

# Design-by-Analogy: Exploring for Analogical Inspiration With Behavior, Material, and Component-Based Structural Representation of Patent Databases

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*Design-by-analogy (DbA) is an important method for innovation that has gained much attention due to its history of leading to successful and novel design solutions. The method uses a repository of existing design solutions where designers can recognize and retrieve analogical inspirations. Yet, exploring for analogical inspiration has been a laborious task for designers. This work presents a computational methodology that is driven by a topic modeling technique called non-negative matrix factorization (NMF). NMF is widely used in the text mining field for its ability to discover topics within documents based on their semantic content. In the proposed methodology, NMF is performed iteratively to build hierarchical repositories of design solutions, with which designers can explore clusters of analogical stimuli. This methodology has been applied to a repository of mechanical design-related patents, processed to contain only component-, behavior-, or material-based content to test if unique and valuable attribute-based analogical inspiration can be discovered from the different representations of patent data. The hierarchical repositories have been visualized, and a case study has been conducted to test the effectiveness of the analogical retrieval process of the proposed methodology. Overall, this paper demonstrates that the exploration-based computational methodology may provide designers an enhanced control over design repositories to retrieve analogical inspiration for DbA practice. [DOI: 10.1115/1.4043364]*

## 1 Introduction

Designers often seek inspiration and direction during ideation and the early stages of the design process. Among various efforts to find such inspiration is design-by-analogy (DbA) [1]. Design-by-analogy involves the retrieval of analogies from a design repository, a “database” of existing design solutions (sometimes simply memory), and the transfer of knowledge from a “source” domain to a “target” domain. To facilitate design-by-analogy in practice, several researchers have studied and developed computational supports to retrieve analogies from electronic patent databases [2,3]. The patent database is deemed an ideal design repository for its innovative ideas across various fields of application and sheer size that grows exponentially worldwide [4]. Unfortunately, our understanding of design-by-analogy practice is inadequate compared to the ever-increasing size of the patent database, restricting designers from being able to utilize the database at its full capacity. To address this research gap, the work presented here uses a computational methodology to explore patents for analogical inspiration, with the goal of facilitating the design-by-analogy practice. Specifically, the work presents following main contributions:

- (1) The authors generate and visualize hierarchical repositories of large-scale mechanical design-related patents in which designers can interactively explore for analogical inspiration.
- (2) The authors generate component-, behavior-, or material-based hierarchical repositories to provide designers

different lenses to influence the way they search for analogies in patent data.

- (3) The authors test computational methodology for its ability to assist with the identification of analogical inspiration within the generated design repositories using a case study.

**1.1 Prior Studies in Design-by-Analogy.** Design-by-analogy has been an active research area [2,5–8], and studies have focused on understanding the effects of analogies on ideation and design outcomes. Many other researchers have contributed to this area, as described next. Linsey et al. explored how various types of representation of information affect the designers’ ability to identify, retrieve, and map analogies to design solutions [9]. Tseng et al. studied how analogous information of different levels of applicability to the design problem affects ideation when the design problem has an open-goal [7]. Several studies also focused on methodologies to retrieve analogies including but not limited to: the WordTree method, which retrieves functional analogies by systematically integrating the knowledge of designers and design database [10]; a computational technique to recognize biological analogies using causally related functions derived from semantic information [11]; D-APPS, which provides functional analogies based on a design’s product requirements [12]; a number of different patent mining tools [3,13–15]. Most DbA tools, including the prior work reviewed here, use a query-based approach or straightforward input–output method to retrieve analogies. In the case of the WordTree method, designers input a word characterizing a design’s functionality and are returned a set of functionally analogical words from various domains, compiled by the algorithm, as source of inspiration [10]. The work presented in this paper is differentiated from the prior work in that our methodology gives designers an entire structured design space for exploration where

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they can freely interact with the design solution and discover analogies from various potential sources. The emphasis on the exploration for analogical retrieval is discussed in the next section.

**1.2 Exploration for Expert Thinking in Design.** Based on the findings of prior research, expert designers have exhibited several cognitive characteristics and abilities during the design process. First, they have been shown to have better spatial memory than novices, being able to process more information [16,17]. Bjorklund found that experts gather more information than novices to ideate design solutions for a given problem [18]. Other researchers found that experts can also cognitively organize the information and conceptualize abstract ideas by viewing the problems objectively [19,20]. Experts have been found to have a systematic approach to design [19], being able to spontaneously adapt to the design constraints [21] and develop heuristics or “rules of thumb” to approach the problem [17,22]. The dynamic, flexible, and systematic characteristics of the expert designers that have been discovered in prior research indicate that the explorative approach is better matched with their cognitive mechanisms. The explorative approach allows the designers to retrieve analogical inspiration by interactively exploring a design repository and autonomously recognizing analogical connections among potential design sources, which could have been ruled out by the query-based algorithm. In addition, the user-controlled explorative approach allows designers to personalize their search for analogies using various analogical properties, creating unique representations of the design repository and/or design problem that could lead to diverse creative design output [23]. Some potential analogical properties that could be employed are introduced in Sec. 2.1.

**1.3 Patent Database as Design Repository.** The U.S. Patent database has several features that make it a suitable design repository for the design-by-analogy practice. The prior design solutions in the database are valuable knowledge that are deemed “patentable.” Patentable ideas can be further defined as ideas that are “useful,” meaning that the ideas are functional and operable, and novel. The term “novel” here implies that the ideas have not previously existed before [24]. The database size, already enormous at approximately 10 million patents in 2015 [25], grows continuously in various technical fields and promises designers substantial opportunities to explore for design inspiration in multiple domains. The patent database uses classification systems, such as Cooperative Patent Classification (CPC), to categorize the patents into specific domains for efficient patent-retrieval processes [24]. The characteristics of the patent database not only make it an ideal source of innovation but an efficient means for retrieving analogies.

The vast size of the patent database offers a great opportunity for discovering analogies for design-by-analogy practice, but it simultaneously presents a challenge for effective mining of patents. To address this challenge, many computational tools and

methodologies have been studied. Song and Luo integrated the mining of patent texts, citation relationships, and inventor information to retrieve patents for assisting data-driven design [26]. Murphy used a Vector Space Model algorithm to evaluate functional analogies within patents [3]. These works implement different computational approaches to retrieve analogies from the electronic patent database. They all exemplify the importance of computational support to access the patented knowledge in the design repository.

## 2 Methodology

A structural form of data is essential for providing valuable insights into the data. For instance, Linnaeus’s tree structure for biological species and Mendeleev’s periodic table for chemical elements led to major scientific advancements in understanding nature [27]. Finding a structural form requires a clustering or categorization of data. In text mining and data mining fields, a popular computational technique used for data clustering is non-negative matrix factorization (NMF) [28,29]. NMF is a topic modeling technique that discovers semantically meaningful topics within a large corpus of documents to aid text mining [30,31]. It has been an active research area in text mining for its practical advantages over other semantic techniques such as latent Dirichlet allocation [32]. One advantage is that NMF generates consistent topic clustering results, assuring that users are returned similar results for multiple runs. Also, numerous matrix computation and optimization studies for efficient NMF computation suggest its competency for the large corpus topic modeling [33–36].

