



A knowledge push technology based on applicable probability matching and multidimensional context driving^{*}

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Abstract: Actively pushing design knowledge to designers in the design process, what we call ‘knowledge push’, can help improve the efficiency and quality of intelligent product design. A knowledge push technology usually includes matching of related knowledge and proper pushing of matching results. Existing approaches on knowledge matching commonly have a lack of intelligence. Also, the pushing of matching results is less personalized. In this paper, we propose a knowledge push technology based on applicable probability matching and multidimensional context driving. By building a training sample set, including knowledge description vectors, case feature vectors, and the mapping Boolean matrix, two probability values, application and non-application, were calculated via a Bayesian theorem to describe the matching degree between knowledge and content. The push results were defined by the comparison between two probability values. The hierarchical design content models were built to filter the knowledge in push results. The rules of personalized knowledge push were sorted by multidimensional contexts, which include design knowledge, design context, design content, and the designer. A knowledge push system based on intellectualized design of CNC machine tools was used to confirm the feasibility of the proposed technology in engineering applications.

Key words: Product design; Knowledge push; Applicable probability matching; Multidimensional context; Personalization
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1 Introduction

Knowledge push is one of the key technologies in intelligent product design, which is the future direction of manufacturing (Xu et al., 2013). Knowledge push technology actively provides designers with useful design knowledge in product design, and this can resolve knowledge flooding, knowledge trek, and other issues. The essence is “to push the right knowledge to the right person at the right time in the right way (R4)” (Schreiber, 2000). Current studies are

conducted around these R4 aspects, and contain mainly three types of approaches: collaborative filtering recommendation, content-based recommendation, and mixed recommendation.

Collaborative filtering recommendation was proposed by Goldberg et al. (1992) in the experimental system ‘Tapestry’, and has been rapidly developed later. There are three types of collaborative filtering methods, based on user, project, and model, respectively. The user-based method focuses on the user’s characteristics and pushes the items of interest (Fan et al., 2005; Xu et al., 2013). The project-based method focuses on the characteristics of a project and pushes new items with high similarity to the previous one (Zhou et al., 2009; Jiang et al., 2012). The model-based method uses machine learning and data mining algorithms to build a learning model and push knowledge (Shen et al., 2015; Feng et al., 2016). Content-based recommendation focuses on a specific

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user, building projects and demanding models to match and push knowledge (Liu et al., 2016; Wang et al., 2016; Zhang and Li, 2016). Mixed recommendation mixes and develops several recommendation methods (Yoshii et al., 2008). According to the literature, knowledge matching is the basic goal of knowledge push. Nowadays, personalized knowledge push has attracted more attention.

Knowledge matching aims to find the design knowledge relevant to the design tasks or designer demands to push. Some methods and theories have been proposed to improve the matching accuracy. The most common method is similarity calculation between the design tasks and knowledge, including similarity of text (Wang SF et al., 2007; Wang S et al., 2009; Yan et al., 2016) and semantic distance (Xu et al., 2013). Mao et al. (2012) combined these two methods for knowledge matching. Furthermore, Wang et al. (2016) proposed three different types of semantic similarity calculation with function-behavior-structure (FBS). Shen et al. (2015) calculated the characteristic similarity between function and structure by conditional probability. Some researchers built the mapping relation between cases and design knowledge, and compared the similarity between the design task and cases to obtain the design knowledge to push (Zhou et al., 2009; Jiang et al., 2012). Similarly, Xu et al. (2016) used frequent sequential pattern technology to mine the historical knowledge usage data, and finished knowledge matching and pushing according to the current knowledge sequence. There are some other methods to match knowledge without calculating similarities. For example, knowledge push rules were extracted from variable precision rough sets (Ji et al., 2013), and the matching knowledge can be searched in the ontology model (Wang et al., 2015). Knowledge can be matched through hierarchical spreading activation (Liang et al., 2015) or knowledge clustering collection (Li et al., 2017) in knowledge complex network theory. Dong et al. (2013) simulated the immune process, and proposed a knowledge module-artificial immune algorithm (KM-AIA) combined algorithm and entropy method to match the knowledge.

