A Data-Driven Biological Knowledge Processing Approach for Biologically Inspired Design Enabled by the Five-Dimension Model

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Abstract. It is commonly believed that biology holds huge potential for inspiring engineering design especially for the era of information filled with smart products. The success of biologically inspired design (BID) for ever-growing design requirements keenly depends on approaches to find suitable biological knowledge for design, which is mainly based on functional similarities between biological prototypes and engineering design problems to be solved. This paper aims at providing a data-driven biological knowledge representation and recommendation approach for BID to smooth the selecting and using of biological prototypes in architecting of design schemes. To do so, a variant knowledge representation method for biological prototypes is firstly proposed based on basic ideas from both the function-based ontology and the five dimensions framework originally designed for the digital twins. Through the proposed representation approach, biological prototypes and their inspired bionic solutions are connected through multiple relations besides the functional similarity. Then, the calculation algorithm is presented to recommend suitable biological prototypes with high correlations with design tasks in BID. An exemplar design for bionic wind power blades is used to illustrate the feasibility of the proposed approach to improve the adaptability of BID in resolutions of engineering design problems in the new era of Industry 4.0.

Keywords: Biological Inspired Design, Knowledge Representation, Recommendation Algorithm, Five Dimension Model
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1 INTRODUCTION

Nowadays, the advance of information communication technologies especially the enabling technologies for Industry 4.0 have brought new techniques and methods to refine the domain of engineering design [1]. These technologies in turns have brought about both new challenges and opportunities to the development of Biologically inspired design (BID) that emphasizes using biological knowledge in solving engineering design problems [2]. To be specific, one of the most evident challenges in BID is that the ever-growing requirement for products with smartness, sustainability or other new features, which leads to more complex engineering design tasks [3]. It is commonly believed that natural wisdoms from biology still hold huge potential to inspire product design schemes with features of the smartness and the sustainability [4]. However, the increasing of complexity of BID tasks asks for more effective knowledge process techniques to retrieval and recommend appropriate biological prototypes before being transformed into design schemes [5]. Practically, engineering designers have to understand biological prototypes often described in documents for transfer to given design problems through difficult, labor intensive and time-consuming cognitive processes [6].

As a typical long-range design by analogy (DbA), BID keenly depends on the cognitive psychological mechanism that people tend to solve given problems by mapping solutions from known questions [7], i.e., biology in nature. In general, BID approaches are usually built on knowledge representation model, through which to facilitate the inter-domains knowledge transformations. Therefore, an effective biological knowledge process approach is based on suitable knowledge representation. There are many previous studies have proposed various knowledge representations to model biological prototypes in BID, such as the Design -analogy to nature engine (DANE) [8] and the State-action-place-physical-organ-input- environment (SAPPhRIE) [9]. Both representations depend on the manual computation to model biological prototypes based on perspectives of the functional characteristics, the function-behavior mapping characteristics. Variants of these function-based biological knowledge representation methods are also workable for inspiring smart product design [4]. However, these knowledge representation methods are in short of providing effective ranking algorithms to recommend appropriate biological prototypes to meet complex design requirements.

In recent, advancing in data science and artificial intelligence have paved the way to develop data-driven methods to facilitate applications of analogy encoding, retrieval, mapping and evaluation in DbA [10]. Built on the philosophy of data-driven methods for DbA, this paper aims at proposing a data-driven biological representation and recommendation approach to smooth the creative design through BID in industry 4.0. To do so, a variant biological knowledge representation method is firstly proposed based on both the function-based idea and the five dimensions framework designed for the digital twins [11]. Through the proposed representation approach, biological prototypes and their inspired bionics results are connected through multiple dimensions relations. Built on those relations from different dimensions, correlations between engineering design requirements and biological protypes with their inspired bionic solutions can be calculated, then biological prototypes with high scores can be recommended to engineering designers as appropriate ones for inspiring BID. As results, the proposed approach can improve the adaptability of BID in product innovations in the new era of Industry 4.0 by saving the labor of engineering designers in searching of suitable biological prototypes to be analogized as well as finding exiting examples about how to transform biological prototypes into innovative solutions to multiple design requirements.

The rest of paper is organized as follows. Sect.2 briefly reviews previous studies related to this research, Sect.3 explains the framework of the proposed method, Sect 4 illustrates the exemplar design of bionic wind power blades to address the feasibility of the proposed method, Sect.5 concludes the whole study and discusses its main contributions and limitations.

2 LITERATURE REVIEW

There are three main sections that are relevant to the proposed data-driven biological knowledge representation and recommendation approach. The first part focuses on existing knowledge representation methods to support BID. The second section expounds former efforts on using the five-dimension model in engineering design and innovations. The third section shows the new trend of the data-driven knowledge representation related to DbA and BID.

2.1 Knowledge Representation Methods to Support BID

BID emphasis on the using of biological knowledge to solve engineering design problems. However, not all of engineering designers are expert at biology. Designers have to understand knowledge included in biology prototypes before they figure out design schemes to given problems through difficult, labor intensive and time-consuming cognitive processes [6]. To smooth intra-domains knowledge transformations from biological fields into engineering design, biological knowledge representation methods help designers understand biological prototypes in forms of function basis or the function -behavior-structure (FBS) ontology, which are widely used representations in the domain of engineering design.

Knowledge representations for BID usually take two specific forms including the format textual method and the diagrammatic model [12]. Textual representing methods apply certain format terms formulated by nouns, verbs, prepositions and other affiliates to bridge differences between terminologies of biological and engineering domains [13]. Textual representation methods are simple and able to reveal key functional features in biological prototypes, however, they are limited at representing mutual relations among different biological elements. Diagrammatic models use more vivid graphic elements to illustrate the mutual and causal relations of various elements in biological system. Among those diagrammatic representing methods, models built on the FBS ontologies are important branches. For examples, models of DANE [8] and SAPPhRIE [9] are typical ones belonging to this category. Information about how biological organs, tissues and structures work mutually to facilitate given biological functions are revealed through graphic modeling elements, which are help for designers to understand the mechanism of biological prototypes. Previous effort is also made to combine modeling elements from both DANE and SAPPhRIE in a new model called the unified ontology BID (UNO-BID) [14].