Similar to most semantic techniques, NMF starts with transforming a corpus into a word-document matrix, in which the matrix elements represent the frequency of words (rows) occurring in the patent documents (columns). Mathematically, the word-document matrix is represented by  $X \in \mathbb{R}_+^{m \times n}$ , where  $m$  represents the number of words and  $n$  represents the number of documents in a corpus. Given  $k \ll \min(m, n)$  as a user-specified number of topics, NMF factorizes the input matrix,  $X$ , into two non-negative matrices, namely  $W \in \mathbb{R}_+^{m \times k}$  and  $H \in \mathbb{R}_+^{k \times n}$  such that  $X \cong WH$ . Here,  $W$  is a word-topic matrix whose  $i$ th topic column is represented by the weighted distribution of words. Similarly,  $H$  is a topic-document matrix whose  $j$ th document column is represented by the weighted distribution of the respective topics. The matrix decomposition is illustrated in Fig. 1 [29].

In this work, the patent data were processed to generate the cluster structures shown in Appendix A (Figs. 12–14). First, word-document matrices of patents were prepared. Second, cluster structures of the patents were generated using NMF. Lim et al. conducted NMF study with the U.S. patents to study the computational performance of the topic modeling tool [37]. However, the work presented in this study is the first DbA study to use NMF for retrieving analogies for a design practice. Last, visual representations of the structures were generated. All computations for

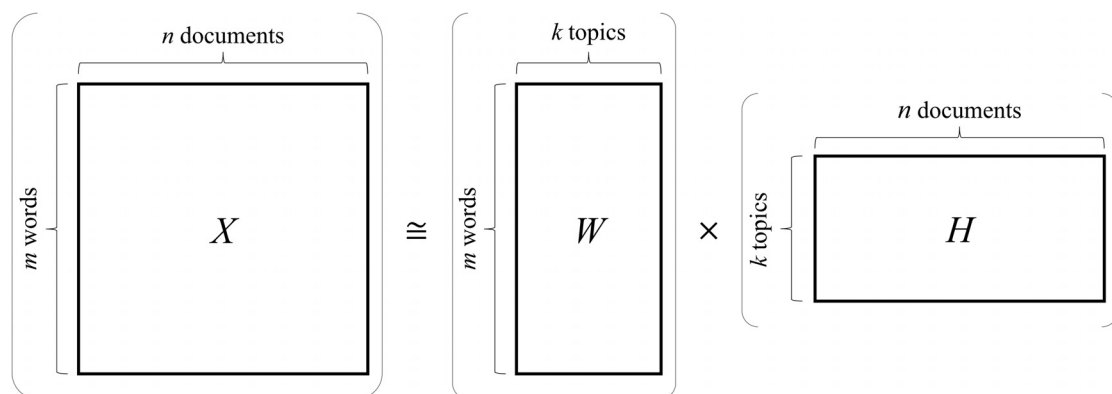


Fig. 1 Illustration of NMF

establishing the algorithmic approach were performed using MATLAB R2016b. Each of these steps is described in detail in the subsequent sections.

**2.1 Preparing Word-by-Document Matrices.** The first part of the computational approach involves retrieving patent data from a data storage system of United States Patent and Trademark Office (USPTO). The database consists of a bulk of U.S. registered patents, each assigned to at least one classification term called CPC. All registered U.S. patents are categorized into one of nine CPC sections and further assigned into a subsection, which provides a general overview of the patent's design features and area(s) of application. To limit the scope of the study, only mechanical design-related patents were used; Fifty-three CPC subsections were chosen by the researchers as shown in Appendix B. For each subsection, 20 patents were selected using a random number generator, comprising a total of 1060 patents. This sample size (>1000 patents) was chosen to capture various analogical structures in the patent space with a goal of addressing the research gap in implementing the computational DbA tool in a larger-scale design repository. Prior work by the authors has been with sample sizes of 100 patents [38]. In future work, the authors hope to continue to scale up the sample size by orders of magnitude. For each patent document, the researchers used only the words in the abstract, claims, and description sections, as they are the most representative of the patent's design features. All other words in prior patent data and reference sections were omitted as they do not characterize the patent's design aspects.

In addition to the patent documents, a design problem statement was also added to the corpus for generating the word-document matrix. Its purpose was to provide a "starting point" in the cluster space to facilitate data analysis and exploration. The design problem statement, which was used in the researcher's prior study, was as following [38]:

*Design a device to collect energy from human motion for use in developing and impoverished rural communities in places like India and many African countries. Our goal is to build a low-cost, easy to manufacture device targeted at individuals and small households to provide energy to be stored in a rechargeable battery with approximately 80% efficiency. The energy is intended to be used by small, low power draw electrical devices, such as a radio or lighting device, hopefully leading to an increase in the quality of life of the communities by increasing productivity, connection to the outside world, etc. The target energy production is 1 kWh per day, roughly enough to power eight 25 W compact fluorescent light bulbs for 5 h each per day, or enough to power a CB radio for the entire day. For reference, an average adult human can output about 200 W with full body physical activity for short periods of time, with a significant reduction for sustained power output.*

After the word-document matrix was generated, the matrix was further processed to characterize three design properties—components, behaviors, and materials. In the early stages of the design processes, designers often have diverse objectives and lenses through which they look when searching for inspiration or external information. By allowing for these different lenses to influence the way the design space is structured and inter-related, we give designer the ability to explore in a more tailored and efficient manner than before. The manipulation of the patent data set was done by first manually compiling a list of words that characterize each analogical property, then reducing the original matrix to contain only the rows of the listed words. The word lists were generated by drawing a master wordlist from the patent corpora and classifying each word into one of the three properties. As a designer searches for analogical inspiration, he/she might, for example, ask the following questions when considering components, material, or behavioral content within their potential analogical sources.

- **Component:** What specific components have been integrated to the system/artifact/technology?

- **Behavior:** What are the attributes of the system/artifact/technology that describe how it behaves?
- **Material:** What materials does the system/artifact/technology use or consume?

After a test run, words that appear too frequently were removed to distinguish one patent from another. As a result, wordlists of components (709 words), behaviors (262 words), and materials (377 words) were compiled as shown in Appendices C, D and E. Cohen's kappa inter-rater agreement analysis was performed to verify the robustness of all the wordlists ( $\kappa = 0.756$ ,  $p < 0.005$ ). The refinement does not alter the matrix's numerical element—the frequency of words occurring in each document—but rather removes any words that are "noise" within the given context. This allows designers to explore the patent space using a particular priority, angle, or attribute. A similar practice was done in the author's previous study, in which function and surface features of patents were explored using verbs-only and nouns-only data, respectively [38]. This study is an extension of the prior study in that the components, behaviors, and materials of the patent data are explored to investigate their potential for facilitating design inspiration. For the final step, inverse entropy weighting was performed on the word-document matrices to assign higher weight to words that appear less frequently and vice versa.