Personalized knowledge push is more challenging. Different designers may need different knowledge in the design process. In the past few years, researchers have paid more attention to personalized knowledge push. The simpler methods are secondary

filtering for knowledge streamlined (Feng et al., 2016) and sorted by importance. Ji et al. (2013) calculated designer's familiarity with knowledge by forgetting curves. Li et al. (2017) proposed an acquaintance immune strategy to guarantee the novelty of the product design knowledge in the subsequent push link. Researchers usually built designer capability models (Feng et al., 2016; Jiang et al., 2017), personalized interest models (Zhi et al., 2011), or compound knowledge frameworks (Fan et al., 2005) for personalized knowledge push. Intent capture is an effective way for personalization (Xu et al., 2013; Wang et al., 2016). Chen et al. (2015) used an acoustic energy feature and creative segment theory to capture intent and demands during sketching. With the development of the Internet, big data collection and mining can help analyze the designer's behavior in the web and the knowledge usage for personalized knowledge push (Li et al., 2015).

The knowledge matching methods, commonly using similarity calculation, set the filtering threshold according to experiments and manual intervention. Recent studies have focused on how to reduce human factors and improve intelligence. This is also the innovation of this study. Further, researchers have proposed various methods for personalized knowledge push. Some advanced methods, such as design intent capture, interest acquisition, are in the early stages of research and are not mature. The methods of secondary filtering and sorting have not been further developed. This study improves the relevant theory of sorting used in practical engineering for personalized knowledge push.

In current studies, a new method of knowledge push technology based on applicable probability matching and multidimensional context driving is proposed to solve the two abovementioned problems. As shown in Fig. 1, the design tasks are first imported in the knowledge push system, and then different designers log into the system. Combining design content with the knowledge center, the applicable probability matching method serves knowledge matching by using probability theory. Next, the matched knowledge needs to be processed for personalization. The methods of personalized knowledge push are sorted by multidimensional contexts, including design knowledge, design context, and the designer. Finally, the highly demanding knowledge can be ranked first in the push queue.

3 Applicable probability knowledge matching method

3.1 Hierarchical design content modeling

The design content in the product design process is described as a design feature vector. In particular, this vector has impact on the push results. The different abilities in the design process lead to the different knowledge requirements for different designers; thus, a hierarchical design content model is built for personalized knowledge push. The design department will prejudge the designer's ability when assigning the design task, and the ability is divided into three categories: skilled, general, and rusty.

Definition 5 (Design feature vector) The design feature vector is $\mathbf{content} = \{(\text{word}_1, q_1), (\text{word}_2, q_2), \dots, (\text{word}_t, q_t)\}$, where word_j ($j=1, 2, \dots, t$) is the j^{th} content feature, q_j is the j^{th} feature weight, and t is the total number of content features.

For different designers with the same design content, features are constant and weights are changed. The rusty designers need more knowledge, and thus the values of low weight features should be raised. Conversely, the values of high weight features are reduced for skilled designers. The weights for general designers are unchanged, and the feature weight q is expressed by Eqs. (2)–(4):

$$q_s = \begin{cases} q_g \eta_s, & q_g > \alpha_s, \\ q_g, & q_g \leq \alpha_s, \end{cases} \quad (2)$$

$$q_g = \frac{\left(\sum_{m=1}^4 \delta_m \text{tf}_{jm}\right) \cdot \text{idf}_j}{2 + \left(\sum_{m=1}^4 \delta_m \text{tf}_{jm}\right) \cdot \text{idf}_j}, \quad (3)$$

$$q_r = \begin{cases} q_g \eta_r, & q_g < \alpha_r, \\ q_g, & q_g \geq \alpha_r, \end{cases} \quad (4)$$

where q_s , q_g , and q_r denote skilled, general, and rusty weights, respectively. q_g is similar to s_k in Eq. (1), η_s , η_r are variable-weight coefficients, and α_s , α_r are variable-weight intervals. The variable-weight design feature vector can filter the push results properly, but the parameters need to be determined by repeated experiments.

3.2 Applicable probability matching

In this study, knowledge matching is performed using the method of applicable probability matching.

