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Personalized knowledge push system based on design intent and user interest

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Abstract

Existing knowledge provides important reference for designers in mechanical design activities. However, current knowledge acquisition methods based on information retrieval have the problem of inefficiency and low precision, which mainly meet the requirement for knowledge coverage. To improve the efficiency of knowledge acquisition and ensure the availability of design knowledge, this paper proposes a knowledge push service method based on design intent and user interest. First, the design intent model, which is mainly the formal expression of the target function of conceptual design, is built. Second, the user interest model that consists of domain themes and operation logs is built, and an automatic updating method of user interest is proposed. Third, a matching method of design knowledge based on design intent, and a sorting algorithm of knowledge candidates based on user interest are proposed to realize personalized knowledge active push service. Finally, a prototype system called Personalized Knowledge Push System for Mechanical Conceptual Design (MCD-PKPS) is implemented. An illustrative case demonstrates that the proposed method can successfully improve the efficiency and availability of knowledge acquisition.

Keywords

Conceptual design, design intent model, user interest model, user interest update, knowledge push

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Introduction

Product life cycle (PLC) includes a series of phases, sequentially are demand analysis, concept definition, product design, product manufacture, product maintenance, and so on, in which design improvement achieves more social and economic benefits. Product design aims at creating new products, and especially in the conceptual design phase, the constraints on designers are relatively few, which give designers a large space to innovate. Statistics shows that 75% of lifecycle costs have been decided in the product design phase.[1] Meanwhile, other subsequent phases of PLC are difficult to correct or make up for the deficiencies of conceptual design.[2] As a consequence, conceptual design to a large extent determines the market competitiveness of products.

More than 70% of design works are variant design and adaptive design of existing products.[3] Any design activities requires numerous knowledge as a reference, and conceptual design is no exception. If designers can get the design knowledge that completely satisfied their demand, design reuse significantly shorts design times, reduces costs, and avoids repetitive errors. On the other hand, even if the knowledge does not fully conform to the demand, some knowledge with similar function or similar shape may also inspire the creativity and imagination of designers, and then impel designers to look for other ways to get satisfied knowledge. However, it costs a lot of time and energy to manually search information from Internet or local design cases in traditional mechanical design. The most common way of knowledge acquisition is keyword-based knowledge retrieval, such as Google. In the mechanical conceptual design phase, designers are usually only knowledgeable about desired functions and do not have idea of the mechanical structures and names of desired knowledge, so only keyword-based knowledge retrieval method cannot satisfy the requirement of conceptual design in essence. Meanwhile, making selection from search results mainly relies on experience and intuition, and it is hard to ensure the availability of search results. In recent years, more advanced and efficient ways of knowledge acquisition have been proposed to construct domain knowledge system and facilitate knowledge reuse, such as product development-oriented knowledge acquisition in knowledge grid,[4]

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knowledge acquisition based on machine learning,[5] knowledge acquisition based on expert system,[6] knowledge acquisition based on data mining,[7] knowledge acquisition based on human–computer interaction,[8] design knowledge acquisition based on ontology semantic retrieval,[9] and so on. However, the initiator of knowledge acquisition from knowledge system is still humans, and still with the search method based on keyword rather than functional semantics requirements. Thus, the knowledge systems are still a disadvantage for conceptual design in essence. Therefore, there is an urgent need of an efficient and accurate knowledge acquisition method, which is much helpful to implement the design reuse and conceptual innovation design. The proposed knowledge push method based on conceptual design intent and user interest in this paper paves a new way for it.

Knowledge push system can intelligently understand user requirements, and then actively push proper knowledge to users at the proper time after personalized knowledge matching and filtering. Knowledge push will improve the efficiency of knowledge acquisition and the availability of design knowledge, thus making up for the inadequacy of traditional knowledge acquisition methods. Knowledge push evolved from the concept of information push, and it was first presented by Ricadela, the chief editor of InformationWeek, in 2000 and defined as a new networked knowledge service mode.[10] At present, the studies on knowledge push mainly focused on marketing and information science, and the pushed knowledge were mainly business information.[11–13] With the change of customer demand in business-oriented enterprise, knowledge push service accelerated the transfer of knowledge and improve the reuse efficiency of enterprise resources.[11–13] There are some similarities between the knowledge push in mechanical design and in enterprise business, but comparing with business process, mechanical design activities also have additional characteristics that the sources of knowledge are extensive and the types of knowledge are various. Only a few studies and applications of knowledge push were carried out in the domain of mechanical design. For the shortage of existing systems that knowledge cannot be pushed actively to the proper designer at the proper time, Wang et al.[14] proposed a knowledge active push framework based on knowledge management and workflow. Ji et al.[15] proposed a design knowledge push technology based on ontology and rough sets, and they established the ontology models of product design task and design knowledge, and then extracted knowledge push rules from design knowledge using log.

Existing research cannot satisfy the requirement of knowledge acquisition in the conceptual design phase. The main arguments of knowledge push in the mechanical conceptual design phase are design intent and user interest. Design intent is the reflection of the design idea in designers' brain. Some researchers believed that the design intent of conceptual design is the reflection of product function in design process, and designers can express design intent by expressing target function.[16,17] Mun et al.[16] defined design intent as the functional requirements provided by customers, and proposed a macro-parametric approach based on the modeling commands sequence of operations issued to express design intent. Feng et al.[17] proposed that the design intent of product correlation structures could be extracted from the function description information of product evolutionary design. Sun et al.[18] proposed a representation method of design intent in design thinking process model, and they divided design intent into designers' intent and design process intent, in which designers' intent was mainly the expression of target function. Chen et al.[19] presented a method to mine design intent from products and used function model to express design intent. On the study of some prototype design systems, design intent was captured by users' strokes of sketching behaviors when users interacted with the system, and the prototype systems were mainly used for the conceptual design of product shape.[20,21] Eddy et al.[22] presented an e-Design framework that enabled the implementation of integrated design information throughout the entire design process. The design intent was captured by the complete set of modular ontologies during the conceptual design to improve the transparency of design knowledge from design conception to completion. But the design intent model was not given in the paper.

Designers are the main part of mechanical design activities, as well as the receiver of knowledge push service. The domains that designers interested largely reflect their demand for knowledge. Personalized service system based on user interest is a hotspot in the domain of marketing and e-commerce, while similar knowledge push service is few in product design process. Feng et al.[23] analyzed and summarized the actual demand of knowledge in customer service center, and then proposed a method of constructing knowledge push system that oriented customer interest. Wu et al.[24] proposed a user interest modeling method based on dynamic self-organizing map neural network, the process of user interests modeling was mapped into a clustering and cluster-maintenance process, and the update of user interests was depicted by neural cell change. Li et al.[25] constructed user interests model based on the analysis of multi-agent search behavior, and thus enabled the results of search engine closer to user needs. Yan et al.[26] proposed a personalized recommendation algorithm on the basis of constructing ontology-based user interest model and improving model stability by updating. Widyantoro et al.[27] proposed an adaptive algorithm to learn user interest dynamics with a three-descriptor representation, and the three-descriptor model maintained a long-term interest descriptor to capture user's general interests and a short-term interest descriptor to keep track of user's recent fast-changing interests. User interest model was also commonly used in personalized summarization system to improve the accuracy of text summarization.[28,29]

In conclusion, knowledge push will improve the efficiency of knowledge acquisition and ensure the availability of design knowledge, and while the research and application of knowledge push service used in mechanical conceptual design is few, there is still much space for a deeper and more extensive research. Therefore, this paper proposes a knowledge push method based on design intent and user interest, which provides more accurate support for conceptual innovation design. The rest of the paper presents the proposed methods and their implementation. The following section builds the formal design intent model of conceptual design. Then building and updating of user interest model are introduced in the next two sections. On the basis of design intent model and user interest model, a knowledge push method is proposed to realize better personalized service. Finally, the architecture of the prototype system, together with an application case, is illustrated to verify the availability of the proposed knowledge push method.

Design intent model of mechanical conceptual design

Design intent is the primary argument of knowledge push service. Formal expression of vague design intent will facilitate the mapping between design intent and the knowledge in repository. By establishing design intent model, the knowledge acquisition in conceptual design phase is transformed into the problem of standardized knowledge matching based on design intent model. Design intent derives from actual demand, and the target function of product is the best reflection of design intent in conceptual design phase, so the design intent model is built by the formal expression of target function. According to different types of design knowledge in mechanical domain, the formalization of function adopts three different representation methods which, respectively, are *keyword representation*, *verb–noun representation*, and *input–output flow representation*. The schema of design intent model is shown in Figure 1.