**2.2 Processing With Topic Clustering Algorithm.** The cluster structures of the three patent data sets were generated using NMF. The computational algorithm requires a user-specified number of topics,  $k$ , to process the word-document matrix. It is critical that an appropriate topic number is selected for the algorithm, as overly or inadequately clustered data leads to an inaccurate clustering result. Unfortunately, computing an appropriate topic number is still an ongoing research [39], and thus questions the effectiveness of the topic clustering, especially for a large-scale data whose range of topics may vary exceedingly. To cope with this challenge, a computational method similar to Du et al.'s divide-and-conquer non-negative matrix factorization (DC-NMF) was used [33]. As illustrated by a hierarchy structure in Fig. 2, NMF with  $k = 2$ , or rank-2 NMF, was performed recursively on an input word-document matrix. The rank-2 NMF, which has fast computational speed [40], divides the input matrix into two output matrices of clustered patents. These clusters are then used as inputs for the next iteration. The iteration continues until the processed output cluster contains less than or equal to ten patents. The stopping criterion is an important factor for determining the clustering quality, as it could result in overly or inadequately clustered structures. We acknowledge that the current stopping criterion was experimentally determined and that it generates cluster structures whose qualities are sufficient for analyzing the analogical relationships among patents. However, the stopping criterion of the iterative method is an important area of improvement for an effective topic clustering in future studies.

Throughout the process of generating structures, a label was generated for each cluster so that the analogical relationships among the clustered patents become more transparent and interpretable [38]. In each iteration of NMF, the algorithm outputs  $\mathbf{W}$ , word-topic matrix, and  $\mathbf{H}$ , topic-document matrix. Here,  $\mathbf{W}$  represents the probabilistic distribution of words for each column of topic, implying that the word that has the highest probability score in the  $j$ th column in the matrix contributes the most to the  $j$ th topic's description. In this study, the columns of words in  $\mathbf{W}$  were sorted in descending order, and the top five words in the column were used to create the cluster label.

**2.3 Visualization.** The cluster structures of the three patent data sets were visualized using MATLAB's graphing tool to enable the exploration and interpretation of the large-scale cluster space. This section details two visualization methods used to analyze the clustered patent structures.

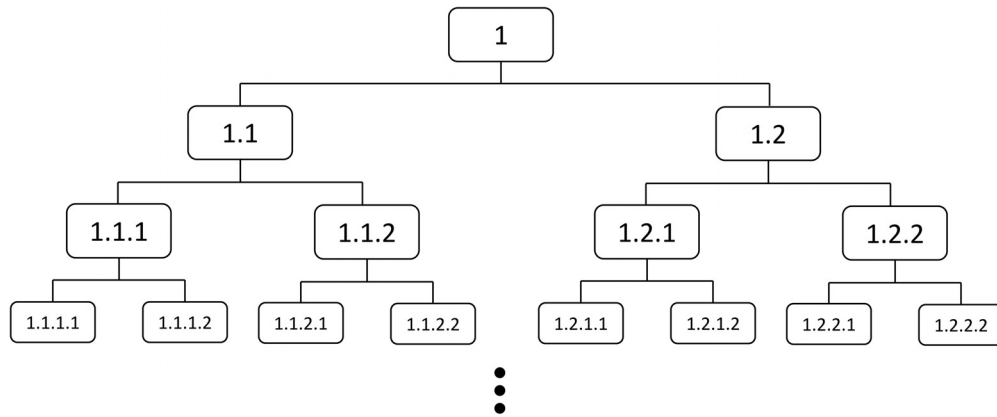


Fig. 2 Illustration of rank-2 NMF iterations

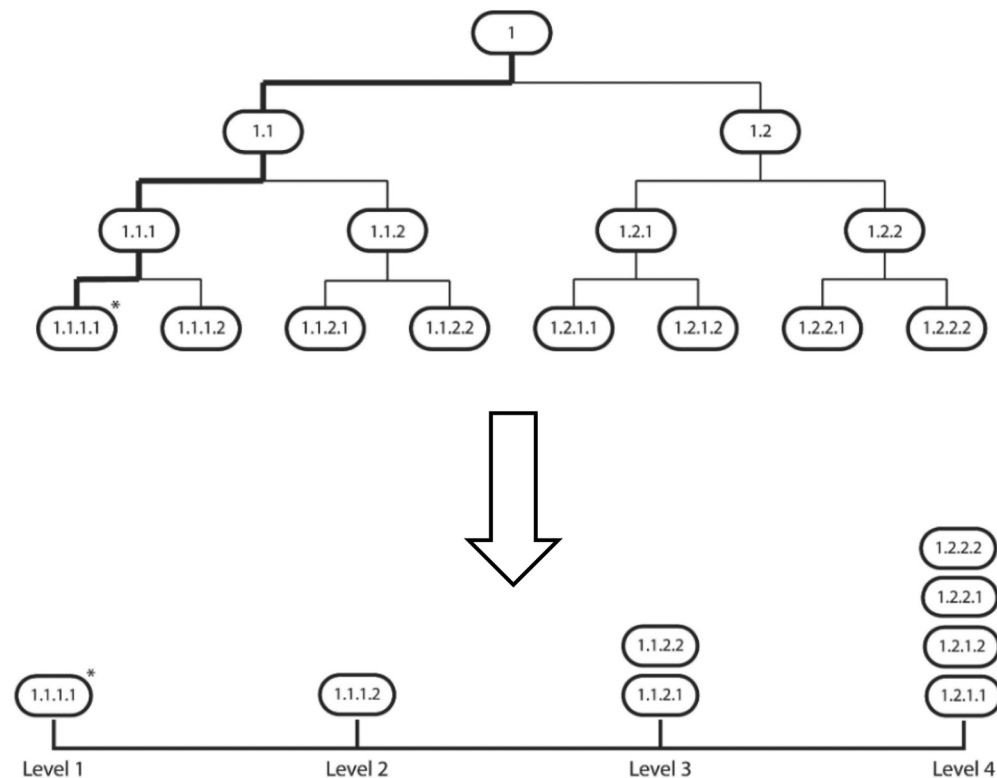


Fig. 3 Transformation of 3D visualization to 2D visualization

**2.3.1 Three-Dimensional Hierarchical Visualization.** Three-dimensional (3D) hierarchical visualization was used to interactively explore the cluster space. The hierarchy structure is composed of nodes, or clusters of the patent documents, and lines, or the connections between the clusters. The structure contains the initial input data, or “root node” at the center. Starting from the root node, two child nodes branch out recursively outward until all clusters at the end, or “leaf nodes,” contain less than or equal to 10 patents. For exploration of the space, the user can rotate or zoom into the structure to search for a node and select the node to view its cluster label and cluster ID number, used for retrieving patent titles. The 3D structure, as shown in Appendix A, was generated using MATLAB’s “digraph” function with “force3” layout. The force3 layout generates 3D force directed plot, where the coordinates of nodes and length of edges are determined based on the structure and size of the input graph.