Two probability values, i.e., application and non-application, are calculated to describe the matching degree between knowledge and content. λ_{ci} is the matching result and is expressed as

$$\lambda_{ci} = \begin{cases} 1, & \text{application,} \\ 0, & \text{non-application,} \end{cases} \quad i = 1, 2, \dots, N. \quad (5)$$

If the applicable probability $P(\lambda_{ci}=1|\mathbf{content})$ is larger than the non-application probability $P(\lambda_{ci}=0|\mathbf{content})$, $\lambda_{ci}=1$ and doc_i applies to $\mathbf{content}$, and the knowledge set $\{\text{doc}_i|\lambda_{ci}=1\}$ shows the push results in this design content.

The Naive Bayes classifier (Friedman et al., 1997) is adopted to calculate the applicable probability based on training sets. There are N knowledge description vectors to be matched with the design feature vector $\mathbf{content}$, and it is necessary to classify the $\mathbf{content}$ N times. The classification result is described by Eq. (5), and defined as ε in the following.

Using the Bayesian theorem the posterior probability can be transformed into an a priori probability:

$$P(\varepsilon|\mathbf{content}) = \frac{P(\varepsilon)P(\mathbf{content}|\varepsilon)}{P(\mathbf{content})}, \quad (6)$$

where $P(\varepsilon)$ is the a priori probability, $P(\mathbf{content}|\varepsilon)$ is a class-conditional probability, and $P(\mathbf{content})$ is the normalized evidence constant (Friedman et al., 1997).

$$P(\varepsilon) = |\chi_\varepsilon|/|\chi|, \quad (7)$$

where χ_ε is the set of ε cases in χ , and $|\cdot|$ means the number of elements in the set.

$P(\mathbf{content}|\varepsilon)$ is defined in Eq. (8), if features are independent of one another. q_{cj} is the j^{th} feature weight in $\mathbf{content}$, d is the total number of features in the training data set, and $P(q_{cj}|\varepsilon)$ is described in Eq. (9).

$$P(\mathbf{content}|\varepsilon) = \prod_{j=1}^d P(q_{cj}|\varepsilon), \quad (8)$$

$$P(q_{cj}|\varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_{\varepsilon,cj}} \exp\left(-\frac{(q_{cj} - \mu_{\varepsilon,cj})^2}{2\sigma_{\varepsilon,cj}^2}\right). \quad (9)$$

As shown in Eq. (9), the feature weight is calculated using a probability density function, where $\mu_{\varepsilon,cj}$ is the weight mean and $\sigma_{\varepsilon,cj}^2$ is the weight

variance in the ε cases set. $P(q_{cj}|\varepsilon)$ is calculated in the training set.

According to Eqs. (6) and (8), the matching result in Eq. (5) is defined by comparing $P(\lambda_{ci} = 1) \cdot \prod_{j=1}^d P(q_{cj} | \lambda_{ci} = 1)$ with $P(\lambda_{ci} = 0) \prod_{j=1}^d P(q_{cj} | \lambda_{ci} = 0)$, where $P(\varepsilon) \prod_{j=1}^d P(q_{cj} | \varepsilon)$ is the applicable probability relative value.

4 Sorting personalized push results driven by multidimensional context

4.1 Multidimensional context-driven sorting rules

The multidimensional context decides the final sorting rules from the four dimensions, including design knowledge, design context, design content, and the designer. The following four requirements should be met:

1. The sorting method is based on design knowledge. The knowledge in the push queue is divided into five categories based on the classification in the knowledge description vector **doc**.

2. The sorting method based on design context is influenced by different contexts in product collaborative design. In the scheme design stage, the drawing knowledge and case knowledge are placed in the head of the push queue. In the technical design stage, text knowledge, chart knowledge, and formula knowledge are placed in the head of the push queue. Each design task has its matching context and is related to each other. As shown in Fig. 3, the inheritance and feedback information of the design content result is defined as τ , which should be noted and is the feedback in real time.

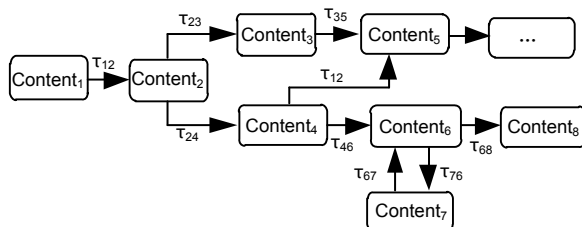


Fig. 3 Flow diagram in design context

3. The sorting based on design content is carried out according to the design specification in the various stages of product design. If there are keywords in the design specification, such as ‘calculate’, ‘check’,

and ‘formula’, formula knowledge will be sorted before chart knowledge. If the keywords are ‘compare’, ‘inquire’, and ‘select’, chart knowledge will be sorted before formula knowledge.