Keyword representation

Keyword representation is adopted to formally express the function of document knowledge. The functions of design documents are expressed with a limited number of keyword set. Keywords are divided into two levels: domain theme vocabularies and detailed knowledge vocabularies. Domain theme vocabularies include the regular categories of mechanical design, such as connectors and fasteners, shaft and its fitting design, bearing, mechanical drive design, mechanism design, etc. Detailed knowledge vocabularies are the further classifications of each domain theme. The list of keyword vocabularies are shown in Table 1.

Verb-noun representation

Verb–noun representation is adopted to formally express the function of 3D model knowledge.

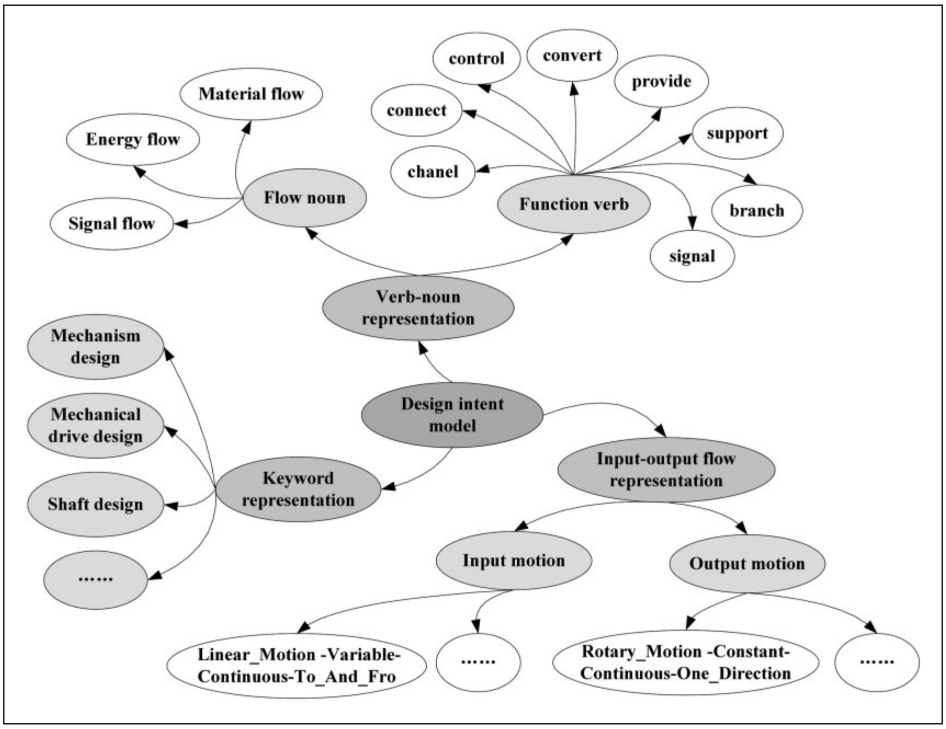

Figure 1. The schema of design intent model.

Table 1. Keyword vocabularies listing.

Theme vocabularies	Detailed knowledge vocabularies
Connectors and fasteners	Hexagon bolt, square-head bolt, cross recessed flat head screw, set screw, hexagon nut, round nut, washer, ring, flat key, feather key, woodruff key, taper key, spline, cylindrical pin, taper pin, cotter pin, safety pin, etc.
Shaft and its fitting design	Arbor, transmission shaft, spiale, crank shaft, flange coupling, parallel shaft coupling, roller chain coupling, universal coupling, diaphragm coupling, spring coupling, elastic pin coupling, friction clutch, electromagnetic clutch, hydraulic clutch, pneumatic clutch, etc.
Bearing	Cylindrical roller bearing, conical roller bearing, needle bearing, deep groove ball bearing, angular contact ball bearing, self-aligning ball bearing, self-aligning roller bearing, thrust ball bearing, cylindrical roller thrust bearing, tapered roller thrust bearing, journal bearing, plain thrust bearing, thrust-purnal bearing, self-aligning sliding bearing, etc.
Mechanical drive design	Flat belt drive, V-belt drive, multi wedge belt drive, synchronous belt drive, roller chain drive, cylindrical gear drive, bevel gear drive, worm drive, planetary gear drive, reducer gear drive, lead screw drive, etc.
Mechanism design	Planar linkage mechanism, hinge screw mechanism, slider-crank mechanism, guide bar mechanism, rock slider mechanism, sine mechanism, tangent mechanism, cam mechanism, ratchet mechanism, geneva mechanism, intermittent gearing mechanism, cam linkage combined mechanism, gear linkage combined mechanism, etc.

The formal expression of the function of 3D model takes the functional basis[30] as reference, in which product function was characterized in a verb-object (function-flow) format. Clear definitions and consistent classifications of the function basis were intended to comprehensively describe the mechanical design space of conceptual design. In functional basis, flows were classified into three basic categories: material flow, energy flow, and signal flow; functions were classified into eight basic categories: branch, channel, connect, control, convert, provide, signal, and support. The basic classes of flows and functions were subdivided again. In this paper, some modifications are made for the flows and functions in functional basis, to both ensure the classifications as few as possible and own the ability to comprehensive describe the function of 3D model. For example, the solid flow is farther subdivided into parts, tool, clamp, workpiece, and Raw_material. Stop is subdivided into the subfunction of "control" instead of the subfunction of "support", and contain and bear are added to the subfunctions of "support". As a result, the function of guide rail is described as 'bear-parts, guide-parts'. Figure 2 shows the flow classifications, and Figure 3 shows the function classifications.

Input–output flow representation

Input–output flow representation is adopted to formally express the function of mechanism knowledge. Mechanism is the moveable connection of components to achieve required motion, so the function is expressed by describing the motion behavior of mechanisms using *input–output flow representation*. Motion behavior is described with a combination of five attributes: motion type, motion stability, motion continuity, motion direction, and the interchangeability between input motion and output motion. For ease of the matching of motion behavior, motion behavior is represented as a standard coding sequence in this paper. For example, the motion types (Linear_Motion, Rotary_Motion, Rocking_Motion, Other_Motion) are, respectively, encoded as (0, 1, 2, 3). The detailed coding definition for each attribute of motion behavior is shown in Table 2. According to above standard definition, the motion code of slider-crank mechanism is described as '(10000, 01010)'.

User interest model

Designers' subject area can be inferred from user interest, and user interest is the secondary argument of knowledge push service in mechanical design activities. User interest has a strong dynamic. With the change of user demand, some new interest will generate, some old interest will be eliminated, and some interest will remain stable. As a consequence, the user interest model here contains two parts, one is the domain theme that describes long-term interests and the other is the operation log that describes short-term interests. In the later illustrative case, the initial defined items (e.g. crank shaft, slider crank mechanism, etc.) in Figure 11 are all long-term interests, and the newly added items (e.g. crosshead, cam-linkage mechanism, etc.) in Figure 13 are short-term interests. The schema of user interest model is shown in Figure 4.

Domain themes of user interest model

Domain themes are the summarization and classification of subject knowledge that designers are interested for a long time. Knowledge in the same domain theme usually has similar forms and

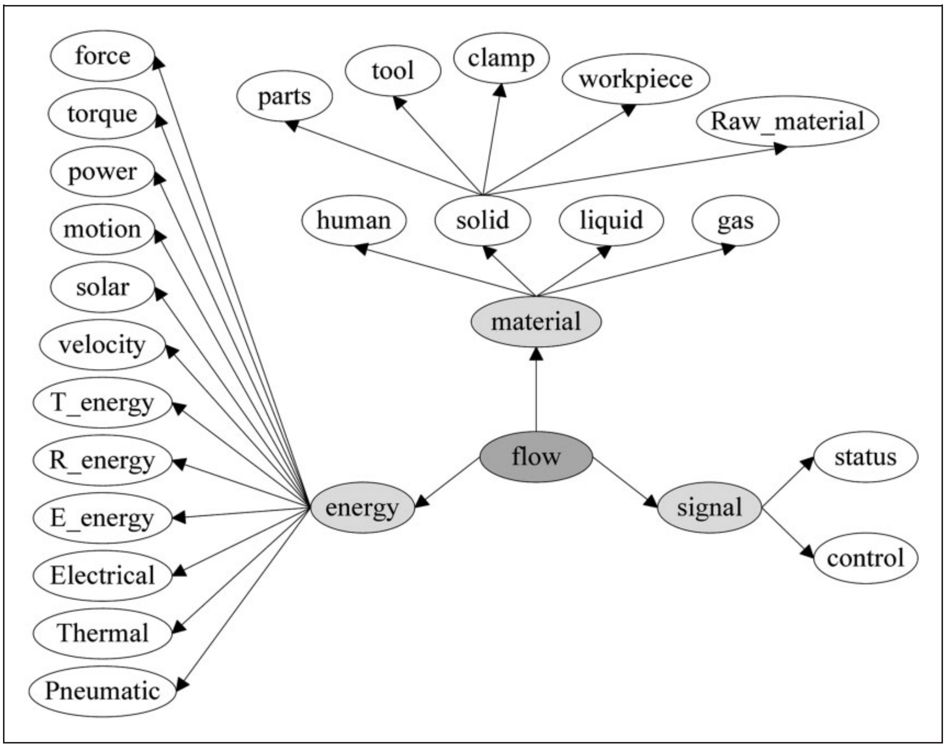

Figure 2. The classifications of flows.