**2.3.2 Two-Dimensional Bar Graph Visualization.** Figure 3 illustrates the transformation of the three-dimensional hierarchy

visualization into a two-dimensional (2D) bar graph visualization. Note that the 3D hierarchy structure in the figure is represented on a 2D graphing space for an effective understanding of the transformation. In the 3D structure, the node of patents iteratively breaks down into two child nodes based on their topic similarity. This implies that the most similar patents in the entire data set would be clustered in a leaf node after a series of NMF iterations. In this manner, if that leaf node is “1.1.1.1” in Fig. 2, the next similar set of patents would be clustered in a leaf node, “1.1.1.2,” derived from the same parent node, “1.1.1.” Accordingly, the least similar set of patents would be separated in the first iteration performed on the initial node, “1.” Once the set of patents is separated, it would go through another series of NMF iterations resulting in several leaf nodes on the other side of the hierarchy structure. This iterative concept was visualized in a two-dimensional bar graph diagram. In the diagram, the horizontal axis represents the level of the hierarchy, equivalent to the series of nodes on the bolded path in Fig. 3. On each level of the hierarchy is a set of leaf nodes with cluster labels that are generated with the separated set of patents at each



level. This way, the leaf nodes are distributed across the level of the hierarchy in the order of similarity from a starting leaf node (indicated with an \* symbol) in Fig. 3. For consistency of the study, the design problem node—or a leaf node that contains the design problem statement—was chosen as the starting point.

The screenshots of the cluster structures are shown in Appendix A. In the 3D visualizations, the design problem node was selected to display its cluster label and highlight its path from the root node in the center. In the 2D visualizations, all leaf nodes are plotted in the order of similarity to the design problem node on the first level. The two visualization methods were used interchangeably to evaluate the patent data's cluster space. For instance, the 3D visualization was used to view the entire cluster space where individual clusters can be explored by their labels. Two-dimensional visualization was used to sort all clusters on the two-dimensional plane to view the leaf clusters by their similarity to the starting leaf cluster. The analysis results are presented in the next section.

### 3 Results

The clusters in component, behavior, and material analyses exhibit different characteristics. For the component result, the clusters consist of patents of similar functionality. The functions of the individual components correspond to the subfunctions of the integrated design. The patents in the behavior result are clustered by the design's descriptive quality. The patents in the material result are clustered for two different aspects—(1) material that the design is composed of and (2) material that the design uses or consumes.

The three cluster results are visually unique, suggesting that different design insights can arise from a single patent data set [23]. To confirm this, the researchers first selected three random patents (“pocket tool,” “ice gripping sandal,” and “shower bath apparatus and spray nozzle”); then, using the computer-generated cluster labels, the researchers evaluated their analogical relationships with other clustered patents as shown in Fig. 4. The figure is a simplified version of 2D bar-graph visualization, where each cluster containing the node number, cluster label, and list of patents is laid out on the order of similarity. In this section, the analogies of the clustered patents are evaluated to understand the clustering mechanism for component-, behavior-, and material-based patent data. However, the meaning of the level of similarity is not discussed due to the limited information to interpret the analogical distance among

different clusters. Future studies need to investigate the meaning of the “level” and its utility during the analogical exploration.

#### 3.1 Example 1: Component-, Behavior-, and Material-Based Analogies for Pocket Tool.

The component result shows patent pocket tool and patent “electric toothbrush” in a cluster label of “switch, circuit, battery, house, port,” suggesting that they are composed of small electronic components. The behavior result shows the same patent pocket tool and patent “method for protecting electric line” in a cluster label of “electronic, electric, peripheral, mechanic, secure,” suggesting that they have a commonality of protecting and securing electronic components. Lastly, the material result shows the same patent “pocket tool” and patent “deburring knife with replaceable blade” in a cluster label of “arrow, metal, solid, waste, stem,” suggesting that they are either made of metal or use metal.

#### 3.2 Example 2: Component- and Behavior-Based Analogies for Ice Gripping Sandal.

In a second example, the component result shows patent ice gripping sandal and patents “weight distributing knee pad” and “balance assist for rotating recreational device” in a cluster label of “port, strap, case, mount, heel.” The behavior result shows the same patent ice gripping sandal and patents “abrasive tool” and “hairpiece and fitting method therefor” in a cluster label of “secure, flex, light, sole, alternative.” Although the cluster labels of the component and behavior results are different, the patents, interestingly, share a common functionality of securing or fixing something to something else. This is an example of discovering patents of similar design attributes from various apparel domains using component and behavior data. For instance, patent ice gripping sandal is from the footwear domain, weight distributing knee pad is from wearing apparel domain, and hairpiece and fitting method therefor” is from headwear domain.

#### 3.3 Example 3: Component- and Material-Based Analogies for Shower Bath Apparatus and Spray Nozzle.

In a third example, the component result shows patent shower bath apparatus and spray nozzle and patent “transmucosal hormone delivery system” in a cluster label of “nozzle, spray, bath, body, valve,” suggesting that they use certain components to deliver fluids. The material result shows the same patent shower bath apparatus and spray nozzle and patent “humidifier” in a cluster label of “water, fluid, air, steam, carbon