4. The sorting method based on the designer is divided into two parts, explicit behavior and implicit behavior. Designers with different abilities would have different knowledge requirements in the same design process, which is the most uncontrollable factor, and thus personalized knowledge push requires much work and effort. This sorting method is based on designer’s abilities and knowledge application.

Explicit behavior is defined as the designer participation in old cases. We compare the designer who completes a drawing or has case knowledge in the push results with the designer in the current context. If they are the same, this knowledge will be put in the back of the push queue; otherwise, this knowledge has precedence and will be put in the front.

Implicit behavior is defined as a designer’s knowledge, adopting the Ebbinghaus forgetting curve (Dong et al., 2017). Through the application in **doc**, the familiarity with design knowledge is calculated among all designers in Eq. (10), and the knowledge in the push results will be sorted second in categories.

$$W_t = 68.2 \exp(-1.068\Delta T) + 31.8 \exp(-2.88 \times 10^{-4} \Delta T), \tag{10}$$

where W_t is the familiarity (the maximum value is 100), and ΔT is the time interval in days.

4.2 Workflow of design knowledge push

Fig. 4 shows the workflow of knowledge push based on applicable probability matching and multidimensional context driving. It consists of the following four stages:

1. Knowledge and case models are built and the training set is generated;

2. Knowledge is matched according to the applicable probability, and the results to be pushed are obtained;

3. The multidimensional contexts including design knowledge, design context, design content, and the designer affect the sorting rules for personalized knowledge push;