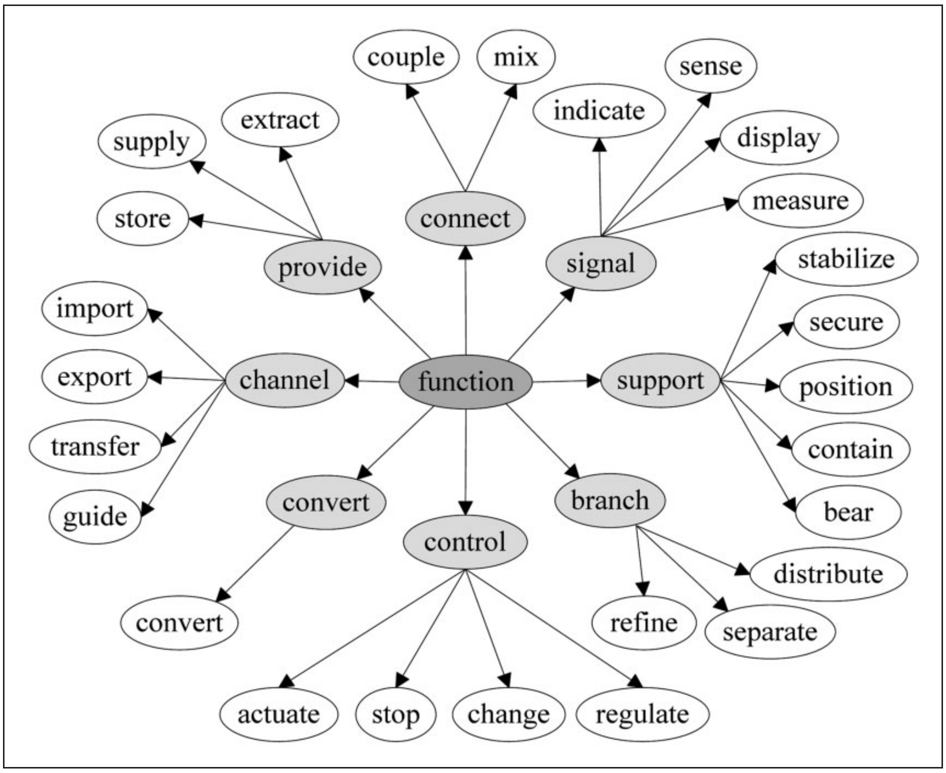

Figure 3. The classifications of functions.

attributes. A four-layer tree structure is used to represent the domain themes of user interest model. The top layer node is users, the second layer nodes are domain themes, the third layer nodes are the detailed knowledge items, and the fourth layer nodes are the attributes of detailed knowledge item. The hierarchical model of domain themes tree is shown in Figure 5.

Each node of the second and the third layer of domain themes tree is expressed with keywords. The keywords of domain themes and domain items come from the standard vocabularies that are listed in Table 1. The attributes of detailed domain items are some characteristics of design knowledge, such as intensity, rigidity, precision, stability, operating speed, bearing capacity, shock resistance, wear resistance, structure complexity, etc. Need to mention here, item attributes are not the argument of knowledge matching and sorting in this paper. Item attributes are introduced mainly as advice for the selection from knowledge push options, as well as for subsequent design phases.

Operation logs of user interest model

Operation logs record the past operation information of designers and reflect the fast-changing interest points that users focused recently. Designers' operation behaviors in knowledge service system mainly include knowledge scan, knowledge retrieve from repository, knowledge selection from search result, knowledge selection from push options, and knowledge download. Each operating behavior has a corresponding weight to display the different influence on user interest. The weight of each operation is shown in Table 3.

Table 2. Motion attribute codes and their meanings.

Motion attribute	Code	Code meaning
Motion type	0	Linear_Motion
	1	Rotary_Motion
	2	Rocking_Motion
	3	Other_Motion
Motion stability	0	Constant
	1	Variable
Motion continuity	0	Continuous
	1	Intermittent
Motion direction	0	One_Direction
	1	To_And_Fro
Interchangeability between input and output motion	0	interchangeable
	1	Not_interchangeable

The updating of user interest model

User interest has a strong dynamic. There are two situations of user interest model: initial user interest model and mature user interest model. Initial user interest model only contains the domain themes that assigned by the user when he/she used knowledge service system for the first time. Mature user interest model contains both domain themes and operation logs. Each domain theme item and operation log item has a weight; the higher the weight means the more interested. High frequency interest items and new interest items are more important, while the importance of infrequent interest items will gradually weaken over time. The operation log item whose weight reaches a threshold will be converted to a domain theme item, and the domain theme items that are unused for a long time will be removed. When new interest items generate, or old interest items eliminate, or the weights of interest items change, an updating rule is required to ensure the real-time and effectiveness of user interest model.

The approach to updating user interest model

There are two approaches to updating user interest model: automatic update and manual update. Automatic update with the help of agent technology is the main update approach, while users can also correct user interest model manually if the result of automatic update is not satisfactory. Agent is a software entity that resides in a computing environment

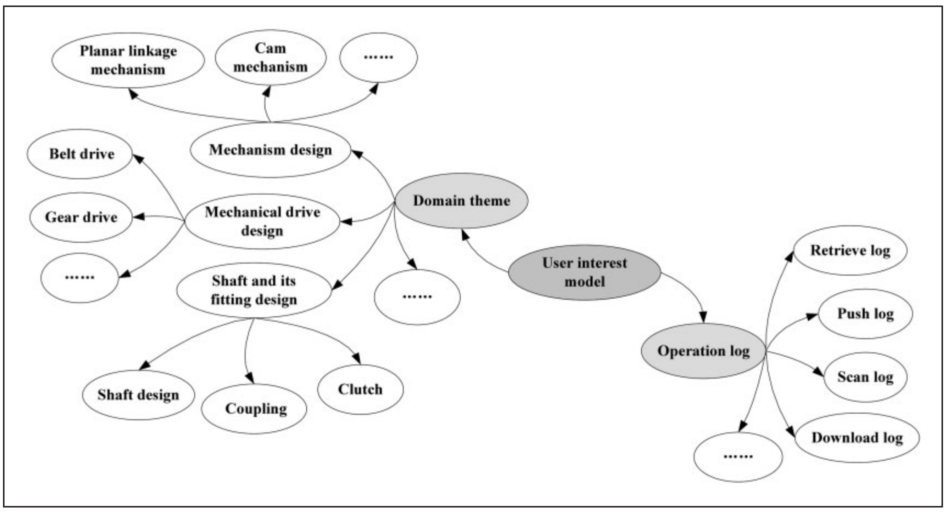

Figure 4. The schema of user interest model.

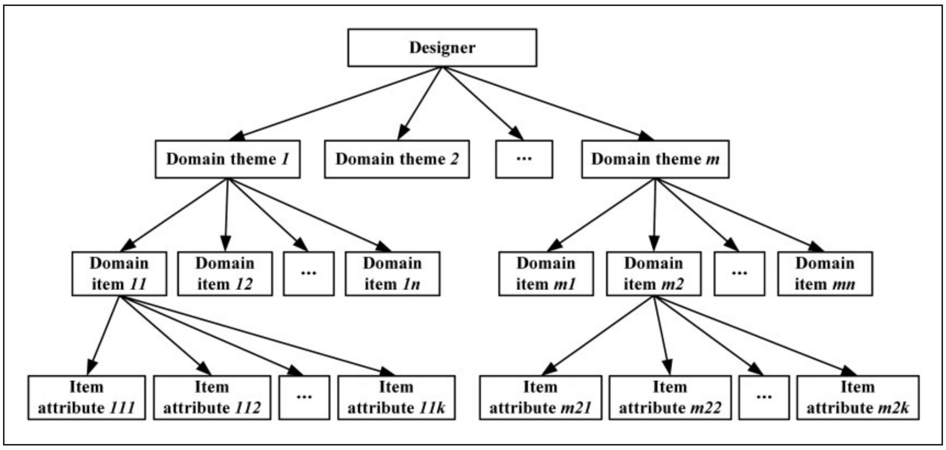

Figure 5. The tree model of domain themes.