Biological knowledge representation methods on one hand help engineering designers understand mechanism to facilitate given functions in biological prototypes, on the other hand, they facilitate feature recognition of biological knowledge. With help of textual representations, engineering users are able to recognize functional features of biological prototypes by reading format descriptions that are usually in forms of function basis [15] or its variants adapted for BID, i.e., the engineering to biology thesaurus [16-17]. Similarly, diagrammatic models also depend on specific terminologies to identify characteristics of biological prototypes [18-20]. However, traditional biological knowledge representations have evident limitations to be adapted to engineering design tasks with ever-growing difficulty and interdisciplinary backgrounds since more modeling elements in representation hinder its understandability.

2.2 Applications of the Five Dimensions Models in Engineering Design

The five dimensions model was originally proposed for modeling the complex system constitution and process embedded in the digital twins (DT) covering interdisciplinary information about physical entities, virtual entities, connections, data and services [11]. As an important modeling approach in the DT, the five dimensions models are widely used in constructing frameworks of complex and synergic engineering systems with DT applications, such as the smart factory [21], the automatic warehousing system [22]. The wide applications of DT mainly focus on the its potential in optimizations of smart manufacturing system by improving their efficiency, resilience and intelligence through the intensive cyber-physical connection, real-time interaction, and in-depth collaboration [23].

There are also applications of the five dimensions models at conceptual design stage of product development due its capability to represent multi-disciplinary knowledge. The five dimensions model from the DT has been applied in modeling and analyzing the development of complex mechanical products in collaborative design [24]. A former study once provided a new hybrid function modeling approach by integrating the substance field analysis (SFA), i.e., the function model approach in TRIZ with the five dimensions model to help construct the conceptual design schema of smart products by representing the complex relationships between digital twin objects and their attributes [25]. In this hybrid function modeling method, TRIZ function model is used to describe components and their interactions in technological system, moreover, the five dimensions model from the DT help extent the range of the SFA by providing feasible ways to represent cooperation of various components, behaviors and rules in each of five modules in complex engineering system. This modeling method has been further developed for assessing functional values of counterparts in constituting the conceptual solutions to the smart products services system [26]. The five dimensions model has potential to be used to support BID, since the requirements for smart products and systems closely rely on the proper using of multidisciplinary knowledge. However, there is no existing study on using the five dimensions model to cope with tasks of knowledge representation and processing in BID.

2.3 Data-driven Knowledge Processing Methods for DbA and BID

The early data-driven DbA methods usually took forms of knowledge-based expert systems, such as the ARGO [27], the KRITIK [28] that enable the analogical retrieval for solving new problems by using existing design cases based on the rule-based graphs or the functional information. With the development of data science and information technology, various new data-driven methods have been developed to smooth the process of DbA by searching of general knowledge from interdisciplinary domains using the text mining or semantic networks [29-30]. After decades of development, current data-driven DbA methods though in various specific types can provide at least four applications: representation, retrieval, mapping, and evaluation to facilitate analogy [11].

As a particular type of DbA, BID has been supported by several data-driven biological knowledge processing methods and tools to use natural phenomenon wisely in engineering design [31]. With the development of BID knowledge representation methods, systematic data-driven biological knowledge processing methods are developed such as the Four-Box method that are designed to represent multiple facets of design problems based on FBS models and to evaluate analogies through a heuristic T-chart model [32]. Moreover, to make wise decisions in BID, data-driven BID knowledge processing methods also take forms of automatic text classifiers to identify textual stimuli in improving BID performance [33], online biological knowledge databases, for example the Asknature, which employs a special taxonomy to manage around 2000 specific biological prototypes and biomimetics solutions [34], rules-based text mining approaches those enabling scalable search of biological prototypes for solving given engineering design problems [35], the function-based software to facilitate the analogy matching between biological concepts and engineering concepts [36], and an artificially virtual librarian named as IBID to support engineering designers in search of relevant biological articles through understanding of mechanism of biological systems [6]. Based on the aforementioned review of data-driven approaches for processing biological knowledge, it is clear that those approaches are usually synergic since they involve knowledge representation and process strategies, on the other hand, knowledge representation applied by data-driven are often built on multiple facets of knowledge consisting of not only biological prototypes but also biometric solutions to improve BID performance.

2.4 Summary of the Literature Review

In the era of Industry 4.0, there are ever-growing complex design tasks faced by BID. The existing BID knowledge representation methods are mainly in forms of manual computations, which are labor intensive and time-consuming. The ever-growing difficulty of engineering design tasks evidently hinder usability of those manually computational BID knowledge representation. Moreover, pillars of Industry 4.0 such as the DT and other advanced information technology and artificial intelligence methods also provide enabling technologies to develop new data-driven knowledge processing approach for BID. There is also a trend of integrating the five dimensions models from the DT with the functional analysis methods and other conceptual design methods from the domain of engineering domain due to their compatibleness. BID knowledge representation and recommendation methods are originally designed for users in engineering design domains, the majority of them root from engineering design methods such as the function basis, FBS structures. Therefore, it is feasible to propose a new knowledge processing method for BID using both the function-based modeling and the five dimensions model to cope with new challenges and opportunities in BID.

3 FRAMEWORK OF THE PROPOSED METHOD

The proposed data-driven BID knowledge processing approach by integrating the function-based systematic modeling method and the five dimensions model used in the DT to support engineering designers solving engineering design problems using BID. The proposed method mainly includes three sections: a variant BID knowledge representation, data-driven self-updating strategies for BID knowledge representation, and a recommendation algorithm of appropriate biological prototypes to solve given design problems.