4. Knowledge push is completed, and the data including the training set and the application in **doc** is updated.

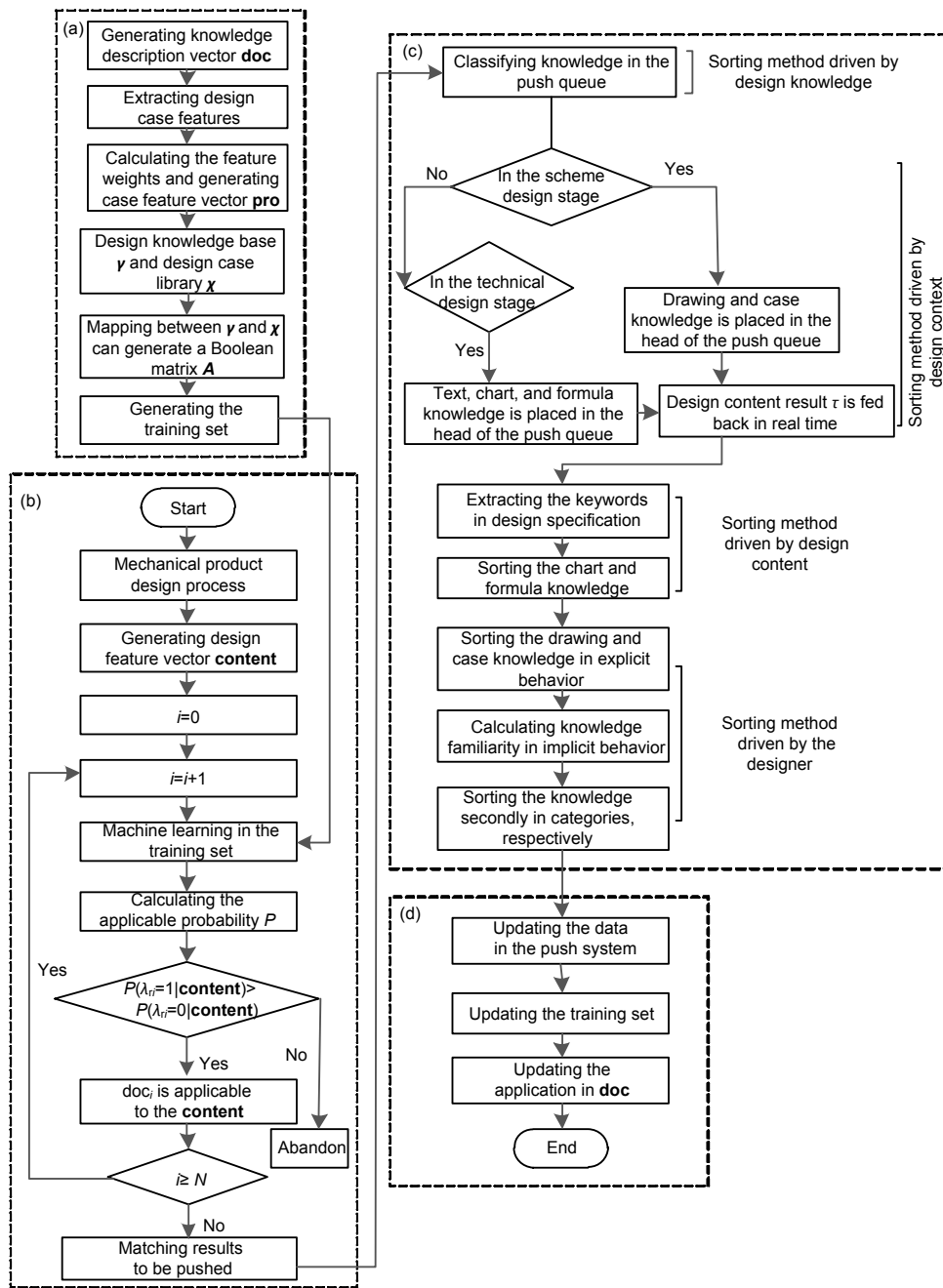


Fig. 4 Flow diagram for design knowledge push: (a) generating the training set; (b) knowledge matching; (c) personalized knowledge push; (d) completing and updating

5 An illustrative example

A knowledge push system based on applicable probability matching and multidimensional context driving was developed and used in the intellectualized design of CNC machine tools. As it is typical in

complex mechanical equipment, there is a lot of design knowledge in designing CNC machine tools. The horizontal lathe guides are the main parts of the machine. These are taken as an example to evaluate our proposed method in the design platform of CNC machine tools.

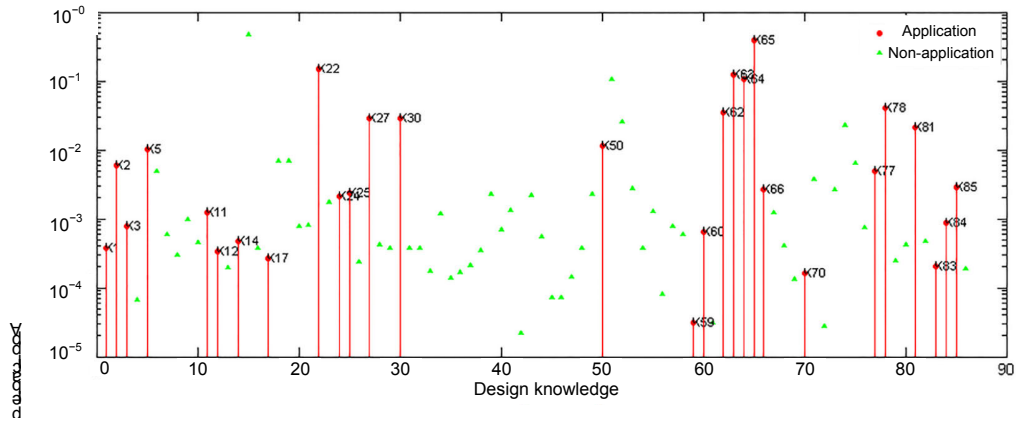


Fig. 6 Results for design knowledge matching (References to color refer to the online version of this figure)