Table 3. The weights of different operations.

Operating behavior	Level of interest	Weight
Knowledge scan	general	1
Knowledge retrieve	general	1
Knowledge selection from search result	moderate	2
Knowledge selection from push options	moderate	2
Knowledge download	strong	3

to complete autonomous, goal-oriented operations continually.[31] Due to the self-adaption and active learning ability, user agent is used to track design behaviors in real time and record all operation information related to knowledge service. Then domain theme items and operation log items are updated after the analysis and processing of operation information. The automatic update of user interest model is implicitly implemented. The schema of automatic update process is shown in Figure 6.

The automatic updating algorithm of user interest model

From the viewpoint of not only guaranteeing the real-time and effectiveness of user interest model, but also making update convenient and normative, this paper stipulates that the updating of user interest model is controlled by the start and finish buttons of knowledge push service. When the knowledge push service is running, other modules of the system are not available. User interest model will be updated automatically after knowledge push service completes each time. If knowledge push service is given up halfway, user interest model will not be updated. Users can modify interest model manually at any time except when the knowledge push service is running. The update process includes new interest items generation, interest items evolution, interest items elimination, and the weights change of interest items. An operation log item will convert to domain theme item when its weight reaches a threshold. The amount of domain theme items also has a threshold, and if the number of domain theme items is beyond the threshold, the domain theme item whose weight is the smallest will be removed. The flow chart of automatic updating algorithm is shown in Figure 7.

The degrees of interest between domain theme items and operation log items are different, so their update strategies are also different. Operation logs mainly record recent fast-changing interested knowledge, and the weight update strategy only depends on the frequency of operations without considering the time decay. There are two optional methods to calculate the weights of operation logs: one is accumulating all weights of every operation when users are in the use of system, the other is only choosing the maximum weight when several operations happen to the same knowledge item. In knowledge service system, some operations are largely interrelated, so the latter method is chosen as the weight calculation method. For example, if a user downloads a knowledge item after it is scanned, the increased weight of the knowledge item is 3 (i.e. the weight of download). The calculation formula of operation logs is given in equation (1), where W_n and W_{n+1}, respectively, refer to the accumulation weight of an operation log item when a user logs out the system for the n time and the $n+1$ time, and $w_1, w_2, \ldots, w_m$ are the weights of the operations when the user uses the system for the $n+1$ time.

$$W_{n+1} = W_n + \max(w_1, w_2, \ldots, w_m) \tag{1}$$

Domain themes describe relatively stable long-term interests of designers. Domain themes are more important than operation logs, and the weight update strategy is based on the time decay function

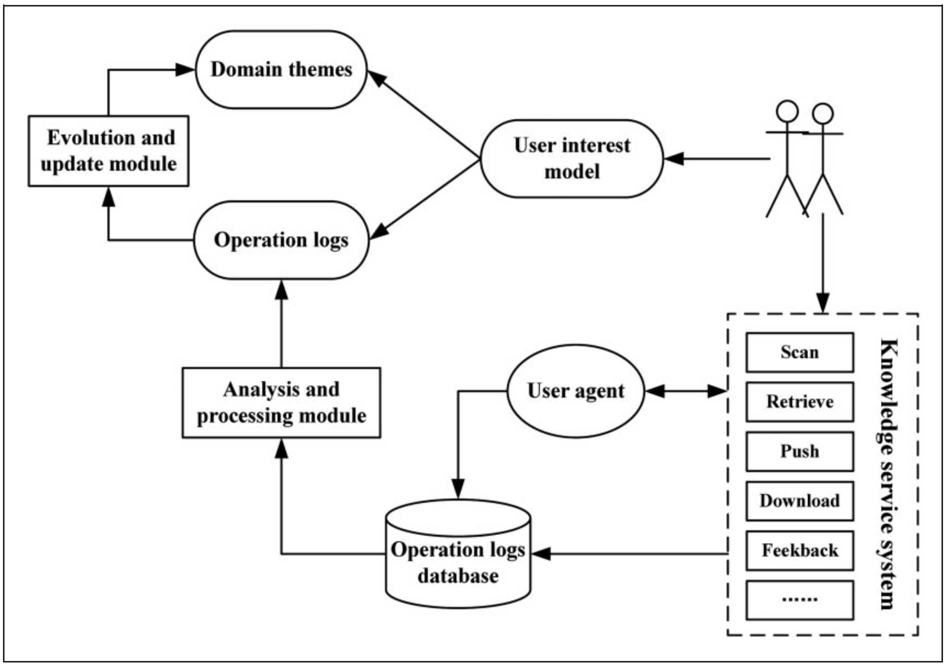

Figure 6. The automatic update process of user interest model.

that is in accord with the order of nature. For the domain theme items that are not involved when a user uses the system, the weight calculation formula is given in equation (2). For the domain theme items that are involved, the weight calculation formula is given in equation (3). In equations (2) and (3), W'_n and W'_{n+1}, respectively, refer to the accumulation weight of a domain theme item when the user logs out the system for the n time and the $n+1$ time, γ is the decay factor of domain theme items, $\gamma \in (0, 1)$, and γ is much close to 1.

$$W'_{n+1} = \gamma W'_n \tag{2}$$

$$W'_{n+1} = \gamma W'_n + \max(w_1, w_2, \ldots, w_m) \tag{3}$$

The basic principle of setting the initial weight, decay factor, and evolution threshold is as follows: For the initial domain theme items that are involved when the user uses the system for the first time, their updated weights cannot be smaller than their initial weights. In this paper, the initial weight of each initial domain theme item is set to 20 when a user registered the system, the decay factor γ is set to 0.95, the threshold that operation log item converts to domain theme item is also set to 20, and the threshold of the amount of domain theme items is set to 30.

The knowledge push mechanism based on design intent and user interest

This paper proposes a knowledge push method based on design intent and user interest. The design intent model plays a major role in the process of knowledge matching that interacts with repository, and the user interest model plays a major role in the sorting of knowledge candidates. Driven by the design demand, the designers divide design task into different subtasks, and then construct design intent models for the subtasks. According to the different representations of design intent, different knowledge matching methods are adopted to get knowledge candidates from repository. The knowledge candidates are pushed to designers after sorted by user interest model. Designers select appropriate knowledge from the push candidates to assist design activities, and then the system will update the user interest model implicitly. The mechanism of knowledge push is shown in Figure 8.

The knowledge matching methods based on design intent

The knowledge solving of active push service is realized by the matching between design intent model and the knowledge in repository. The bottom of design intent model is function units that cannot be subdivided. For the three function representation methods, the corresponding knowledge solving methods are described below.

1. For the document knowledge that is expressed with keyword set, the method of keyword matching is suitable. The process of document knowledge push is first traversing all keyword sets in document repository and getting the documents that contain the keywords of design intent model, and then by