3.1 A Variant BID Knowledge Representation based on the Framework of Five Dimensions Model

The first section is a variant BID knowledge representation, which is built on basic ideas of the function-based modeling and five-dimension model from the digital twin, aiming at containing knowledge about biological prototypes and their inspiring engineering solutions. Therefore, users of the proposed approach who usually come from engineering domain can reach not only knowledge about how biological prototypes work but also knowledge about how these biological prototypes had been transformed and used in real engineering design schemes.

The framework of the proposed built on the five-dimension model from the digital twins that differs the proposed BID knowledge representation approach from other exiting representations such as the DANE or SAPPhRIE. The five-dimension model for the digital twins was firstly proposed by Prof. Tao to organize complex constitutions of the digital twin in engineering domain. Afterwards, the five-dimension model has been widely applied in architecting, simulation and optimizing of engineering system through the digital twins [11,21-25]. The framework of the five-dimension model is shown as Figure1, which consists of five parts: Physical entity (PE), virtual entity (VE), services, digital twin data (DD) and connection. To be specific, the PE stands for the real engineering system, while the VE includes information on facets of geometry, physical, behavior and rules to describe the corresponding PE. Service involves both functional service and business service to meet needs from both inner and outer users. DD stands for the digital twin data involving specific data from sections of PE, VE and service, as well as other knowledge data and fusion data. Connection plays the role of the bridge to connect different sections, which are mainly in forms of data channels.

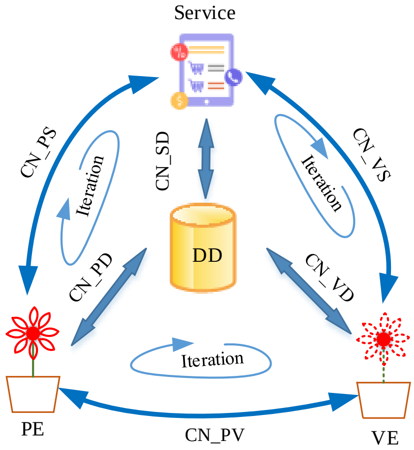

Figure 1: The traditional five-dimension model for the digital twins.

A variant BID knowledge representation is proposed by this study by adopting to the framework of the five-dimension model from the digital twins. In the proposed BID knowledge representation, there are five sections by referring to the five dimensions, which aims at putting all kinds of knowledge related to BID together for engineering designers. Fig.2 is the framework of the proposed variant BID knowledge representation.

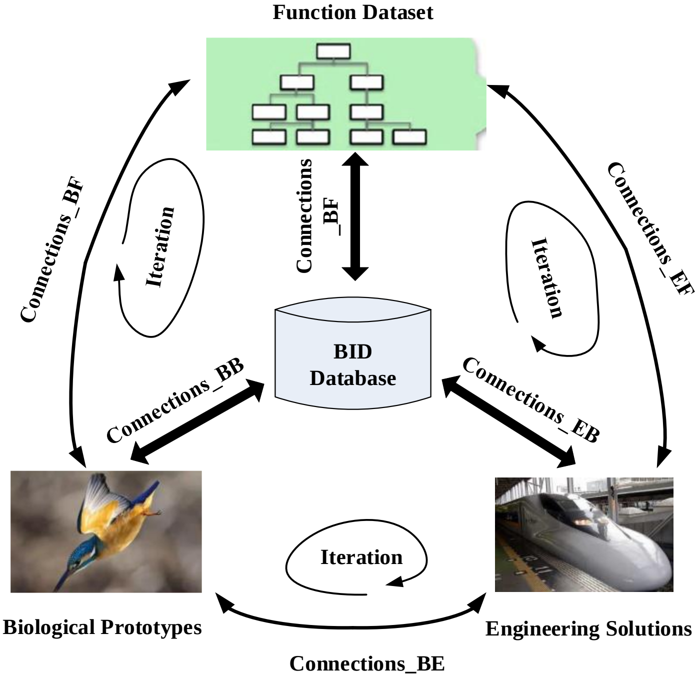

Figure 2: The framework of the proposed BID knowledge representation.

In Figure.2, there are five parts in the proposed BID knowledge representation by referring to the five-dimension model in the digital twins. Correspondingly, the biological prototype takes the place of the physical entity, which includes biological prototypes with potential to inspiring engineering design, while the engineering solutions play roles of virtual entities containing information about engineering design schemes that have been inspired by biological prototypes. The former DD section is replaced by the BID database which includes specific information about how biological prototypes and engineering solutions realize their functions, as well as their function structures. The function set replaces the former service section that involves main functions, assistant functions and auxiliary functions extracted from both facets of biological prototypes and engineering solutions. The connection section is kept in the proposed representation to indicate correlations between two other sections, which contain mapping and data sharing strategies.

There are several evident features of the proposed BID knowledge representation compared with existing modeling methods such as the DANE and SAPPhRIE. First of all, the proposed representation method can present information from both biological prototypes and bionic engineering design schemes, which help engineering designers understand long-range analogies in the transformation from biological prototypes into engineering solutions. On the second place, the proposed knowledge representation approach provides an effective way to accumulate BID knowledge, therefore, engineering designers can find various biological prototypes and exiting bionic engineering solutions related to given design problems, which is useful for inspiring creative ideas. Thirdly, bionic engineering solutions also contains important information about how to realize biological function in engineering applications.

3.2 The Data-driven Self-updating Strategy of BID Knowledge Database

The second section introduces the self-updating strategies of the proposed BID knowledge representation. In the proposed knowledge representation model, all the subsections of the proposed knowledge can be renewed with new inputting data. As an open BID database, amounts of biological prototypes and bionic engineering solutions will increase with continuously efforts from various contributors.