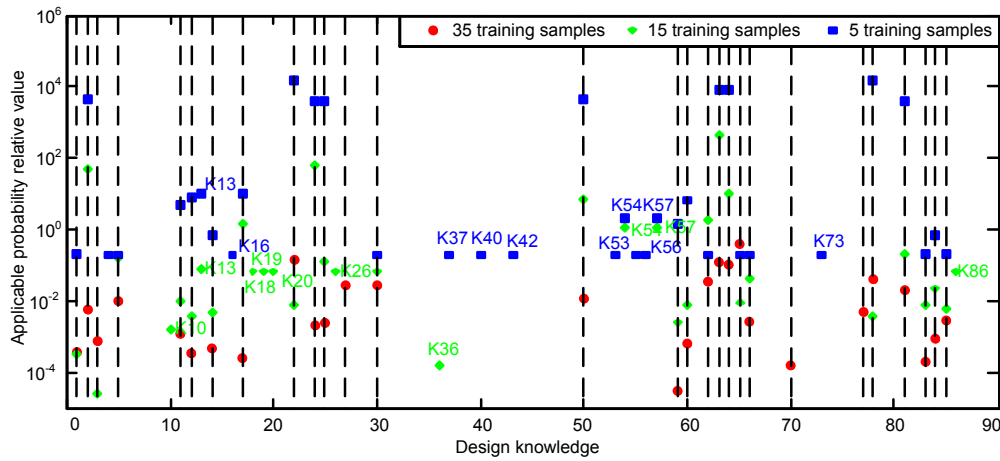


Fig. 7 Results for design knowledge matching in different training sets (References to color refer to the online version of this figure)

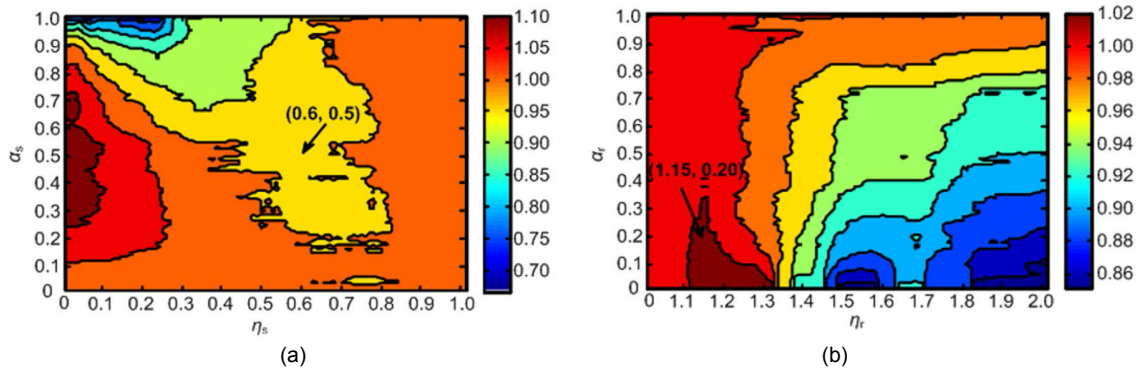


Fig. 8 Evolution of design knowledge matching results: (a) variable-weight coefficients η_s and intervals α_s for skilled designers; (b) variable-weight coefficients η_r and intervals α_r for rusty designers (References to color refer to the online version of this figure)

The results show that the design knowledge matched by applicable probability can avoid manual setting of the filter threshold, which makes up for the shortcomings of similarity calculation in previous studies. Furthermore, some researchers (Zhou et al.,

2009; Jiang et al., 2012) found design cases similar to the design content from the knowledge center to obtain the push results. However, if there is no design case similar to the design content, knowledge matching will not be realized. The applicable probability