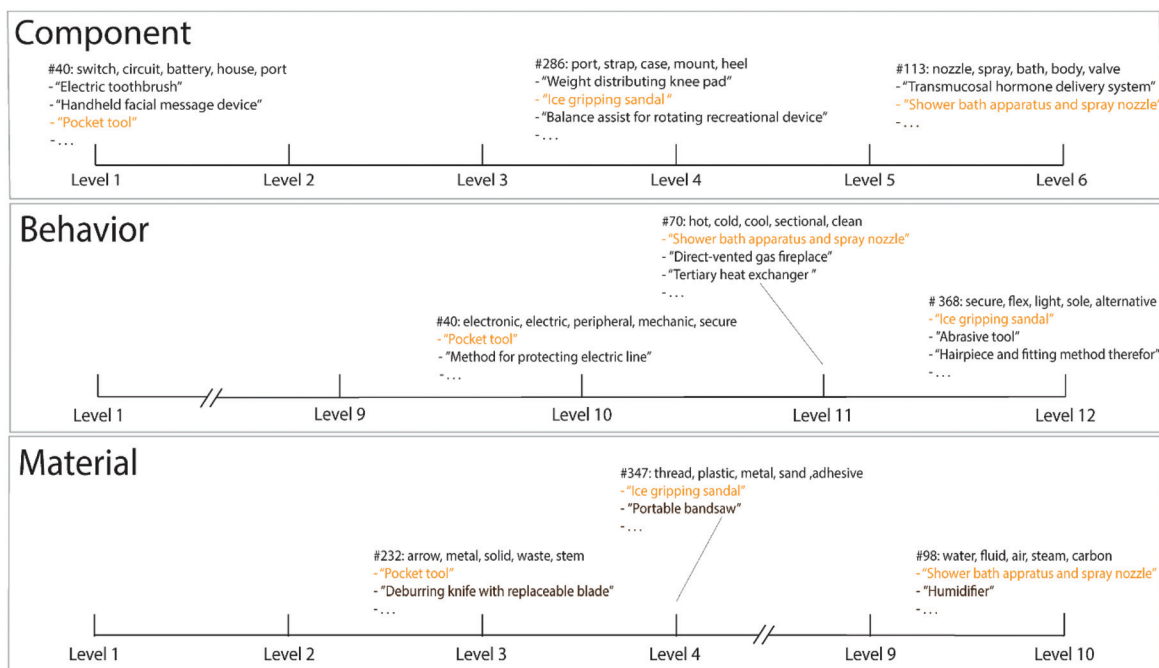
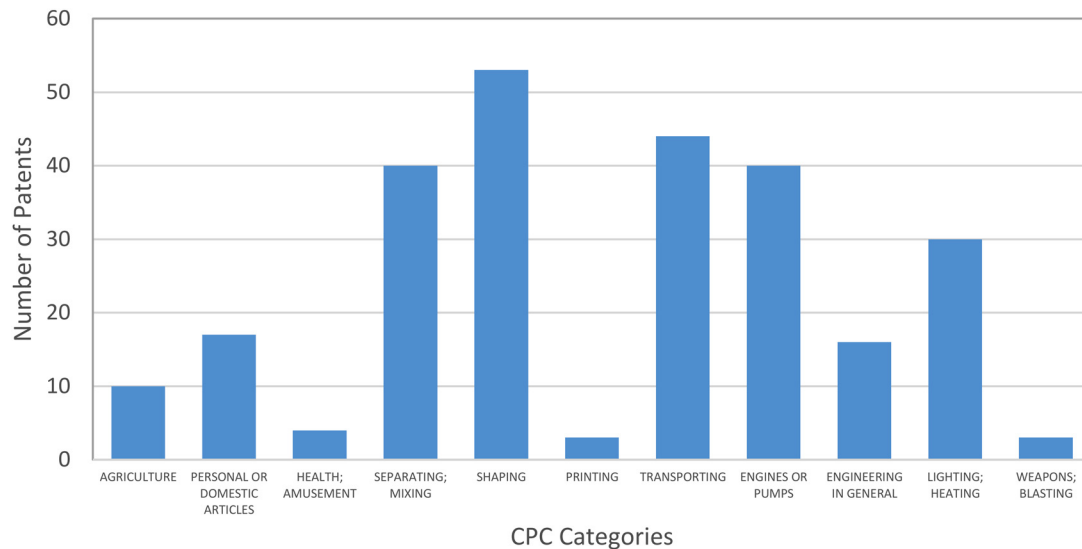


Fig. 4 Comparison of component, behavior, and material results



**Fig. 5 Number of patents in different CPC categories**

**Table 1 Retrieved patents in different CPC sections**

Cluster number (cluster label)	Patent title (patent number)	CPC section
134 (shoe, mount, boot, heel, generator)	“Inflatable boot liner with electrical generator and heater” (4845338)	A43 (Footwear)
123 (motor, generator, shaft, detector, crankshaft)	“Gravity motor and method” (7768142)	F3 (Machines or engines for liquids)
121 (disk, shaft, wheel, ramp, transmission)	“Continuously variable transmission” (7147586)	B62 (Land vehicles for travelling otherwise than on rails)

air, steam, carbon,” suggesting that water or fluid is the common material used by the two designs. Although the two cluster labels represent different analogical relationships, they all have a common functionality of delivering fluids—one that is implied by the components such as “nozzle” and “spray” and one that is implied by the liquid material that the design uses.

As shown in the examples, exploring different representations of the patent data leads to retrieving multiple analogies that can be valuable for design-by-analogy process. In practice, a designer may explore the multiple representations to retrieve more analogies to improve the idea generation [8]. Also, they may explore a specific representation of the patents that is better matched with their individual perspective or way of thinking.

#### 4 Case Study and Discussion

To test the usefulness of the generated patent structures to design-by-analogy practice, a case study has been conducted to examine the retrieval of analogies for idea generation. The case study is hypothetical use case scenario, in which one of the researchers used the computational methodology for idea generation. The case study introduces two patent exploration methodologies, referred to as (1) searching similar patents in different CPC sections and (2) searching patents by suggested cluster label. This section discusses the step-by-step procedures of retrieving analogies from the component- and behavior-based patent structures to solve the human motion energy collection problem introduced in Sec. 2.1.

**4.1 Method 1: Searching Similar Patents in Different Cooperative Patent Classification Sections Using Component Data.** For the given design problem shown in Sec. 2.1, a designer first brainstorms relevant terms for generating electrical energy from human motion. For example, if the designer wants to explore

patents by their components, a list of terms might be “generator,” “turbine,” “wheel,” “shaft,” “gear,” “rotor,” “tooth,” “pulley,” “disk,” and “crankshaft.” These component terms are selected for their rotational movement, which is the most common type of mechanical energy that is converted to electrical energy. The designer then uses the list to select patents whose cluster label matches the component terms. As discussed in Sec. 2.2, the cluster label is composed of the top five most important words to the group of patents in the cluster, determined by NMF, that characterize the cluster’s topic. In such a case, the large patent dataset is refined to a few clustered patents that are operated by or composed of the components that involve rotational energy/movement. After the patent data are reduced, the designer categorizes the patents by their CPC section. Categorizing the patents by their CPC sections not only helps the designer to understand patent’s usage and application, but also helps the designer to recognize similar technology in various domains. Consequently, this method results in a reduced dataset of 193 patents in 11 different fields of application as shown in Fig. 5.

The number of retrieved patents and analogies are expected to increase with an increased input patent corpus size, which is currently set to 1060 patents in this study. The designer then explores the refined patent data by the field of application. Table 1 lists three patents from machine, footwear, and land vehicle domains that have useful analogies to solve the design problem. For example, one resulting design concept is an inflatable floor mat (inspired by patent “inflatable boot liner with electrical generator and heater”) that uses human body weight to pump and direct air across an electrical generator. Furthermore, the designer can implement a gravity motor (inspired by patent “gravity motor and method”) that uses gravitational energy to rotate a shaft or continuously variable transmission (inspired by patent “continuously variable transmission”) that improves the shaft’s torque efficiency. The concepts generated are shown in Fig. 6.