Different sections in the BID knowledge representation are correlated through different types of connections. Therefore, a database built on the proposed BID knowledge representation holds a wide range connected knowledge graph. Since the proposed BID knowledge database is designed for collaborative innovations, self-updating strategies are important for its workability. There are two main strategies to facilitate the self-updating of the BID database. The first one is the inspiring data inputting strategy, which requires data builders to consider and make decision about all kinds of connections when they input new information into the database. The second one is the iteration strategy which decides degrees of correlations based on inputting results from multiple contributors during the collaborative design.

Specifically, Figure.3 illustrates the basic mechanism of the inspiring data inputting strategy. Refers to Figure.3, database builders usually start from inputting biological prototypes data to inputting engineering solutions by following five operations:

Operation1: Input BPs information to create the New_CS_BB

At the operation of inputting BPs, new connections between the BPs and BID databases are created by asking builders to provide as much as biological knowledge about prototypes to be inputted. As the original biological knowledge usually takes forms of natural language texts, builders need to interpret and abstract main features of biological prototypes. Specific information about biological prototypes mainly includes the functional mechanism, the structural features, and the behavior causal relations. Therefore, inputted biological prototypes can be used from different perspectives to meet requirements in targeted engineering design, which can be added into the BID databased as the new inspiring stimuli for the future BID practice. Moreover, new connections between the new added biological prototype and existing ones (New_CS_BB) can be created based on their similarly functional, behavioral or structural characteristics.

Operation 2: Built function-based models of BPs to update the CS_BF

In the second operation, data builders are required to construct functional models of BPs and rank the importance of each function unit included in BPs to be built, meanwhile connections between the BPs and the FDs are updated based on analyzing results from different data builders. As results, the correlation strength between certain BP and its potential functions in engineering implementation can be determined. Therefore, data about correlations between BPs and functional units (CS_BF) can be updated with new correlations between existing units in function dataset and BPs to be inputted formed.

Operation 3: Input the function dataset for BID to create the New_CS_FB

In the third operation, data builders are required to input all the function units with their weighted importance values into the BID database. Then, the whole functional architecture of the given BID design task can be constructed by following intercorrelations among different function units. In other words, engineering users mainly define the main function requirement and figure out the functional structure in forms of the functional tree during this step. The BID function dataset can be continuously updated with new function units created and being added into the whole functional architecture of BID tasks that are formerly stored in the BID database, since the new connections between functional units and BID tasks (New_CS_FB) are created.

Operation4: Model functional architecture of biomimetic engineering design solutions to update CS_EF

In this operation, data builders need to input information about functional models of biologically inspired engineering solutions and indicate the importance of each function unit. Therefore, connections between the engineering solutions and the function dataset (CS_EF) can be updated based on functional analyze results of targeted engineering solutions.

Operation 5: Input new biomimetic engineering design solutions to create New_CS_EB

In the fifth operation, builders are required to input specific information about new biomimetic engineering solutions to be inputted to create new connections between the engineering solutions and the original biological prototypes (New_CS_EB), meanwhile, connections between the BPs and the ESs are then updated.

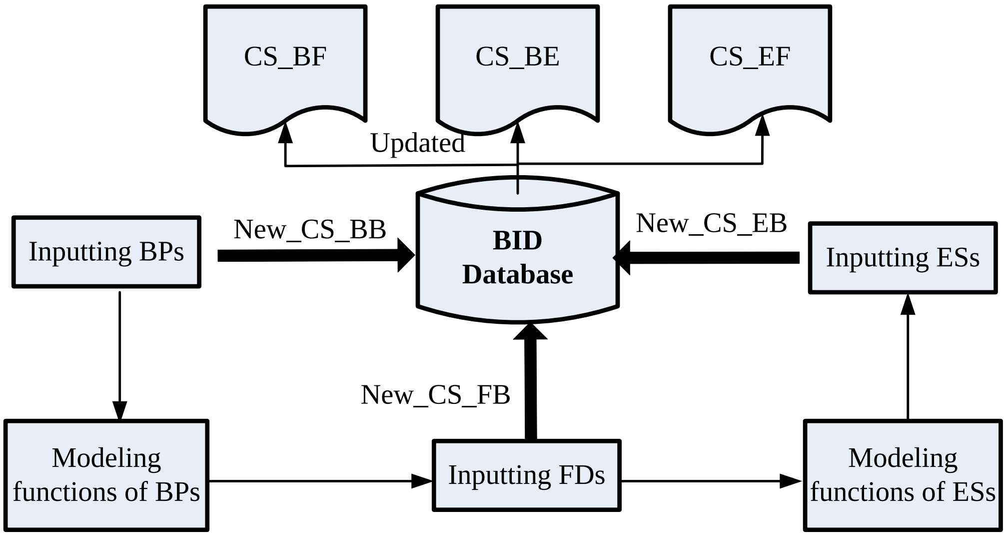

Figure 3: Main operations to facilitate the self-updating strategy.

Another new feature of the proposed BID knowledge processing method is the iteration strategy. The iteration strategy closely depends on collaborations of multiple contributors. With more information contributed by different builders, more reasonable connections in the proposed BID knowledge database will formulate. All the connections in the database have strength values to indicate the strength of relation. Calculation of each strength value depends on the frequency of correlations marked from contributors, which can be automatically achieved using remarking results of data builders.

3.3 The Algorithm to Recommend Analogical Prototypes for BID

The third section will expound the algorithm to recommend appropriate biological prototypes for BID. Based on the proposed BID knowledge database and the self-updating strategies, algorithms to recommend analogical prototypes help smooth the long-range knowledge transformation from biological domains to engineering design. However, exiting algorithms only recommend biological prototypes to meet engineering design requirements using functional similarity, such as the Asknature which is one of the most popular online BID knowledge sources. Previous studies ever revealed that knowledge about former successful BID cases is helpful for engineering designers to build their own creative solutions, since the generation of creative ideas usually depends on the case-based reasoning process. Therefore, both biological prototypes and biomimetic solutions are helpful for inspiring engineering users to generate creative solutions to given BID design tasks.