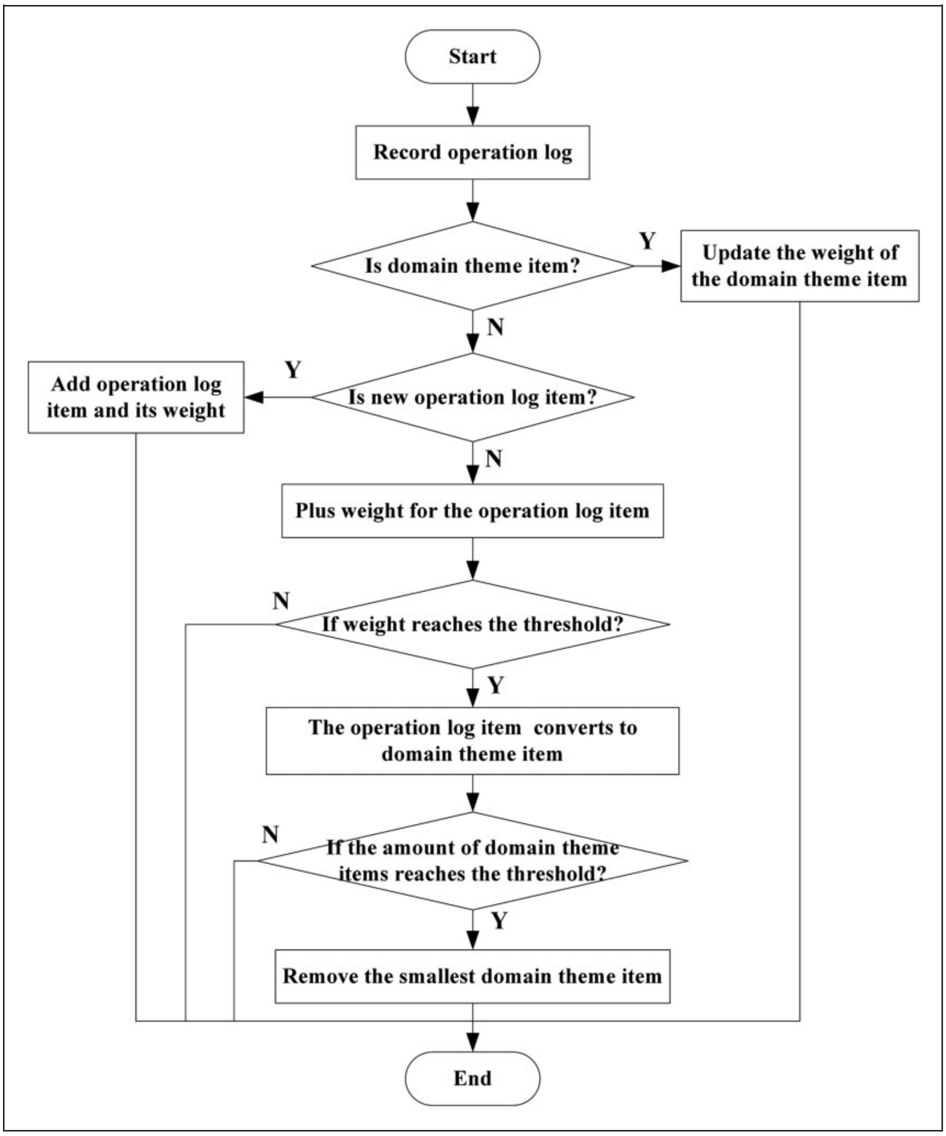

Figure 7. The updating algorithm of user interest model.

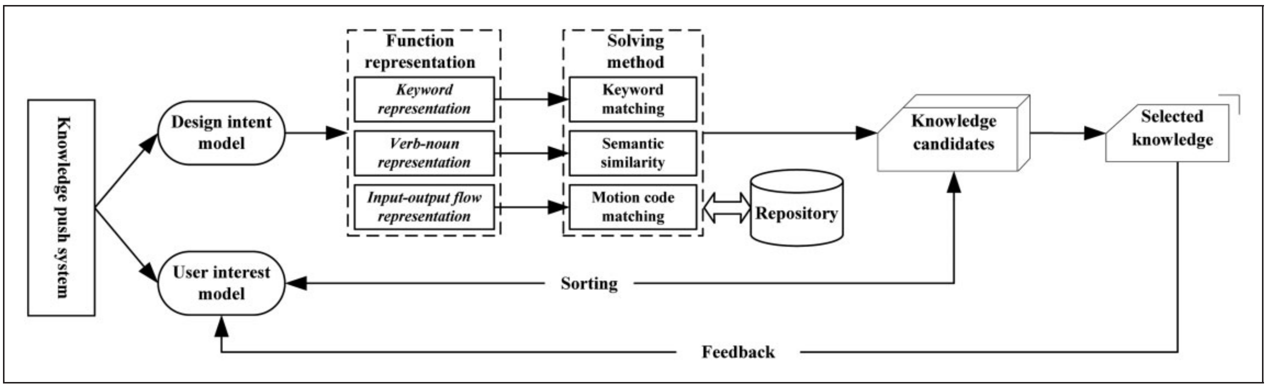

Figure 8. The realization mechanism of knowledge push.

sorting the documents based on user interest, eventually the top 50 documents are pushed to designers.

2. For the 3D model knowledge that is expressed with verb–noun, the method of functional semantic similarity calculation between 3D models and design intent model is suitable. By extended semantic similarity calculation based on 3D model functional semantic ontology,[32] more tacit knowledge in semantic level is explored than the method of keyword matching. Semantic similarity is a metric to a pair of concepts based on the

likeness of their semantic meaning;[33] its value ranges over [0, 1]. The distance of a shortest path between two concepts in semantic ontology is regarded as the semantic distance.[34] Semantic similarity and semantic distance have inverse relation.[35] For two concepts x and y, $S(x, y)$ is their semantic similarity and $D(x, y)$ is their semantic distance, and the relation between $S(x, y)$ and $D(x, y)$ can be expressed by equation (4).

$$S(x, y) = \frac{1}{D(x, y) + 1} \tag{4}$$

The function expression of 3D model uses *verb–noun representation*, and the semantic similarity of two function items is the product of their verb similarity and noun similarity. The verb similarity and noun similarity can be calculated by equation (4). Both the function expression of 3D model and the function items of design intent model may have more than one function unit. Given $X(x_1, x_2, \ldots, x_i, \ldots, x_m)$ is a function item of design intent model, $Y(y_1, y_2, \ldots, y_j, \ldots, y_n)$ is the function expression of a 3D model, x_i and y_j are function units expressed with *verb–noun representation*, $x_{i,v}$ and $y_{j,v}$ are verb, and $x_{i,n}$ and $y_{j,n}$ are noun. The semantic similarity between X and Y is calculated by equation (5).

$$S(X, Y) = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} s(x_i, y_j)}{N} \tag{5}$$

In equation (5), $N = \max(m, n)$

$$\begin{aligned} s(x_i, y_j) &= s(x_{i,v}, y_{j,v}) \cdot s(x_{i,n}, y_{j,n}) \\ &= \frac{1}{D(x_{i,v}, y_{j,v}) + 1} \cdot \frac{1}{D(x_{i,n}, y_{j,n}) + 1} \end{aligned} \tag{6}$$

3. For the mechanism knowledge that is expressed with input–output flow, the method of motion code matching is suitable. Given $P(p_i, p_o)$ is the motion code of a function unit of design intent model, $Q(q_i, q_o)$ is the motion code of a mechanical mechanism, p_i and q_i are the motion codes of input flow, and p_o and q_o are the motion codes of output flow. The process of mechanism knowledge push is first finding all mechanisms that meet the conditions of p_i equals q_i and p_o equals q_o, and then by sorting the mechanism knowledge based on user interest, eventually the top 30 mechanisms are pushed to designers.

The sorting algorithm of knowledge candidates based on user interest

In the last section, the knowledge candidates are got after the knowledge matching method based on design intent. The sorting algorithm according to user interest model plays an important role in preferentially electing knowledge items that are more likely to conform to users' requirements from many candidates, which help to shorten the selecting time from push results and increase the availability of knowledge items, so as to realize better personalized knowledge push service. For the knowledge candidates that are got by keyword matching and motion code matching, the similarity values are all 1, so the sorting only based on user interest model. The knowledge candidates that are got by semantic similarity calculation are preferentially sorted by semantic similarity values in descending order, for the knowledge candidates that have the same semantic similarity values are resorted based on user interest model.

The sorting algorithm is constructed according to the premise that users' interests reflect their knowledge demands. Domain themes are the relatively stable interests that are more important to designers, so domain theme items have a higher priority than operation log items in sorting algorithm. Within the same priority of domain themes or operation logs, the knowledge candidates are sorted by the weights of interest items in descending order.

Given $A(a_1, a_2, \ldots, a_i, \ldots, a_m)$ is the set of domain theme items, $a_1, a_2, \ldots, a_i, \ldots, a_m$ are domain theme items sorted by weights in descending order. Given $B(b_1, b_2, \ldots, b_j, \ldots, b_n)$ is the set of operation log items, $b_1, b_2, \ldots, b_j, \ldots, b_n$ are operation log items in descending order. Given $C(c_1, c_2, \ldots, c_k, \ldots, c_l)$ is the set of knowledge candidates that are got by knowledge matching. The sorting algorithm is briefly described in Table 4.

In Algorithm 1, using the domain themes to exactly match knowledge items and elect similar knowledge items from candidates, Step 2, Step 3, and Step 4 exhibits the time complexity of $O(N^2)$ using the operation logs to prioritize knowledge candidates and Step 5 also exhibits the time complexity of $O(N^2)$, and Step 6 exhibits the time complexity of $O(N)$. Thus, the total time complexity of Algorithm 1 is: $O(N^2) + O(N^2) + O(N) = O(N^2)$. Considering the threshold of the amount of domain theme items has been set to 30, so the size of $C2$ cannot be a large number either. The amount of operation log items cannot be a large number either. Thus, the actual time complexity of Algorithm 1 is $O(N)$. The running time of Algorithm 1 is determined by the number of knowledge candidates (i.e. N), and "N" is reduced in each iteration, so the efficiency of Algorithm 1 is acceptable.

