An Intelligent Equipment Training System Based on Incremental Learning

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Abstract. Facing complex and lengthy equipment usage instructions and training materials, an intelligent equipment training system can effectively enhance the operational capabilities of personnel and the training capabilities of management departments. This article analyzes the problems existing in equipment training management work and constructs an intelligent equipment training system based on incremental learning. It mainly includes three functional modules: equipment training knowledge base generation module, question generation and score assessment module, and training knowledge base update module. This system overcomes the limitations of traditional manual extraction of expert prior knowledge, enabling the intelligent construction of equipment training knowledge bases and improving the management efficiency of equipment training knowledge resources. Based on training data mining, personalized questions are generated according to the differences of learners, and learners' scores are intelligently evaluated based on their answers. Considering the generation of new knowledge in equipment training, incremental learning is introduced to dynamically update the equipment training knowledge base. This research represents a new expansion of methods in the field of artificial intelligence applied to equipment training.

Keywords: Equipment Training; Knowledge Extraction; Incremental Learning; Knowledge Graph

1 INTRODUCTION

Due to the characteristics of technological novelty, professional precision, and complex systems possessed by a large number of new equipment, there are higher demands on the distribution and usage of equipment for relevant departmental equipment management. This study aims to enhance equipment management efficiency, improve the quality of equipment training in relevant departments, and reduce the management costs of equipment information resources. Through the automatic creation and updating of equipment training knowledge bases, generation of personalized question banks, and

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formulation of training score assessment methods, it develops an intelligent equipment training system based on incremental learning, which uses knowledge extraction, knowledge graphs and incremental learning and other methods. This system achieves personalized question generation and automated learning score assessment, as well as intelligent creation, updating, and management of equipment knowledge bases.

2 RESEARCH STATUS

Currently, research on equipment training mainly focuses on areas such as equipment training in virtual battlefields[1], training with large-scale weapon equipment[2], and medical education-related equipment training[3]. After reviewing the current status of equipment training research, it is found that the following problems persist:

(1) Inability to update training systems and knowledge bases promptly: Knowledge base construction is still in the stage of manual knowledge extraction. It is a need to apply modern AI technologies such as large models to construct intelligent knowledge base generation methods.

(2) Lack of personalized training methods for learners at different levels: Currently, training plans, content, and evaluation methods for equipment training are uniform. However, in reality, different learners have personalized training questions and evaluation methods to enhance training effectiveness.

(3) Lack of standardized training evaluation mechanisms: Assessment indicators and methods exhibit arbitrariness and blindness, with vague assessment content. There is a need to establish a scientific, objective, and quantitative evaluation mechanism.

Therefore, this study attempts to address the existing problems in equipment training by applying advanced technologies from the field of AI to construct an intelligent equipment training system.

3 BASIC FUNCTIONS OF THE INTELLIGENT EQUIPMENT TRAINING SYSTEM

The intelligent equipment training system constructed in this study mainly realizes the following three functions, and the functional requirements diagram is shown in Figure 1.

(1) Intelligent equipment training knowledge base generation. Through the way of knowledge extraction to extract the effective knowledge contained in the original data, and stored in the knowledge base for the generation of subsequent training question bank to provide material. This part should realize intelligent management of equipment training knowledge.

(2) Personalized test bank generation and result evaluation. According to the training knowledge base automated generation of the test bank, the trainees through the test training to test the mastery of the equipment knowledge. In the test training process, taking into account the differences in work experience, learning ability, etc., to generate targeted, personalized training test bank.

(3) Automatic update of equipment training knowledge base. Intelligent equipment training system through the introduction of incremental learning on the equipment training knowledge base for timely updating, able to identify and delete outdated information from the existing knowledge base, generate new knowledge items, to help trainees quickly learn new equipment training knowledge.