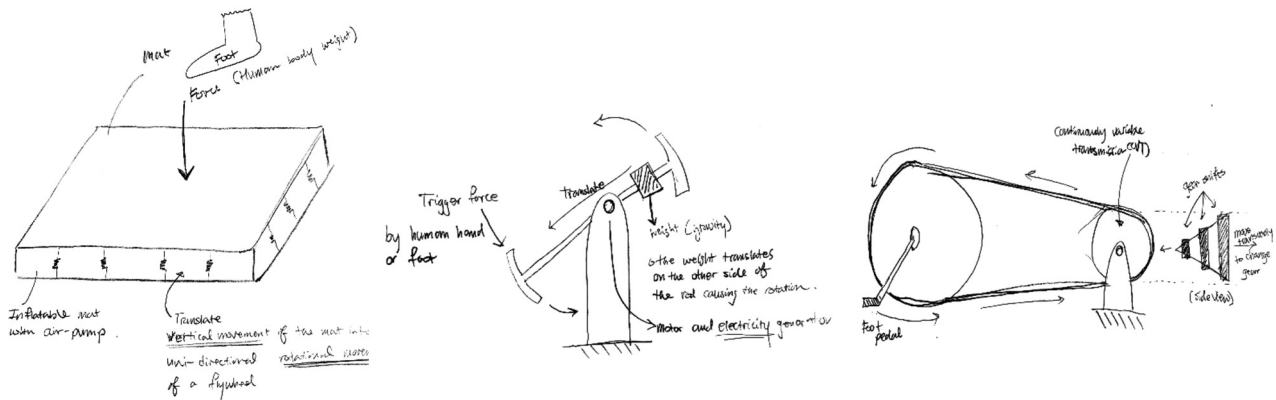


Fig. 6 Concepts generated using method 1

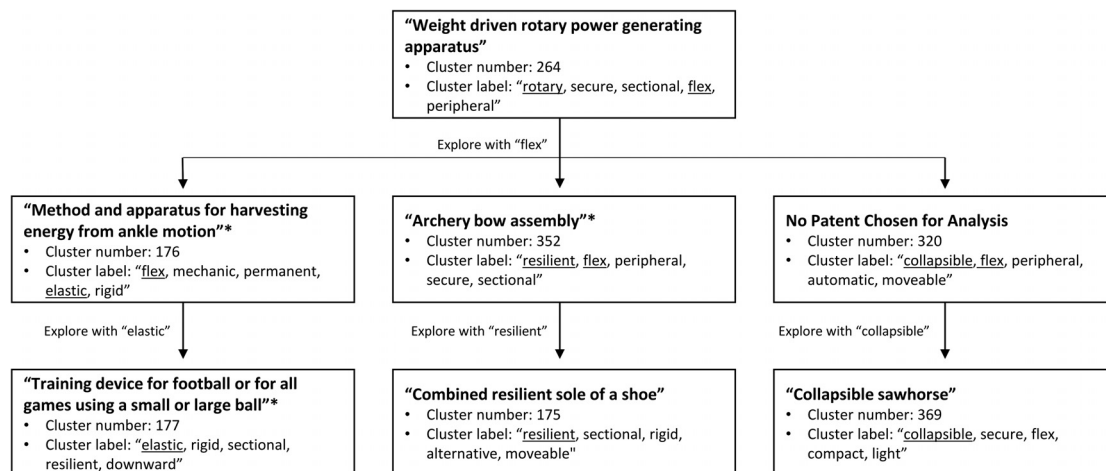


Fig. 7 Patents (bolded) retrieved using suggested terms (underlined)

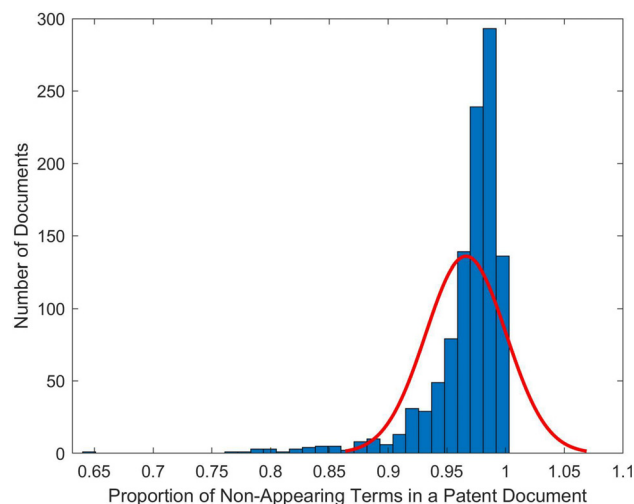
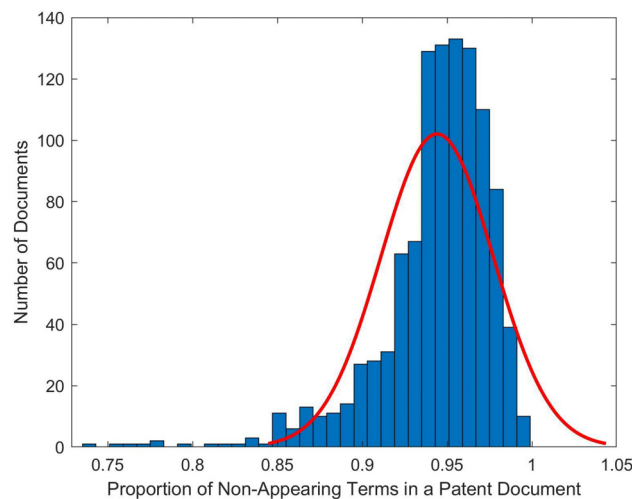
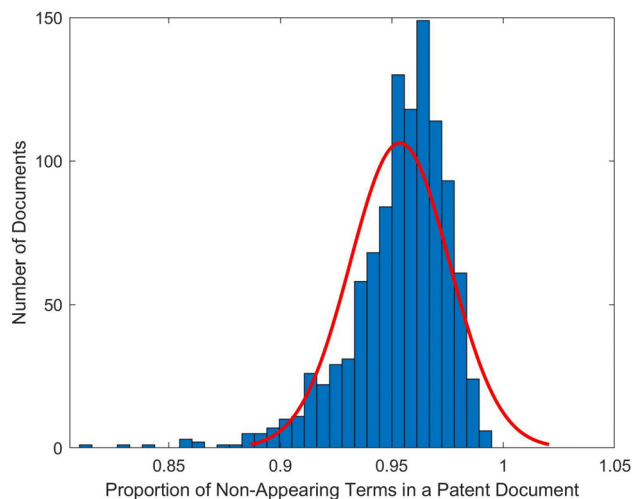
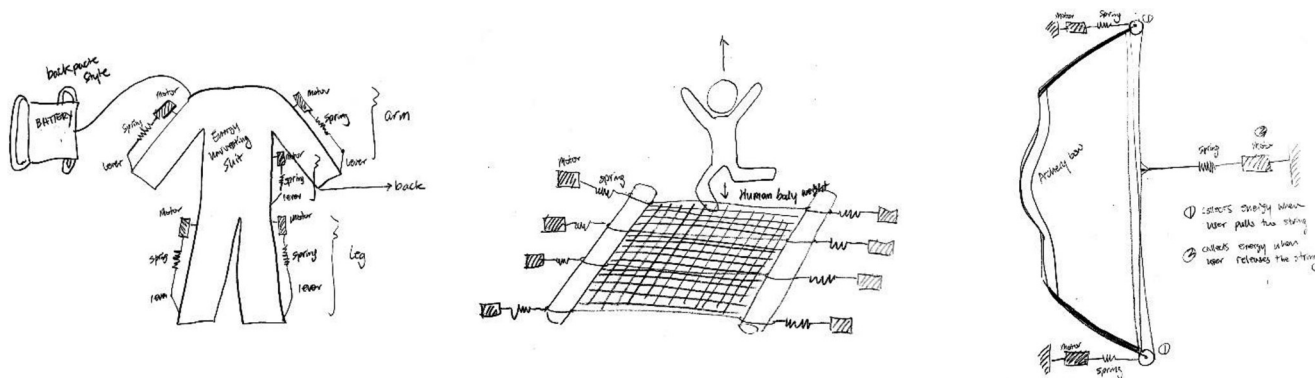
**4.2 Method 2: Searching Patents by Suggested Terms in Cluster Label Using Behavior Data.** For the same design problem, an alternative method may be used to retrieve more analogies from the patent data. Similar to the first method, the designer first generates a list of relevant terms for the design problem. For example, if the designer wants to explore the behavior-based patent structure, a set of behavior terms would be “rotational” and “rotary” as the rotational movement is conventionally used for generating electricity. The designer then explores the patents by matching their cluster labels to the behavior terms. The cluster label consists of the top five words that are closely related to each other by an NMF-determined topic. Figure 7 demonstrates that the designer first retrieves a patent in a cluster “rotary, secure, sectional, flex, peripheral.” In this label, the designer discovers another term “flex,” implying that some patents may integrate both rotational and spring behaviors. Using the new keyword, “flex,” the designer retrieves two more patents and discovers three more keywords “elastic,” “resilient,” and “collapsible” that result in retrieving three more patents. Interestingly, in Fig. 7, patents with an asterisk mark (\*) after the title represent patents with combined elastic and rotational behaviors. This exemplifies the retrieval of analogies using distinct yet suggested terms in the cluster label, with an emphasis on exploration and discovery. Figure 8 shows three example design concepts generated using patents “method and apparatus for harvesting energy from ankle motion,” “training device for football or for all games using a small or large ball” and “archery bow assembly.”