System structure

On the basis of the theory and method research, a browser/server architecture-based prototype system called Personalized Knowledge Push System for Mechanical Conceptual Design (MCD-PKPS) is designed and developed using Java and Flex in

Table 4. The sorting algorithm of knowledge candidates.

Algorithm 1 The sorting algorithm of knowledge candidates

1. Import the set of knowledge candidates $C(c_1, c_2, \ldots, c_k, \ldots c_l)$, the set of domain theme items $A(a_1, a_2, \ldots, a_i, \ldots, a_m)$, and the set of operation log items $B(b_1, b_2, \ldots, b_j, \ldots, b_n)$.
2. Get the domain theme item with the highest weight (i.e. a_1) from A, traverse each knowledge item in C. If there exist a knowledge item c_k is the same as a_1, take out c_k from C and put c_k into a new knowledge item set $C1$, the size of C minus 1; If there exist a knowledge item c_k is not the same as a_1, but c_k and a_1 belong to the same domain theme, take out c_k from C and put c_k into another new knowledge item set $C2$, the size of C minus 1.
3. Get the domain theme item with the second highest weight (i.e., a_2) from A. First traverse each knowledge item in $C2$, if there exist a knowledge item c''_k is the same as a_2, take out c''_k from $C2$ and put c''_k into the end of $C1$, the size of $C2$ minus 1. Then traverse each remaining knowledge item in C: If there exist a knowledge item c_k is the same as a_2, take out c_k from C and put c_k into the end of $C1$, the size of C minus 1; If there exist knowledge items that are not the same as a_2, but belong to the same domain theme, move them from C into the end of $C2$.
4. Repeat the same work as Step 3, get $a_3, \ldots, a_i, \ldots, a_m$ in turn from A. First traverse each knowledge item in $C2$, the exactly matched knowledge item is moved into the end of $C1$. Then traverse each remaining knowledge item in C, the exactly matched knowledge item is moved into the end of $C1$, the knowledge items that belong to the same domain theme but not exactly matched are moved into the end of $C2$ in turn. When all domain theme items have been got, if there still remains knowledge items to be sorted in C or $C2$, go to the next step; If all knowledge items in C are moved into $C1$ after sorted, go to Step 7.
5. Get operation log item $b_1, b_2, \ldots, b_n$ in turn from B. First traverse each knowledge item in $C2$, then traverse each knowledge item in C, the exactly matched knowledge items are moved into the end of $C1$ in turn. When all operation log items have been got, if there still remains knowledge items to be sorted in C or $C2$, go to the next step; If all knowledge items in C and $C2$ are moved into $C1$ after sorted, go to Step 7.
6. For all the remaining knowledge items in $C2$, move them into the end of $C1$ in turn. Then, for all the remaining knowledge items in C, move them into the end of $C1$ in turn.
7. Finally, export the sorted set $C1$, end the algorithm.

MyEclipse 9.0 as the web application development tool and Tomcat 7.0 as a web server; using MySQL as the backend database to store design knowledge, user information, operation logs, etc; and using SSH (Struts2 + Hibernate3 + Spring3) frame as business logic. The MCD-PKPS and illustrative case are run on a PC with 3.50 GHz CPU (Intel Core i7-3770K) and 4GB RAM, under Windows 7 32-bit system. The structure of prototype system is shown in Figure 9.

The system is divided into three layers: technical support layer, application service layer and user interface layer.

1. Technical support layer: the basic technologies that support system running include operating system, programming language, database, server, networking protocol, etc.
2. Application service layer: the core of the system contains all the key technologies of the proposed knowledge push method which includes five modules, i.e. the user workspace, the design intent module, the user interest module, the repository module, and the knowledge push module. User workspace provides the interface to interact with the system, and the operations of knowledge acquisition mainly happen in this module. Design intent module is the starting point of knowledge push service that is mainly responsible for the formal expression of target function, so as to transform the problem of knowledge acquisition into standardized knowledge solving based on design intent model. User interest module is responsible for the construction and updating of user interest model, to ensure the real-time and effectiveness. Repository module provides a storage space for design knowledge, and realizes standardization management that meets the requirements of conceptual design in semantic level, so as to quickly respond to the request of knowledge matching (This section will be presented in detail in another paper, not in this paper). Knowledge push module is responsible for getting knowledge candidates from repository according to the different representations of design intent, and then sorting the knowledge candidates based on user interest model to realize better personalized knowledge push service.
3. User interface layer: the interfaces when designers use the system include the interfaces of design task decomposition, design intent modeling, user interest management, repository management, knowledge push service, etc.

An illustrative case

The knowledge acquisition process in conceptual design of piston pump drive system is illustrated to demonstrate the availability of the system. The whole flow of knowledge push service from user intent model to the results is implemented as shown in the application service layer of Figure 9. Piston pump is used to transport the liquid without solid particles, and the reciprocating motion of piston periodically changes the working space of pump cylinder, thereby realizing the suction and discharge of liquid. Drive

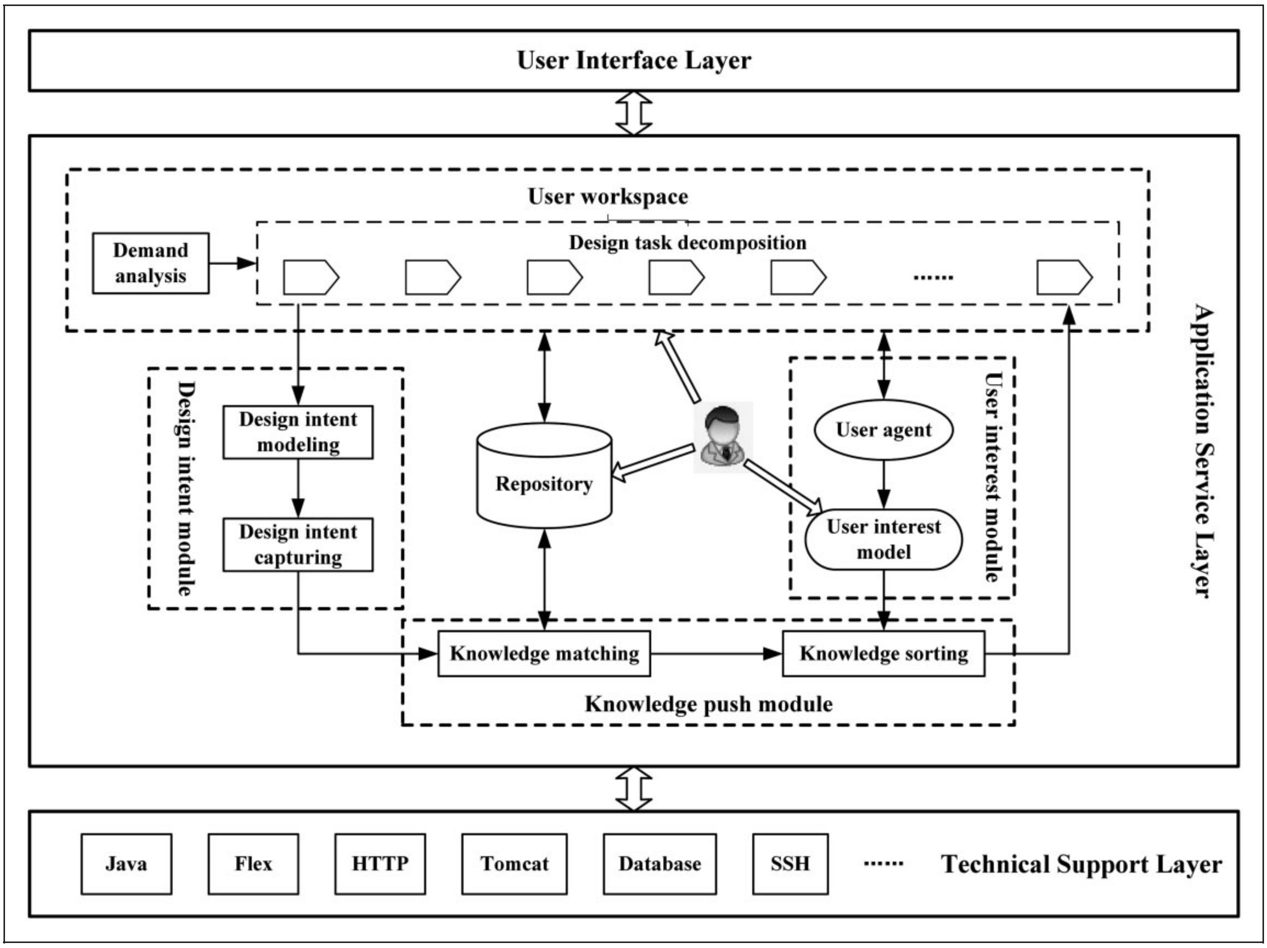

Figure 9. The structure of prototype system.

system is responsible for the reasonable control and distribution of power and motion between power system (i.e. motor) and actuator (i.e. piston). Drive system plays a crucial role, and relevant knowledge is required to be used as reference in the design process. The input motion of drive system is the high speed '*Rotary_Motion-Constant-Continuous-One_Direction*' of motor, and the output motion is relatively low speed '*Linear_Motion-Variable-Continuous-To_And_Fro)*' of piston. The function of drive system is to reduce speed, convert motion type, transfer motion and power, guide the movement of piston within the cylinder, connect parts, bear parts, etc. According to the proposed standardized expression of function, the design intent model of piston pump drive system is constructed as shown in Figure 10.