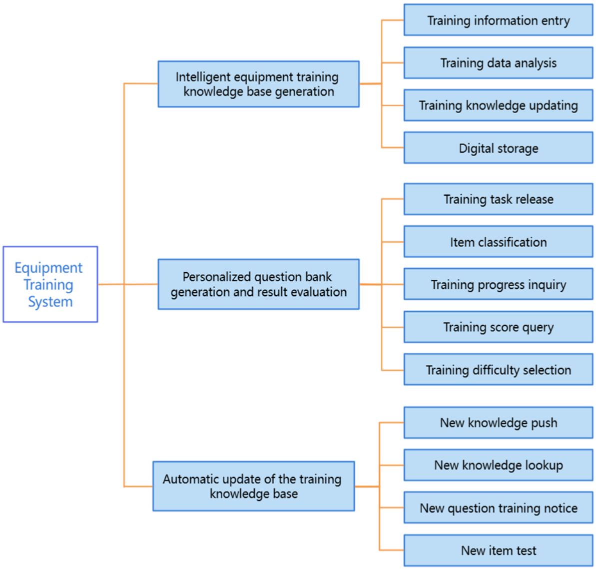

Fig. 1. Functional Requirements of The Intelligent Equipment Training System

Fig. 2. Interface Diagram of The Equipment Training System

4 SYSTEM DESIGN OF THE INTELLIGENT EQUIPMENT TRAINING SYSTEM

The system contains three functional modules: intelligent equipment training knowledge base generation module, test bank generation and training performance evaluation module and incremental knowledge base update module. Figure 2 is the interface design of the equipment training system.

4.1 Constructing Knowledge Base by Using Knowledge Extraction Technology

The equipment training knowledge base is constructed by autonomously mining knowledge items or facts from a variety of unstructured documents. The core knowledge is identified through knowledge extraction methods, and the knowledge elements such as entities, relationships, attributes, etc. are extracted and extracted from the database to construct the equipment training knowledge base. The knowledge mapping technology is used to visualize the training knowledge. Whether it is the knowledge graph of the general domain or the knowledge graph of the military domain, it is essentially a structured semantic knowledge base that stores domain knowledge[4]. The construction method of equipment training knowledge base based on knowledge graph includes the following three main aspects.

(1) Training knowledge ontology modeling: It is to form a collection of knowledge by regularizing and formalizing various training contents, training rules, training standards and other knowledge related to equipment training collected from equipment use instructions, training materials, websites, etc.

(2) Training knowledge storage and representation: It is based on the previous step of training knowledge ontology modeling to extract the "entity-relationship-entity" or "entity-attribute-value" ternary, and store the relevant content in the form of ternary, forming a queryable and deducible knowledge graph model[5]. At the same time, the rule design and decision configuration of the modeling data are carried out to build a knowledge representation model that can generate the equipment training scheme. The knowledge base realizes the representation and invocation of the stored knowledge through query statements and matching algorithms. The architecture diagram of the equipment training knowledge storage is shown in Figure 3.

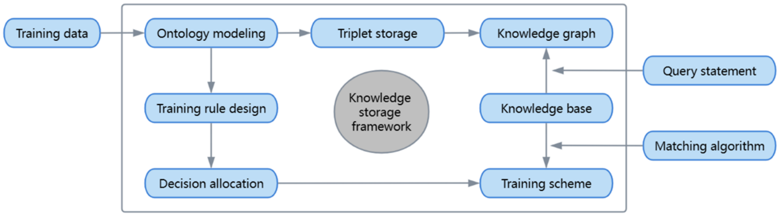

Fig. 3. Equipment Training Knowledge Storage Architecture

(3) Fusion of training knowledge: to ensure the quality of the knowledge in the knowledge base and to make the data logical and hierarchical with each other. In knowledge fusion, there must be many aspects of similarity and difference between the knowledge. Common knowledge similarity calculations generally include distance-based similarity comparison, probability-based similarity comparison and structure-based similarity comparison. Commonly used technical methods mainly include distance calculation, path calculation and semantic analysis. Specifically, such as feature word distribution, LDA topic distribution, and similarity calculation of citation structure network[6].

4.2 Generating Personalized Questions and Grade

In this paper, it is assumed that the question-answer format can be true-false, single choice, multiple choice, or numerical questions. Personalized test questions are developed for the trainee based on the trainee's basic information and daily training performance to solve the problem of the variability of the trainee's training level. Here, KCP-ER, the test item recommendation method proposed by Wu ZY[7], is adopted. It uses recurrent neural networks (RNNs) to predict the coverage of knowledge concepts, and Deep knowledge tracking (DKT) to predict students' mastery of knowledge concepts based on their practice response paper records. The algorithm framework is shown in Figure 4. The process is shown in Figure 5. The system uses the prediction results of the algorithm to filter the question bank, and generates a subset of the questions according to the diversity, difficulty and novelty of the questions. In this way, by solving optimization problems, you can get a complete list of recommended questions.