The two patent searching methods can be used interchangeably for an effective retrieval of analogies. The first method demonstrates that if a list of keywords for the desired technology is available or can be generated by a designer, a patent structure can be

refined with the keywords and further refined by CPC sections. The refining or categorizing of the patent data can enable designers to systematically and efficiently retrieve similar analogies in various application fields. If the list of keywords is not available, the second method demonstrates that the patents can be iteratively searched with the suggested terms in the cluster labels. This approach is more spontaneous as designers can determine the exploration paths using the cluster label while interacting with the patent structure.

As demonstrated by the two methodologies, the patent exploration depends significantly on the usage of keyword search, as it greatly reduces the analogical information that designers need to process. Moreover, the user-defined keywords allow the designers to tailor the patent exploration to focus on specific analogies that satisfy the designers’ objectives for a design problem. In the case study, the component and behavior terms relating to the rotational movement/energy are used to solve the human motion energy collection problem. As discussed earlier, designers may have diversified design objectives, implying that the list of the terms is just one of many paths to approach the design problem. These motivations call for future studies to generate lists of words that address specific working or physical principles of patents and investigate the effectiveness of refining the patent structure using the pre-established list of words.

**4.3 Clustering Quality of Material Data.** In the case study, the material-based patent structure has not been studied due to the difficulty of identifying and retrieving analogies. Unlike the component and behavior results, the cluster labels in the material result do not carry definite topics. For instance, terms like “water,” “fluid,” “air,” “gas,” and others appear in many cluster labels, causing the clusters to be indistinguishable from one another. To



understand why the cluster quality is relatively poor for the material data, the word-document matrices of component, behavior, and material data are studied. Figures 9–11 show the histograms of three different datasets that represent the distribution of the number of patent documents (y-axis) by the proportion of terms that *do not* appear in each document (x-axis). The proportion value varies from 0 (the document contains all terms listed in a wordlist) to 1 (the document does not contain any of the terms listed in a wordlist). The histograms show a general bell curve for all datasets, where the mean values are 0.954 for component data, 0.944 for behavior data, and 0.966 for material data. Although the mean values are similar, it is clearly observed that the histogram for the material data is skewed to the right. The skewed data represent approximately 500 patents that contain less than 3% of the material terms and approximately 150 patents that contain zero of the material terms. This finding explains the poor cluster quality of the material data, as NMF would randomly determine the topic of the patent documents whose column cells are empty. As discussed in Sec. 2.1, the wordlists for the component, behavior, and material properties in Appendices C, D and E were compiled by drawing a master wordlist from the entire patent data and manually categorizing the words into an appropriate property. This ensures that the compiled material wordlist captures all material words of the input patent data. In such a case, the absence of material words in many of the patent documents raises some interesting research questions about the nature of patent documents: to what extent do patent documents describe the materials that the system/artifact/technology use? When documenting for patents, do designers or inventors detail the functional features of the system/artifact/technology to protect the functional quality of the intellectual property, but omit what the input or comprising

materials in the system/artifact/technology to ensure the broadest protection from infringement? Future studies need to investigate whether certain types of words are used more frequently than others for documenting patents. Interviews with patent lawyers on their writing process and choices may help to uncover some of the driving factors behind the composition of the semantic data. Understanding the unique traits of patent documents could help researchers to improve the quality of topic modeling of patent data.



**4.4 Limitations and Future Work.** There are several limitations in the proposed methodology that are important to acknowledge. It has been observed that the clustering quality is poor when there is a substantial number of patents that contain ambiguous or indeterminable topics. This suggests that the clustering performance of the current methodology may not be competent for a larger set of patents. It is also uncertain that the current visualization methods are appropriate for interpreting the larger patent data. Collaborations with computer scientists on investigating clustering and visualization methods may lead to developing more effective DbA tools for designers. The case study shows that the material-based clustering is not useful in assisting the design-by-analogy process. This may be a product of the dataset examined in the study or a more widespread phenomenon, such as how patents are documented, that needs to be investigated in future studies. In addition, the wordlists that are manually compiled may not capture all relevant content in the patent data. However, we expect the content of these lists to reach saturation as larger data sets are tested in future studies. Other limitations and future work have been discussed throughout the paper including, but not limited to, the implementation of improved stopping criterion for the iterative NMF process to generate the clustering structures and investigation of the meaning of the “level of similarity” for its utility during analogical exploration process.

## 5 Conclusion

The goal of this work is to provide designers a computational design-by-analogy tool to explore a design repository for analogical inspiration. The computational methodology utilizes a topic

modeling technique called NMF to generate a hierarchical cluster structure of the U.S. patent database where designers can visualize and retrieve analogies to solve given design problems. In this work, a user-driven exploration technique has been implemented on the patent database, processed to contain only component-, behavior-, or material-based content to generate a unique and valuable representation of the patent database; a case study was conducted to demonstrate the systematic and interactive retrieval of analogical inspirations from patents for concept generation. Through the demonstration of retrieving analogical inspiration from the structured patent database for concept generation, the proposed methodology shows promise as an effective design-by-analogy tool that facilitates the systematic and interactive exploration of patents to support innovative design idea generation.