In the proposed approach, the proposed algorithm uses multiple norms besides the functional similarities aiming to match biological prototypes according to the overall ideality that considers engineering design criteria such as the operational environment, main functionality, systematic specification and performance indicator with their normalized weighted values to evaluate the appropriateness of biological prototypes, which are determined by specific design requirements of BID tasks. The first four indicators used in Table 1 is adapted from the exiting study [2] to evaluate the matching degree of biological prototypes in engineering design. Moreover, parameters to indicate features of biological prototypes in the data-driven BID knowledge database also play essential roles in making wise decisions about appropriate analogical prototypes for BID. These parameters used by the proposed knowledge processing approach mainly includes three kinds: frequency, which indicates how often a certain biological prototype is used by existing biomimetic engineering design solutions. For example, if there are n out total m data builders have pointed out correlations between the certain BP and the certain FD, then the strength of relation can be calculated as the n/m, which ranges from 0 to 1. Variety, measures the various degree of all the biomimetic engineering design solutions that were inspired by the same biological prototype; Novelty indicates the degree of technological difference of new potential biomimetic solution compared with existing biomimetic solutions. Different indicators can measure priorities of biological prototypes from different perspectives to satisfy different design requirements of BID tasks. There are in total seven indicators that help engineering designers wisely choose appropriate biological prototypes to given BID tasks with specific information shown in Table 1.

Criteria	*Meaning*	*Values*
Operational environment	Environment in which biological prototypes work properly to facilitate given function, which is shown as the input and output of the whole system, locations and conditions and interactions	0.268
Mian functionality	Degree of biological prototypes to meet main functional requirements of BID tasks shown as actions verbs, FBS ontologies, flows and objects	0.323
Systematic specification	Material, morphological, physical and structural characteristics	0.223
Performance indicator	Systematic completeness, sustainability and usage efficiency	0.186
Frequency	Degree to measure how often a given biological prototype to be used in existing engineering design solutions	(0,1)
Variety	Measure application range of a given biological prototype based on technological difference	(0,10)
Novelty	Measure how potential BID solutions differ from the existing engineering solutions	(0,10)

Table 1: Set of choosing criteria for biological prototypes for BID tasks.

In Table 1, the first four indicators are adapted from a former study on assessing biological prototypes for smart products development with their weighted values [2]. They are used to assess potential usability of biological prototypes in engineering design. The other three indicators reflect potential usability on other aspects. To be specific, the indicator of the frequency can be calculated through formula (1). In formula (1), n_i denotes the amount of engineering solutions inspired by the i^{th} biological prototype, N denotes the largest amount of engineering solutions inspired the most popular biological prototype belonging to this domain. The indicator of novelty can be calculated through the formula (2) and (3), while the variety indicator can be obtained by using formula (4), formulas (2) to (4) are adopted from the previous study [37]. In formula (2), M_1 denotes the overall score for the novelty of the concept for m functions on the n abstraction levels in the genealogy tree. Weights of function and abstraction levels denote as f_i, P_k respectively, while S_{1jk} is the novelty value for ideas on the different abstractive level can be calculated through the formula (3). In formula (2), T_{jk} expresses the total amount of ideas produced to meet the j^{th} functional requirement on the k^{th} abstraction level, while the C_{jk} represents the number of the existing solutions or those are originated from the common senses on the corresponding level then it is multiplied by 10 to be normalized [37]. Variety score for participant can be calculated through the formula (4), in which V denotes the final variety score, S_1 stands for the value of physical principles in the first level, i.e., physical law of the genealogy tree, so does the S_i for i^{th} level in the tree; b_i is the number of nodes on i^{th} level in genealogy tree while d_l is the number of differentiations by referring to the detailed information about calculation in the reference [37].

$$f = \frac{n_i}{N}; N = \max n_i, i = (1, m) \tag{1}$$

$$M_1 = \sum_{j=1}^{m} f_j \sum_{k=1}^{n} S_{1jk} \cdot p_k \tag{2}$$

$$S_{1jk} = 10 \times \frac{T_{jk} - C_{jk}}{T_{jk}} \tag{3}$$

$$V = \sum_{j=1}^{m} f_j \left(S_1 (b_1 - 1) + \sum_{k=2}^{4} S_k \sum_{l=1}^{b_{k-1}} d_l \right) \tag{4}$$

The proposed recommending algorithm mainly follows four specific steps to identify appropriate biological prototypes according to design requirements of BID tasks.

Step 1: Define main functional requirements of BID design tasks and search and obtain the set of biological prototypes that meet main functional requirements of BID design tasks.

Step 2: Set the threshold value of feasibility that are commonly decided by the first four indicators in Table 1. It is set as 0.5 for most circumstances.

Step 3: Screen out biological prototypes and calculate the other three indicators of biological prototypes that have scored higher feasibility than the threshold value.

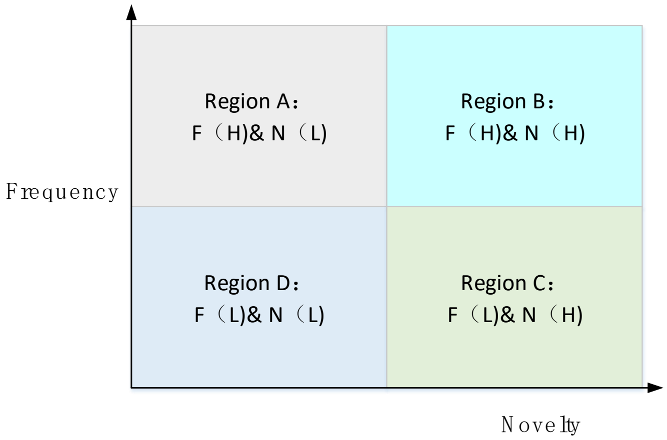

Figure 4: Four biological knowledge clustering results based on recommendation algorithm.