When designers use the knowledge service system for the first time, they are reminded to assign their initial user interest models. Initial user interest model only contains domain themes, and does no contains operation logs. The initial weight of each initial domain theme item is 20. A designer assigns his/her initial user interest model as shown in Figure 11.

After the design intent model is constructed, the system will actively push knowledge for each function item. The knowledge candidates of function item 1 (transfer-motion, transfer-power, change-velocity) are got by functional semantic similarity calculation, and are first sorted by semantic similarity values in descending order, as shown in Table 5. The knowledge candidates that have the same semantic similarity values are re-sorted based on user interest model. The final push order of knowledge candidates is: planetary gear drive, V-belt drive, gear drive, flat belt drive, roller chain drive, worm drive, lead screw drive, rack and pinion drive, gear shaft, etc. In consideration of the constraints of work condition, transmission accuracy, structure complexity, and so on, the designer eventually selects V-belt drive as the knowledge carrier of function item 1.

For function item 2 ((10001, 01011), transfer-motion, transfer-power), the function unit of '(10001, 01011)' is primarily considered. So the knowledge candidates of function item 2 are got by motion code matching, and then are sorted based on user interest model. The final push order is: slider-crank mechanism, crankshaft-link mechanism, cam-linkage mechanism, sine mechanism, and tangent mechanism. Crankshaft-link mechanism is more suitable for the function demand of 'transfer-motion, transfer-power' than slider-crank mechanism, and it also has more advantage in intensity and rigidity. The flexible

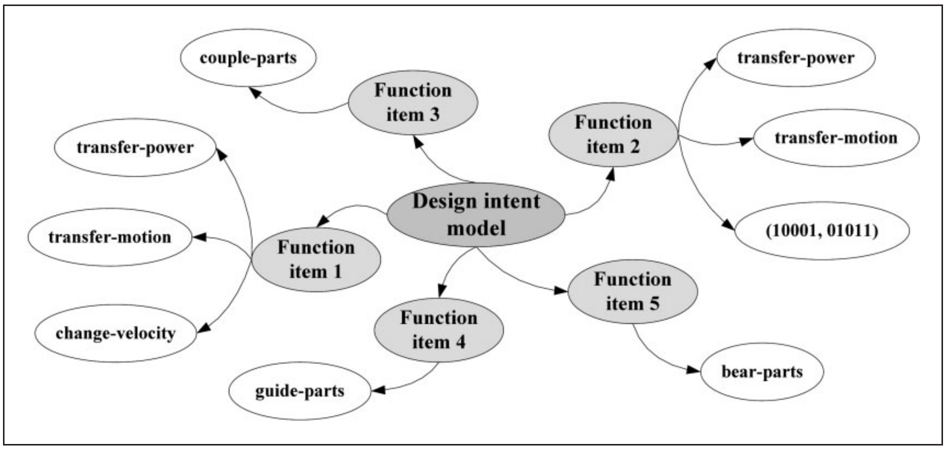

Figure 10. The design intent model of drive system.

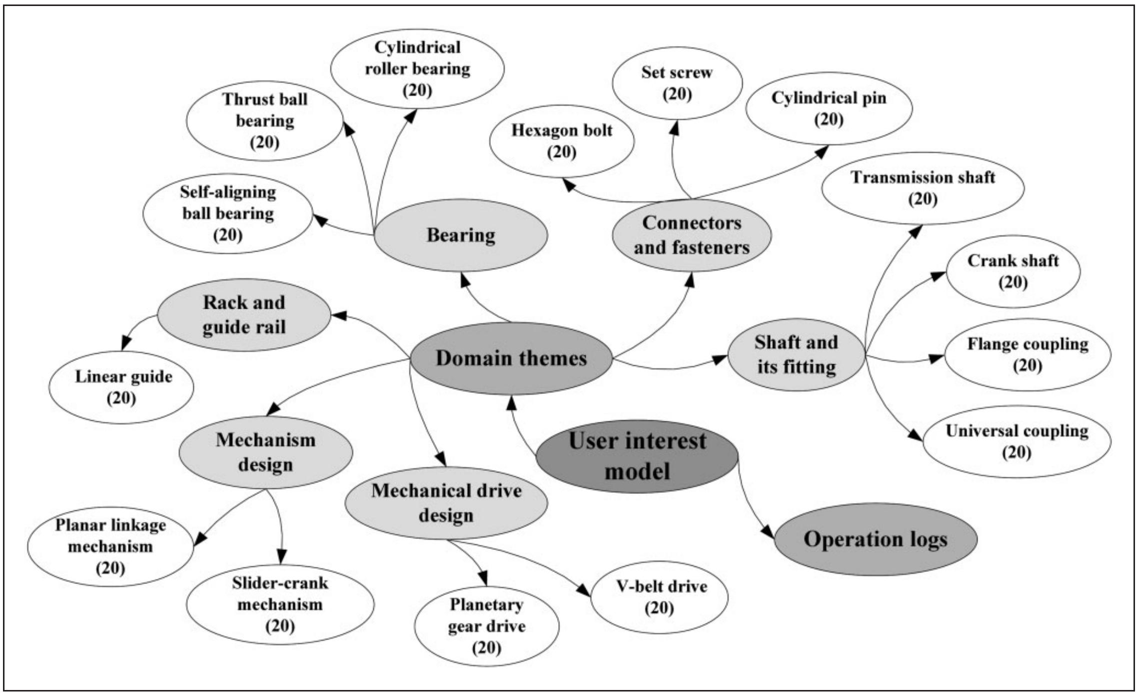

Figure 11. The initial user interest model assigned by a designer.

Table 5. Semantic similarity between the function of knowledge items and 'transfer motion, transfer power, change velocity'.

Knowledge items	Function of knowledge items	Similarity
Gear drive	Transfer-motion, transfer-power, change-velocity	1.0
Planetary gear drive	Transfer-motion, transfer-power, change-velocity	1.0
Flat belt drive	Transfer-motion, transfer-power, change-velocity	1.0
V-belt drive	Transfer-motion, transfer-power, change-velocity	1.0
Roller chain drive	Transfer-motion, transfer-power, change-velocity	1.0
Worm drive	Transfer-motion, transfer-power, change-velocity, convert-motion	0.8
Rack and pinion drive	Transfer-motion, transfer-power, convert-motion	0.73
Lead screw drive	Transfer-motion, transfer-power, convert-motion	0.73
Gear shaft	Transfer-motion, transfer-power, bear-parts	0.67