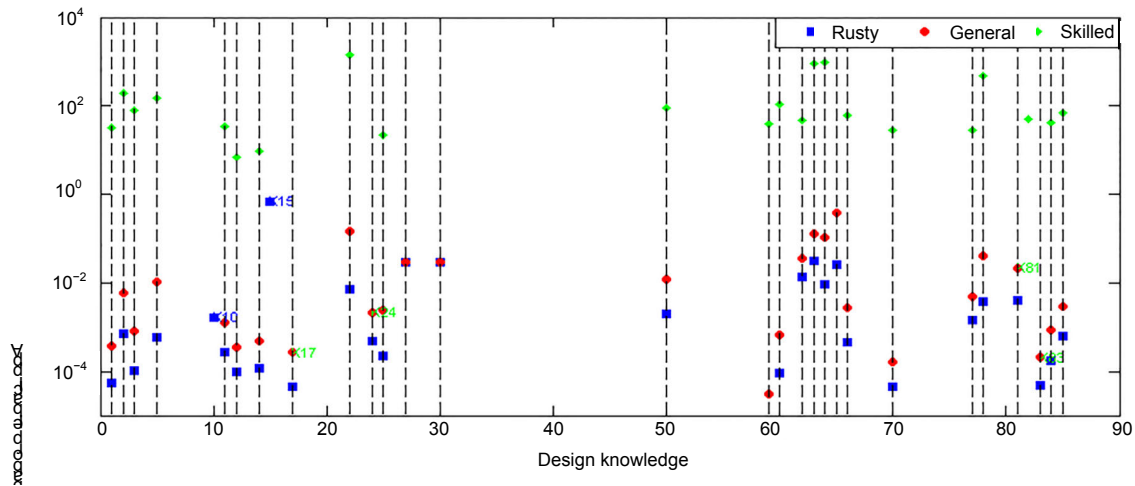


Fig. 9 Results of design knowledge matching for designers with different abilities (References to color refer to the online version of this figure)

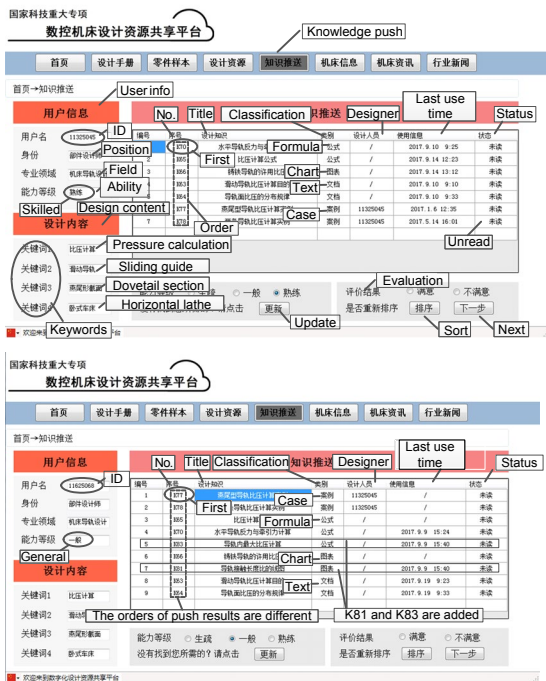


Fig. 10 Push results for two different designers

matching method proposed here can provide accurate matching results even for unknown design content by using a training set and the Bayesian theorem.

The hierarchical design content models and multidimensional context-driven sorting rules are used to serve the personalized knowledge push in this study.

A group of designers made a positive evaluation of the knowledge push system in a machine tool

design test. Designers could benefit from the knowledge in the head of the push queue, which can mostly meet their own demands, and correspondingly they can find the demanding knowledge more quickly. Sorting theory is a simple way to achieve personalization. In this study, we developed and consummated the sorting theory compared with previous studies (Liang et al., 2015; Feng et al., 2016) to make the results more personalized. Some advanced methods, such as intent capture, electroencephalogram (EEG) recognition, and behavior modeling, are still in the early stages of research. In the current stage, the method proposed in this study can be better applied in engineering. Different designers can shorten the time to browse knowledge and improve design efficiency.

6 Conclusions

In this paper, a knowledge push technology based on applicable probability matching and multi-dimensional context driving was proposed to improve the efficiency and quality of knowledge push:

1. We proposed the applicable probability matching method in knowledge matching. Two probability values, i.e., application and non-application, were calculated using a Bayesian theorem to describe the matching degree between knowledge and content. Different from traditional knowledge matching methods, this method can set the filtering threshold automatically.

2. We proposed hierarchical design content models and multidimensional context-driven sorting rules to serve personalized knowledge push. The hierarchical design content models overcame the deficiency that a traditional model cannot meet different designers' requirements. The multidimensional context driven sorting of the push results ensures that designers can find the highly demanded knowledge as soon as possible.

3. We developed a knowledge push system based on the intellectualized design of CNC machine tools and provided an illustrative example on the design of horizontal lathe guides. Experimental results showed that the push results are accurate, and that the system can provide a personalized knowledge push service.

Our proposed knowledge push technology can solve the problems of knowledge matching and personalized knowledge push, but there are some aspects that need to be improved. In hierarchical design content models, the parameter values in Eqs. (2)–(4) are difficult to set; once they are chosen, they cannot guarantee uniformity in different design contexts. This may affect the accuracy and satisfaction in personalized knowledge push. The refinement and personalization improvement of push results will be the focus of our future work.

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