Step 4: Cluster remained biological prototypes according to calculation results of frequency and novelty since the variety is correlated with the indicator of frequency. Divided by two dimensions, all the biological prototypes are categorized into four regions shown in Figure 4. Most of biological prototypes can be clustered into the region A and region C. While the region B has the highest appropriateness to be applied in BID tasks since it has already been applied in similar engineering design problems and proven feasible meanwhile has potential to generate novelty engineering solutions. On the contrary, biological prototypes in region D has higher uncertainty to be applied in engineering design. Biological prototypes belonging to the region A has higher reliability but lower potential to inspire innovative design solutions, while the region C is more ideal for inspired more evident novel engineering solutions accompanied by higher uncertainty.

Step 5: locate the most promising region in the biological prototypes clusters and identify then recommend the most ideal biological prototypes with highest variety value.

The proposed recommending algorithm is able to provide three kinds of knowledge to facilitate the long-range analogies in BID. The first kind knowledge is appropriate biological prototypes that can meet main engineering design requirements which are usually in forms of functional characteristics. The second kind of knowledge recommended by the proposed algorithm is engineering solutions found in exiting products, patents and science documents those origin from matched biological prototypes. Knowledge on the third facet mainly contains key enabling technologies for the realization of biological prototypes in engineering applications.

4 CASE STUDY

In this section, an illustrative example of design for biomimetic wind power blade for slow wind speed environment is used to address the feasibility of the proposed BID knowledge processing approach to support practical BID design tasks. The application of the proposed biological knowledge processing approach is integrated with the problem-driven BID process, which is explained in detail as four main steps as follows.

4.1 Problem Definition

Wind power plays a significant role in coping with serious environmental issue on reducing the global carbon emission by replacing the fossil energy. Until very recent, engineering domain starts to show interests on invent wind device that are able to collect wind power from low wind speed environment such as the urban area or the plain area.

Natural biology is an ideal teacher for engineering to learn the mechanism to exploit the sustainable energy from the low-speed wind since many kinds of biology lives in the air or water can wisely use the hydromechanics of low-speed fluid to move. Therefore, the main functional requirement of the illustrative design task can be defined as the change the wind power into mechanical energy then to be used for generating electricity. In other words, the illustrative design task asks for feasible ways to transform low-speed wind power into mechanical energy. Moreover, other useful information such as the operational environment, structural constraints are also decided by engineering designers, all of the useful information is show in the Table 2.

Items	*Specific defined information*
Mian functionality	Change ***wind (fluid) power*** (in low speed) into the ***mechanical energy*** (rotation, torque), then into the electricity.
Operational environment	Environment with low-speed wind(***fluid***), such as the forest, plain area or urban area, or in other fluid, such as water or oil.
Performance Constraints	Sustainability, usage efficiency, manufacturable and low building cost
Systematic specification	A blade shape like structure for a new wind turbine that is able to utilize the low-speed wind

Table 2: Defined information on main functional requirements of the illustrative design example.

4.2 Build the Variant BID Knowledge Representation Model

This section will briefly introduce how the proposed data-driven variant BID knowledge representation is built gradually to support the given BID design tasks. The building work takes several specific steps as follows.

Step 1: Input biological prototypes

Several online BID knowledge including the Askanture are used as the original sources for inputting biological prototypes. There are roughly 50 biological prototypes obtained from the online knowledge database. Then the manual cleansing is applied to remove irrelevant ones. As results, there are 34 biological prototypes left for further processing. Among those post-cleansing biological protypes, eleven strategies come from birds in their wings and bones features, which take the largest part, ten strategies are from insects in their wings features or other body parts, seven from animal have gliding capabilities such as the fly squirrels and six are from plants in providing protective shells for their seeds.

Step 2: Functional analysis of biological prototypes

Each of post-screening biological prototypes needs further analysis to reveal its main functional features using the variant function modeling methods. For example, the biological prototypes of owl wings have been analyzed and built the functional models in forms of the variant biological knowledge representation, which is shown in Figure.5. Refers to the Figure.5, the biological prototype of the owl wings is firstly inputted into the BID knowledge database, then its inspiring engineering design solutions such as the low-noise fan and the new airfoils with the finlet. The functional model of the biological prototype is also built through the FBS ontology approach to represent the mechanism of biological functions.

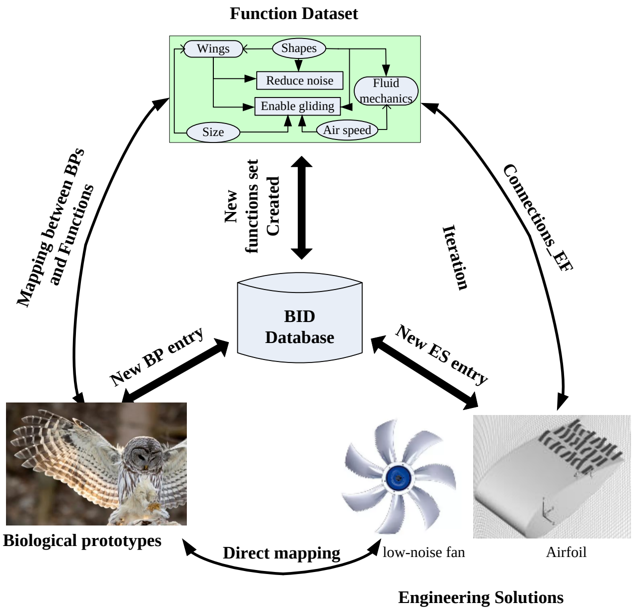

Figure 5: Functional analysis of the owl wings with its functional model built in the variant forms.