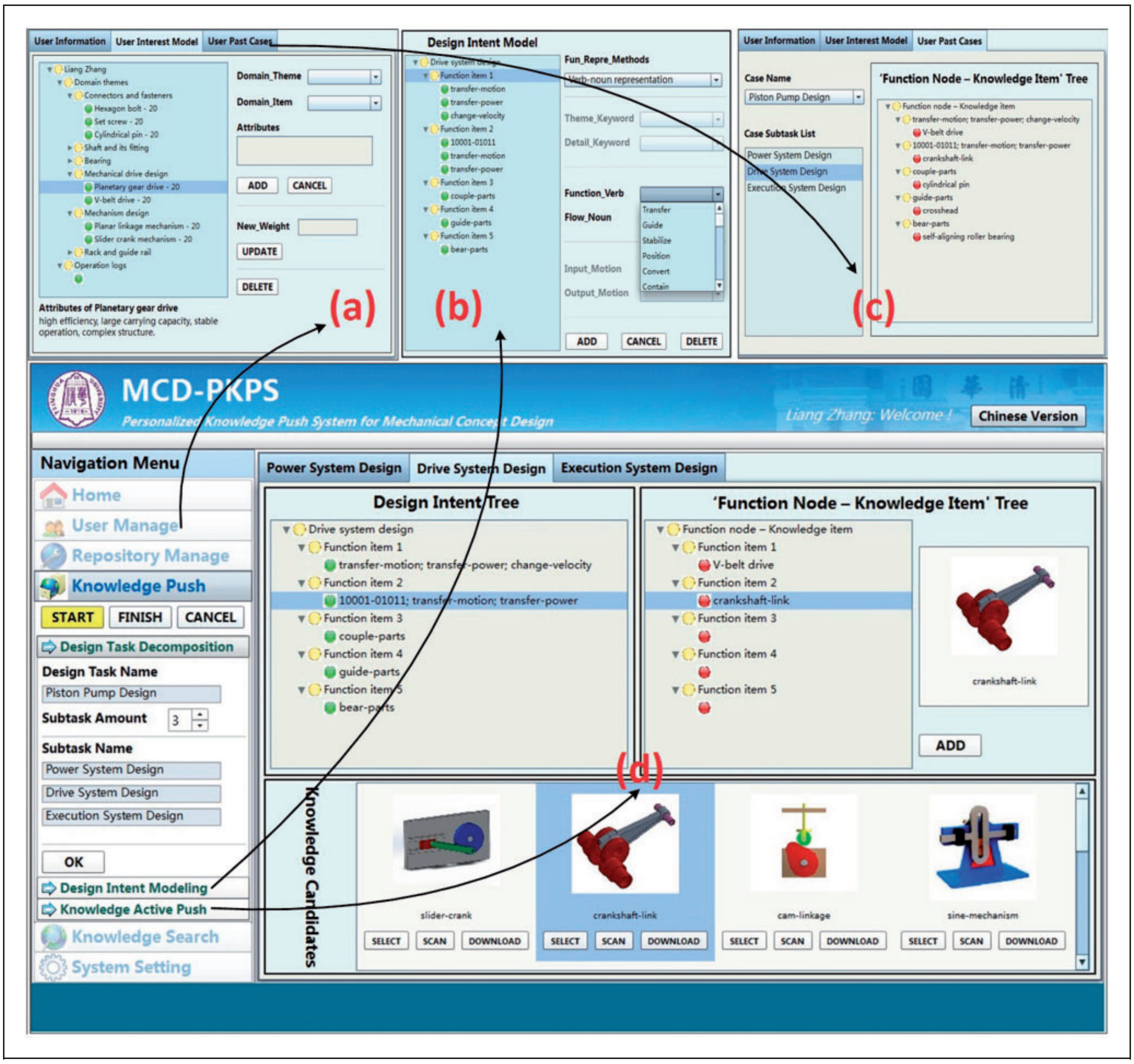

Figure 12. Some interfaces of MCD-PKPS.

impact of cam-linkage mechanism is serious in high speed, and leads to a large mutation rate of inertia force. Sine mechanism and tangent mechanism are not commonly used. So the designer eventually selects crankshaft-link mechanism as the knowledge carrier of function item 2, rather than slider-crank mechanism that is first pushed by the system. Similarly, cylindrical pin is selected as the knowledge carrier of function item 3 (couple-parts), crosshead is selected as the knowledge carrier of function item 4 (guide-parts), and self-aligning roller bearing is selected as the knowledge carrier of function item 5 (bear-parts).

The implementation process of knowledge push service is shown in Figure 12. If the designer is a new registered user, he/she will be reminded to assign initial user interest model when logins the system for the first time in Figure 12(a). Knowledge push service begins after the START button in Figure 12(d) is clicked to highlight, and at this time other modules of MCD-PKPS are not available. First of all, the tree structure of design intent model of drive system is built in Figure 12(b). After the design intent model is built, the Design Intent Tree and 'Function Node – Knowledge Item' Tree are built automatically in Figure 12(d). At this time, the function nodes of 'Function Node – Knowledge Item' Tree are displayed, while the knowledge item nodes are vacant. If a function node is selected, MCD-PKPS will capture the design intent item and adopt appropriate knowledge matching method to get knowledge candidates from repository, and then actively push the knowledge to designers after sorted as shown in the bottom of Figure 12(d). Designers select the optimal knowledge item from candidates to assist design process, the snapshot of the selected knowledge item is displayed in the upper right of Figure 12(d), and the name of the selected knowledge item is added to corresponding knowledge item node of 'Function Node – Knowledge Item' Tree. Satisfactory knowledge items can be downloaded to be reused immediately or after modified. Knowledge push service completes after the FINISH button is clicked, then the START button returns to normal and other modules of MCD-PKPS return to available, also the design case will be added to "User Past Cases" module in Figure 12(c).

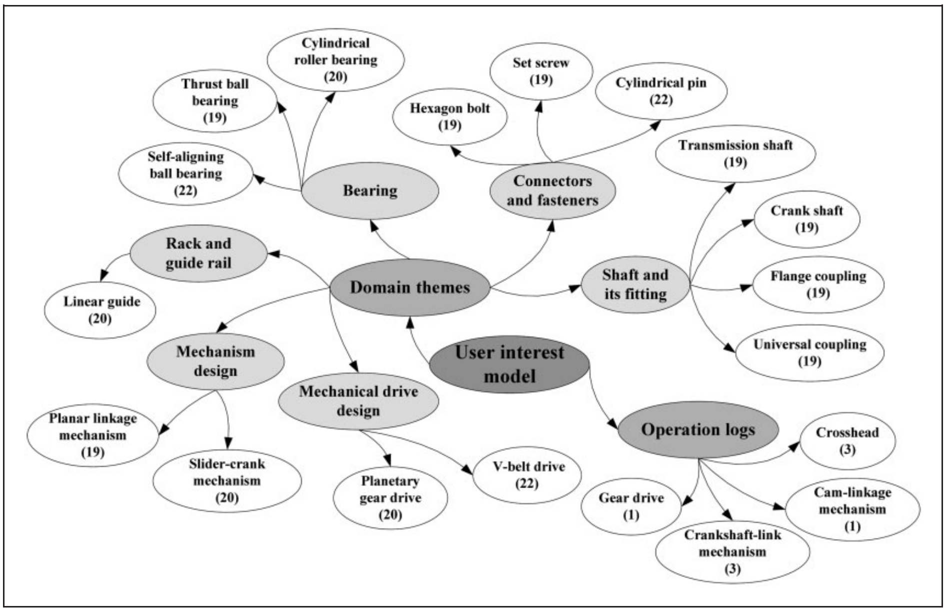

Figure 13. The user interest model after updated.

At the same time of system running, the user agent tracks design behaviors in real time and records all operations and their corresponding weights, and then automatically and implicitly updates user interest model after the FINISH button is clicked according to the method presented in Figure 7. If knowledge push service is given up halfway (Click the CANCEL button), user interest model will not be updated. The user interest model after updated will provide more accurate argument for the knowledge push service in next design activities. The user interest model here is an initial model, and the updating process composes the weights update of domain theme items and the addition of operation log items. The user interest model after updated is shown in Figure 13.

In the above illustrative case, the knowledge matching methods based on design intent and the sorting algorithm based on user interest help MCD-PKPS realize better personalized knowledge push service, so as to improve the efficiency and precision of knowledge acquisition in mechanical conceptual design activities. A deficiency of MCD-PKPS is that comparing to the precision and recall metrics for traditional keyword-based text retrieval and content-based 3D model retrieval methods, there is still no mature system to support functional semantics statistic. Thus, no satisfied metrics is put forward to evaluate the performance of MCD-PKPS at present.

Conclusion

Knowledge is the critical resource of product design, and it is desirable to effectively acquire and reuse knowledge in product innovation design activities. However, no existing knowledge acquisition method is satisfied to support mechanical conceptual design. The main contribution of this paper is that knowledge push system was applied to mechanical conceptual design activities to realize better personalized knowledge service. This paper first emphasized the significance of quickly acquiring knowledge and reviewed related studies on knowledge push, design intent model, and user interest model. To address the problem of inefficiency and low precision of current knowledge acquisition methods, a knowledge push method based on design intent and user interest was proposed. It composed the building of normalized design intent model by the formal expression of target function, the building and updating of user interest model with the help of user agent technology, a matching method of design knowledge based on design intent, and a sorting algorithm of knowledge candidates based on user interest. A prototype system, called MCD-PKPS, has been developed. Overall, compared with traditional knowledge acquisition methods, the originator of knowledge push service is the system rather than users, the active knowledge matching improves the efficiency as well as the personalized knowledge sorting improves the availability. Finally, an illustrative case demonstrates MCD-PKPS is a meaningful tool to support mechanical conceptual design.

Though significant progresses have been made on knowledge acquisition in conceptual design, there is still a lot of work to be done deeply. The further research intends to the automatic modeling and intelligent capturing of design intent by Natural Language Processing, as well as more various representation methods of target function. Furthermore, the detailed attributes of design knowledge will also be considered as the argument of knowledge push service.

Conflict of interest

None declared.

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