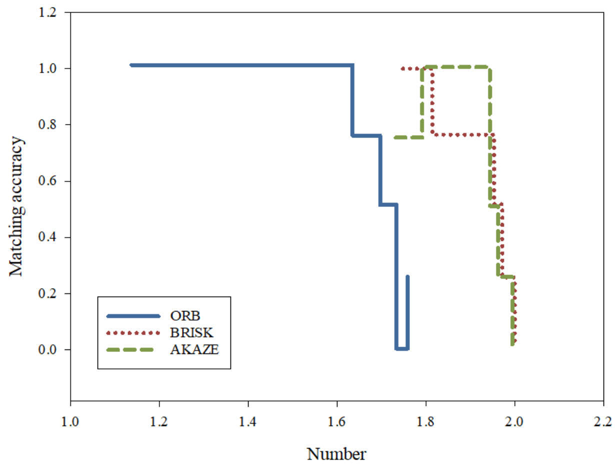

Fig. 4.4: Optimization results of mobile learning control group.

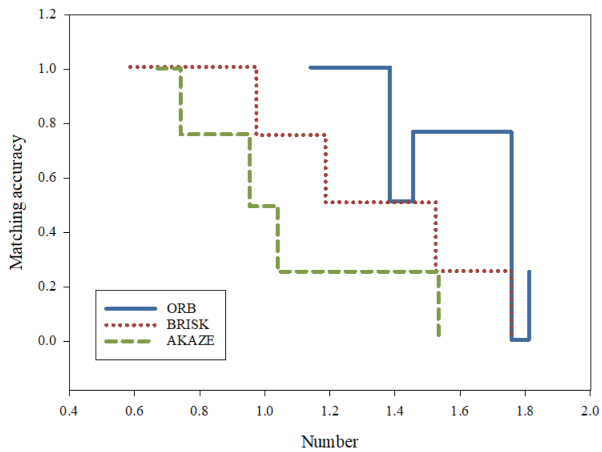

Fig. 4.5: Optimization results of mobile learning control group.

Fig. 4.2 shows the matching accuracy of the three algorithms under different rotation scaling angles. The average matching accuracy of ORB algorithm is 61.2043%, that of BRISK algorithm is 66.5227%, and that of AKAZE algorithm is 74.6991%. ORB algorithm can deal with small rotation and scaling of images well, but it cannot deal with large rotation and scaling of images. BRISK algorithm is stable, and AKAZE algorithm is the most stable.

Fig. 4.3 shows the performance analysis and comparison data of ORB, BRISK and AKAZE algorithms from the two dimensions of matching accuracy and matching time. The ordinate represents the matching accuracy, in percentage form, and the abscissa represents the matching image number in each group of images.

Fig. 4.4 shows the matching accuracy of the three algorithms under different learning durations. The learning durations of matched images decrease in turn. The average matching accuracy of ORB algorithm is 73.1271%, that of BRISK algorithm is 76.6142%, and that of AKAZE algorithm is 81.8454%. The three algorithms are similar to each other in that the image is affected by the change of learning time, but the matching accuracy of AKAZE algorithm is higher than that of the other two algorithms.

Fig. 4.5 shows the matching accuracy of the three algorithms under different fuzzy degrees. The average matching accuracy of AKAZE algorithm is 76.6311%. Both ORB algorithm and BRISK algorithm cannot deal with the situation of blurred images very well. Especially in the matching process of the mobile learning experiment group, the correct rate of using ORB algorithm to match is only 29.2035%, while AKAZE algorithm has better relative performance.

This research combines three algorithms to match the model picture features of the experimental and control groups, allowing for a more thorough comparison and analysis of the performance difference between the AKAZE optimization algorithm and other feature detection algorithms in mobile learning model development.The factors that alter the properties of the taught images—such as picture blurring, compression, light intensity, viewing angle, rotation, and scaling—are configured in the Mularczyk Mobile Learning Database. Five sets of photos were chosen, and for each set of images, six variable values were taken for a specific influencing factor while maintaining consistency with the other factor variables.

5. Conclusion. Based on the development of 5G and other communication technologies, a model of mobile learning and resource sharing in higher education was created in this study. The model was then empirically verified and its algorithmic efficiency was examined. The test probability value P(siq) = 0.00, which is much smaller than the significant level of 0.05, and the overall accuracy rate of 74.7% are obtained after optimizing the model using the AKAZE algorithm, according to the experimental data. As a result, we think that using the m-learning and resource sharing instructional design model can help students achieve better academically. It is particularly crucial to clarify that the test probability value P (siq) = 0.00 denotes a very significant result, meaning that the likelihood of the obtained result in the statistical test is near to zero. This suggests that the model's performance was significantly improved by using the AKAZE algorithm for optimization, and it is highly unlikely that this gain was caused by chance. This results provides more proof of the mobile learning and resource sharing model's dependability and efficacy in raising student achievement. In conclusion, this work not only offers a theoretically sound model of resource sharing and mobile learning, but also conducts tests to validate the model's applicability and viability. Subsequent investigations may refine the model even more to enhance precision and investigate additional communication technology uses in mobile education.

Data Availability. The experimental data used to support the findings of this study are available from the corresponding author upon request.

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