Step 3: Input the function dataset

The function dataset of BID knowledge database is gradually developed with inputting new potential functions inspired by biological prototypes. The primary functional requirement of the given task is to transform wind power into mechanical energy. With the analysis of in total 34 biological prototypes, the overall function dataset is formulated gradually and shown as the functional tree model in Figure 6.

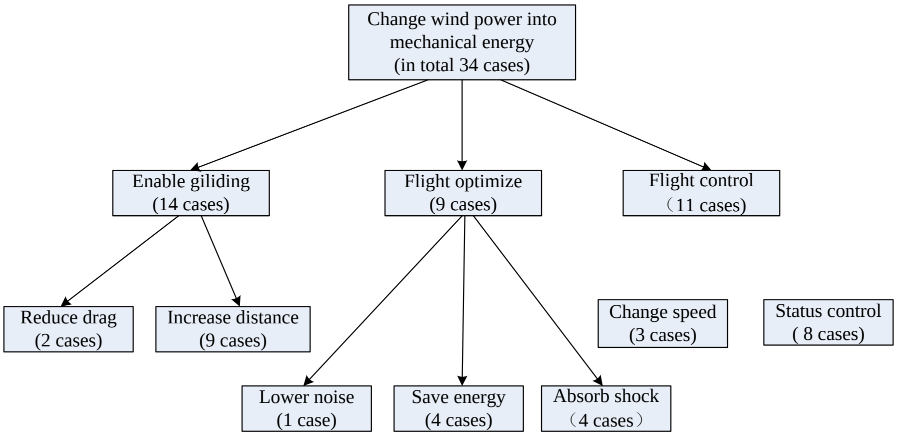

Figure 6: Function dataset is formulated based on functional analysis results of BPs.

Step 4: Analyze and input biomimetic engineering solutions

There are in total fifteen biomimetic engineering solutions firstly retrieved from online biomimetic database. Subsequently, the manually cleaning is then applied to screen out the irrelevant biomimetic solutions. Therefore, only ten engineering solutions that are related to the main requirement of the given BID task. Moreover, mapping correlations among BPs and ESs are analyzed and represented before the engineering solutions being inputted into the BID database. Connections between BPs and ESs can be built as the Figure 7, which also includes the information about analogical design strategies since it is also important for inspiring new creative design.

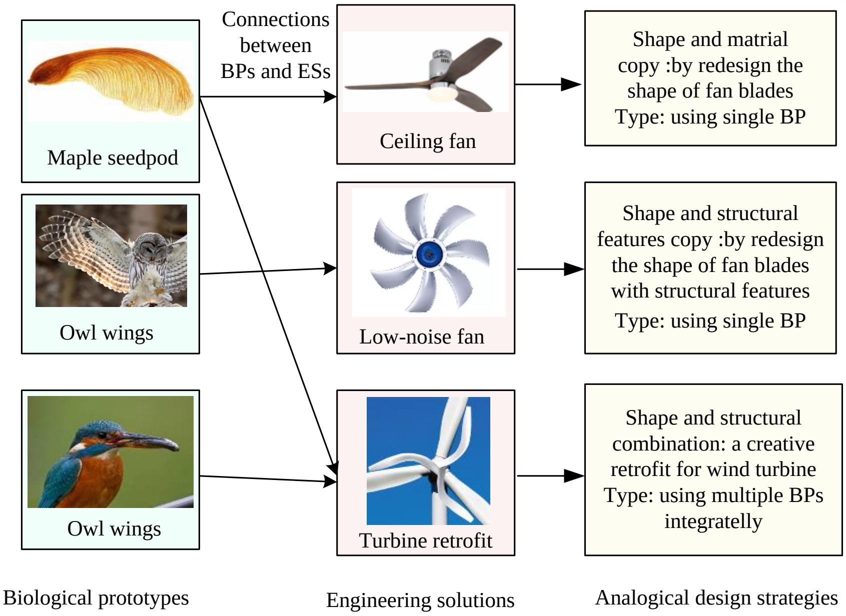

Figure 7: The information structure used in the entry of biomimetic engineering solutions.

4.3 Biological Prototypes Recommended by the Data-driven Processing Approach

Appropriate biological prototypes are recommended for engineering designers by using the proposed recommending algorithm, which evaluates the potential usability of biological prototypes from two dimensions. Indicators belonging to the first-dimension measures degree of biological protypes match main design requirements of given BID projects. The second categories criteria are applied to assess the priority of biological prototypes in given BID tasks based on their possibilities and novelty to be used in generation of engineering innovations.

In the illustrative BID design task, five evaluators with BID design experience are recruited to assess retrieved biological prototypes using first four indicators in Table 1. They commonly agree to set the threshold value of functional match to 0.5. Afterwards, there are only six biological protypes that show high relatedness to the main functional requirement of the given BID tasks. Subsequently, indicators on the second dimension are calculated using formulas (1) to (4) with results are shown in Table 3.

BPs	*Functional match*	*Frequency*	*Variety*	*Novelty*
Wings of fly dragon in gliding	0.523	0	0	0.3
Manuals skins and body parts to enable gliding	0.635	0	0	0.3
Wingtip help gilding in bird fly	0.710	0	0	0.3
Wings of birds help gilding	0.820	0.333	0.3	0.3
Owl wing's structure to enable the low-noise gliding	0.827	1	0.3	0.3
Maple seedpods enable long gilding	0.828	0.667	0.3	0.3

Table 3: Benchmarks of screened out BPs for the given BID task.