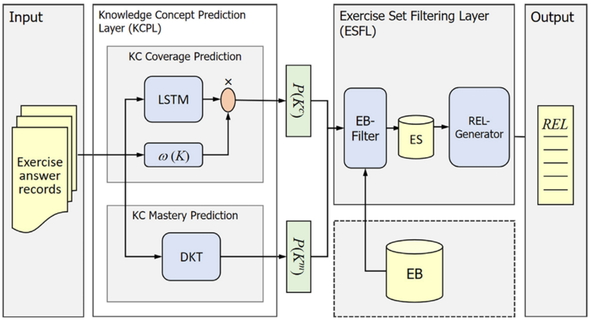

Fig. 4. Framework of KCP-ER[7]

Algorithm 1 KCP-ER

input	$X^1, \ldots, X^K$	// encoded exercise-answer recodes
output	*REL*	// recommended exercises list
require	$\omega(K)$	// weight vector
require	*EB*	// exercise bank
require	δ	// desired difficulty of the exercise
require	*T*	// temperature
require	k_B	// boltzmann constant
require	*c*	// reduction factor
$P(K^c)$	LSTM($X^1, \ldots, X^K$), $\omega(K)$	
$P(K^m)$	DKT($X^1, \ldots, X^K$)	
ES	EB-Filter(EB, $P(K^c)$, $P(K^m)$, δ)	
REL	REL-generator(ES, T, k_B, c)	

Fig. 5. Algorithm Flow of KCP-ER[7]

The test bank module mainly includes two parts: test questions and test papers, of which the management type of test papers can be divided into manual grouping (the trainee sets the type and volume of questions by himself/herself), system intelligent grouping and my test papers. Both test questions and test papers can be used for daily equipment training, but test papers are more comprehensive and suitable for checking the results of recent training.

In order to track the learning effect of the students, the learning curve is introduced to judge the performance of the students in the simulation operation. In 1936, T.P. Wright [8] proposed the learning curve theory, which was firstly applied to the airplane manufacturing industry. The learning and training process of the trainee is in line with the learning curve model. The initial test takes a long time due to the lack of proficiency in theory and insufficient mastery of skills, etc. As the number of training sessions increases and the proficiency in operation improves, the time taken for the training test will decrease. However, after entering the stabilization period, it is difficult to make changes, reflecting that the student's skill mastery level has entered the inflection point, and it is not meaningful to repeat the exercise. The modeling of the student's learning and training process is as follows:

$$S_n = S_1 \cdot n^{-\alpha} \tag{1}$$

Where S1 denotes the score or the number of wrong questions in the first learning test, n denotes the cumulative number of practice sessions, α denotes the learning rate, and Sn denotes the score or the number of wrong questions in the nth learning test.

This system migrates the learning curve model to equipment training, explores the change pattern of the number of exercises and the training effectiveness (the number of test scores or mistakes), and uses this as a benchmark to evaluate the training effect of the whole process of the students. When the results meet the performance threshold required by the training program, and the learning curve tends to stabilize, the students can enhance or maintain the difficulty of training according to their own wishes.

Finally, a management interface with visualization of the trainee's training results is designed to ensure that the trainee can view the learning efficiency, knowledge coverage, and training report analysis.

4.3 Updating Equipment Training Knowledge Base by Using Incremental Learning Technology

The update of equipment training knowledge mainly comes from two aspects: internal update of the system and external update of the system. Internal update refers to the new knowledge generated based on knowledge reasoning and knowledge mining in the knowledge graph; external update is the update of equipment training knowledge when equipment is updated or equipped with new equipment. Internal updates can be realized in the intelligent equipment training knowledge base, while external updates need to be added by system administrators.