Refers to Table 3, all these six biological prototypes have the same potential novelty for the given BID task. Moreover, biological protypes with higher values of frequency and variety have more exiting biomimetic engineering solutions which are also important analogical stimuli for new BID tasks. From this viewpoint, both the maple seedpods and owl's wings are recommended as the appropriate biological prototypes for the exemplar case study.

4.4 Biomimetic Design Solutions

Engineering designers redesign new blades for the wind power generator in the low wind speed environment by using both the maple seedpods and owl's wings separately. During the biomimetic design process, engineering designers mainly apply analogical strategies of the shade and structural features copy and mimic the biological structures. Afterwards, the biomimetic design solutions are shown in Figure 8 and Figure 9 respectively.

The first biomimetic engineering design solution has mimicked structural features of the maple seedpods, moreover, it also considers the tornado-like shape gliding trajectory when the maple seedpod falls from the tree. The second biomimetic solution has utilized the shape and structural features of owl's wing with the purposed to generate torque by using the low-speed wind power. Both biomimetic solutions are newly designed engineering schema, they have addressed the feasibilities of the proposed BID knowledge processing approach.

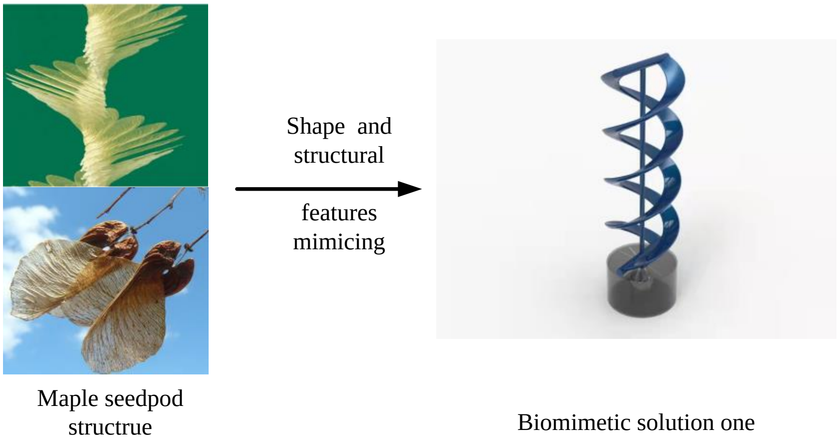

Figure 8: The information structure used in the entry of biomimetic engineering solutions.

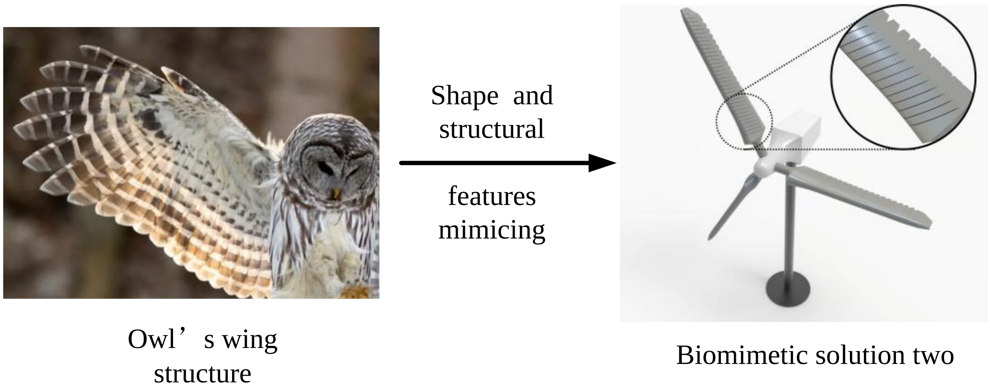

Figure 9: The information structure used in the entry of biomimetic engineering solutions.

5 DISCUSSIONS AND CONCLUSIONS

In face of the ever-growing requirement of engineering design for smart products, this study provides a new data-driven BID knowledge processing approach aiming at facilitating using biological prototypes in the generation of new design scheme. The proposed BID knowledge processing approach is built on a new hybrid BID knowledge representation that has integrated both the functional modeling approach and the five dimensions model from the DT. The proposed approach is validated by an exemplar study of new wind blade design in the low wind speed environment.

There are several contributions of the proposed approach on both the theoretical and practical aspects. Firstly, this approach has attempted to integrate the five dimensions model from the DT with the function-based BID knowledge representation to enable the representation of the interdisciplinary knowledge and their relationships in the realization of biological strategy, in turns the application region of the five-dimension model in engineering design particularly for the conceptual design stage is also extended. Secondly, the proposed BID knowledge processing approach also include algorithms to recommend appropriate biological prototype to given BID tasks, which are developed on the basis of the self-updating strategies. Thirdly, the proposed BID knowledge processing approach can provide a computer aided tool for developing a new training program to educate new engineering designers to use BID approach for solving engineering design problems through a project-based learning strategy, since they can use both biological strategies and biomimetic design solutions as stimuli.

However, limitations of this study are also evident. To be specific, three main problems require further studies. The first one is the proposed BID knowledge processing approach is still at the very preliminary stage of the data-driven approach, therefore, manual labor is still needed to make important decisions on knowledge evaluation, which may hinder the scientific solidness of the proposed approach. Therefore, it requires more intelligent algorithm to assistant even replace professional evaluators. Another problem lies in the absence of the automatic online original BID data collecting method, which leads to the proposed method only can use the existing BID knowledge online database. Therefore, new web crawlers-based tools can be developed in the future to provide efficient ways to enhance the feasibility of the proposed approach. In the third place, the validation of the proposed study mainly depends on the practical usage in the illustrative engineering design case, which is a very early stage to verify its feasibility as a design schema. Therefore, the effectiveness of the proposed requires more solid validations in forms of design experiments or investigations of users' satisfactory about using the sophisticated version of the proposed method as a new software product.

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