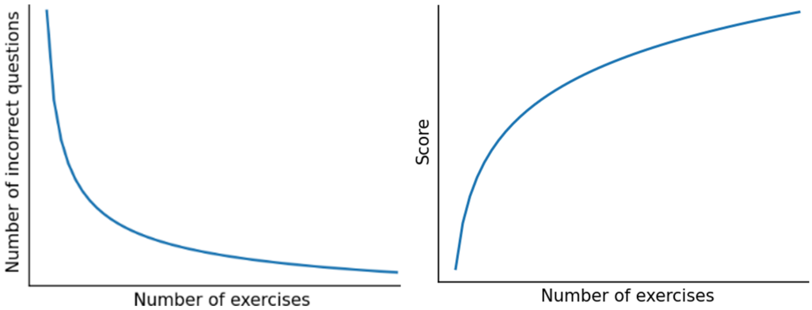

Fig. 6. Learning Curve

Algorithm 2 iCaRL INCREMENTALTRAIN

input $X^s, \ldots, X^t$ // training examples in per-class sets
input K // memory size
require Θ // current model parameters
require $\mathcal{P} = (P_1, \ldots, P_{s-1})$ // current exemplar sets
  $\Theta \leftarrow \text{UPDATEREPRESENTATION}(X^s, \ldots, X^t; \mathcal{P}, \Theta)$
  $m \leftarrow K/t$ // number of exemplars per class
  for $y = 1, \ldots, s-1$ **do**
    $P_y \leftarrow \text{REDUCEEXEMPLARSET}(P_y, m)$
  end for
  for $y = s, \ldots, t$ **do**
    $P_y \leftarrow \text{CONSTRUCTEXEMPLARSET}(X_y, m, \Theta)$
  end for
  $\mathcal{P} \leftarrow (P_1, \ldots, P_t)$ // new exemplar sets

Fig. 7. Algorithm Flow of iCaRL[10]

This study introduces incremental learning algorithms, such as those based on rule sets, based on genetic classification methods, based on Bayesian classification methods, etc., in the updating module of equipment training knowledge[9]. Rebuffi [10] proposed the incremental class learning (iCaRL) strategy, which can achieve incremental learning by using only a portion of the old data rather than all of it, and its algorithmic flow is shown in Figure 7. So we use externally updated new knowledge and a portion of historical knowledge related to it as input for training to obtain new knowledge generated by knowledge mining. After filtering the new knowledge, it is updated to the test module for the trainees to learn.

After updating the knowledge base, the practicality and effectiveness of the new knowledge generated need to be verified by using the feedback and practical application effect of the trainees, and it is expected that through continuous iterative optimization, the knowledge base of the equipment training will be more complete, to satisfy the needs of the trainees' training use. The system collects user feedback through online evaluation and subjective evaluation.

Online evaluation is the process of assessing real user experience metrics and conversion metrics, such as conversion rate, click-through rate, and learning hours per capita, during the process of delivering new knowledge online. The main assessment metrics used in this study are as follows:

$$\text{Average Click-Through Rate (ACTR)} = (T/N) * 100\% \tag{2}$$

Where T is the total number of clicks and N is the total number of generations.

$$\text{Average Conversion Rate (ACVR)} = (C/N) * 100\% \tag{3}$$

Where C is the total number of transformations and N is the total number of generations.

$$\text{Hits Ratio (HR)} = \frac{1}{N}\sum_{i=1}^{N} hits(i) \tag{4}$$

Where N is the total number of users and hits(i) is whether the value of the ith user's actual interaction (clicking, testing, etc.) is in the recommended test question or not, 1 if it is and 0 otherwise.

$$\text{Novelty} = (N_u/N_n) * 100\% \tag{5}$$

Where Nu the number of previously unknown questions by the user in the recommended test questions and Nn the total number of recommended test questions.

After the new knowledge is generated and put online, we can get the real evaluation of the new knowledge by subjective evaluation. After the students learn the new knowledge and complete the test questions, the system actively pushes the evaluation questionnaire to the students, inviting them to score each type of test questions they have completed. The most satisfied is 100%, unsatisfied is 0%. The results of the questionnaire evaluation, combined with the trainees' test scores, were used to evaluate the quality of the new knowledge.

Combining the index calculation of online assessment with the satisfaction score obtained from subjective assessment, the new knowledge generated is evaluated to find out the existing problems, adjust the algorithm and parameters of the system, and optimize and supplement. Only by objectively and scientifically evaluating the effectiveness of the new knowledge and verifying its practicality can the equipment training knowledge base be made more complete and more accurate, and better help the trainees in knowledge learning and equipment training.

5 CONCLUSION

In order to improve the intelligent management level of equipment training and realize the dynamic management of equipment training work and training efficiency, this paper combines the problems of training management and the actual situation of training, combines equipment training management with artificial intelligence, and designs an intelligent equipment training system. The main contributions and innovations of this study include: first, the introduction of incremental learning in the process of creating a knowledge base to realize the automatic update of the equipment training knowledge base. Second, personalized test questions and test papers are generated. Trainees select the difficulty of training according to their own learning situation, set the combination of test papers according to their personal preferences. It supports personalized test adaptive training for trainees. Third, according to the training assessment results and performance thresholds to test the user's understanding of the training knowledge, generate targeted equipment training program.

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