## Acknowledgment

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## Appendix A

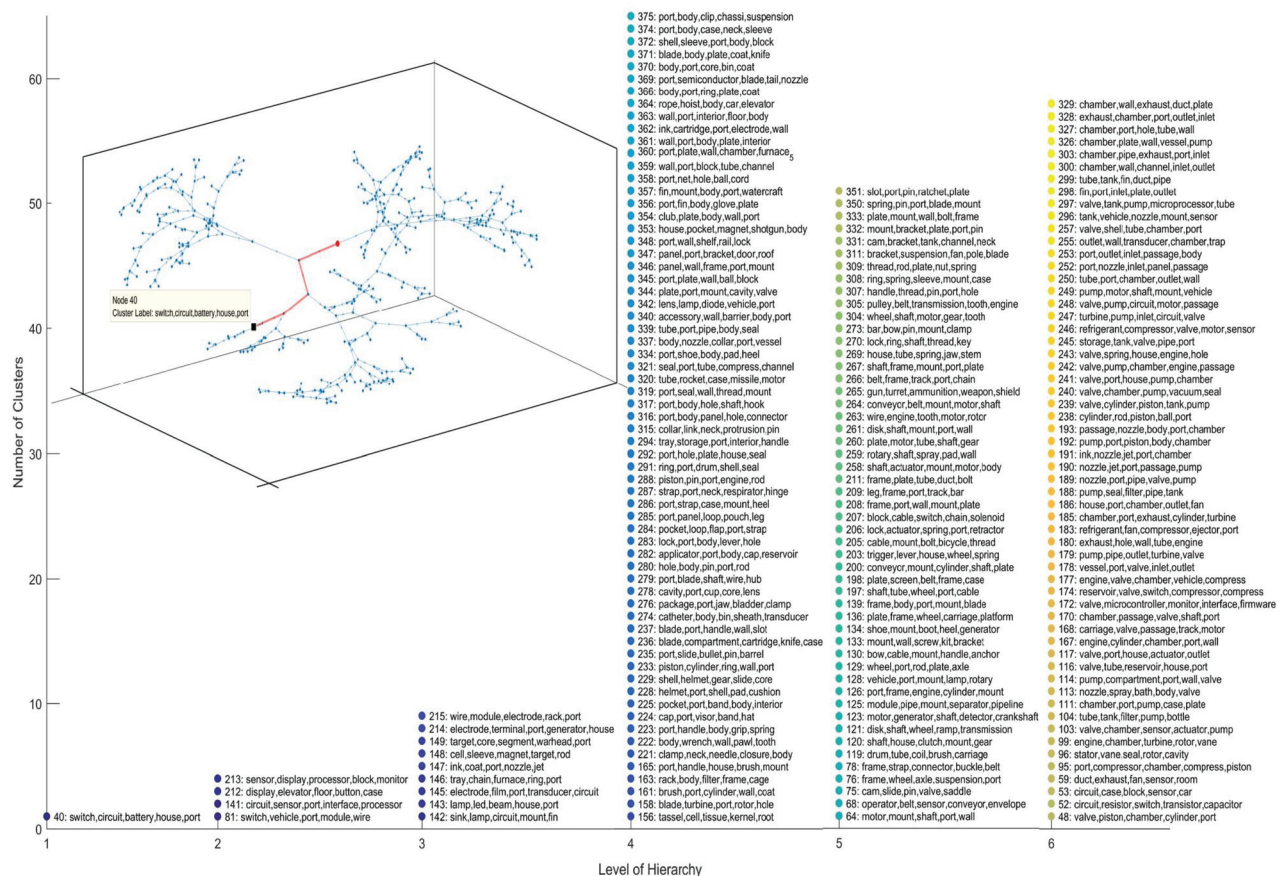


Fig. 12 Three-Dimensional and Two-Dimensional Visualizations for Component Representation of Patent Data



## Appendix B: List of 53 Cooperative Patent Classification Subsections

Section	Subsection	Categories	Description
Section A: Human necessities	1	Agriculture	Agriculture; forestry; animal husbandry; hunting; trapping; fishing
	41	Personal or	Wearing apparel
	42	domestic articles	Headwear
	43		Footwear
	45		Hand or traveling articles
	46		Brushware
	47		Tables; desks; office furniture; cabinets; drawers; general details of furniture
	61	Health; amusement	Medical or veterinary science; hygiene
	62		Life-saving; fire-fighting
	63		Sports; games; amusements
Section B: Performing operation; transporting	2	Separating; mixing	Crushing, pulverizing, or disintegrating; preparatory treatment of grain for milling
	3		Separation of solid materials using liquids or using pneumatic tables or jigs; magnetic or electrostatic separation of solid materials from solid materials from solid materials or fluids; separation by high-voltage electric fields
	5		Spraying or atomizing in general; applying liquids or other fluent materials to surfaces, in general
	6		Generating or transmitting mechanical vibrations in general
	7		Separating solids from solids; sorting
	8		Cleaning
	9		Disposal of solid waste; reclamation of contaminated soil
	21	Shaping	mechanical metal-working without essentially removing material; punching metal
	22		Casting; powder metallurgy
	23		Machine tools; metal-working not otherwise provided for
	24		Grinding; polishing
	25		Hand tools; portable power-driven tools; manipulators
	26		Hand cutting tools; cutting; severing
	27		Working or preserving wood or similar material; nailing or stapling machines in general
	28		Working cement, clay, or stone
	29		Working of plastics; working of substances in a plastic state, in general
	41	Printing	Printing; lining machines; typewriters; stamps
	60	Transporting	Vehicles in general
	61		Railways
	62		Land vehicles for traveling otherwise than on rails
	63		Ships or other waterborne vessels; related equipment
	64		Aircraft; aviation; cosmonautics
	65		Conveying; packing; storing; handling thin or filamentary material
	66		Hoisting; lifting; hauling
	67		Opening, closing (or cleaning) bottles, jars, or similar containers; liquid handling
Section F: Mechanical engineering; lighting; heating; weapons; blasting	1	Engines or pumps	Machines or engines in general
	2		Combustion engine
	3		Machine or engines for liquids
	4		Positive displacement machine for liquids; pumps for liquids or elastic fluids
	5		Indexing schemes relating to engines or pumps in various sub-classes of classes
	15	Engineering in general	Fluid-pressure actuators ; hydraulic or pneumatics in general
	16		Engineering elements and units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general
	17		Storing of distributing gases or liquids
	21	Lighting; heating	Lighting
	22		Steam generation
	23		Combustion apparatus
	24		Heating; ranges; ventilating
	25		Refrigeration or cooling; combined heating and refrigeration systems; heat pump systems; manufacture or storage of ice; liquefaction solidification of gases
	26		Drying
	27		Furnaces; kilns; ovens; retorts
	28		Heat exchange in general
	41	Weapons; blasting	Weapons
	42		Ammunition; blasting



## Appendix C: Wordlist of Components

abaci	barometer	button	cloth	cuspidor
abacus	barrel	buzzer	club	cylinder
absorber	barrier	cabinet	clutch	cytometer
accelerator	base	cable	clutches	dam
accelerometer	basin	cage	coat	dampener
accessory	bath	calculator	cogwheel	damper
accumulator	bathseat	calibrator	coil	dashboard
activator	bathtub	caliper	colander	dashpot
actuation	battery	cam	collar	deck
actuator	beam	camera	collector	decoder
adapter	beanbag	camshaft	collimator	defibrillator
adaptor	bear	candle	combustor	deflector
adjuster	bearing	canister	commutator	defroster
adjustor	bed	cannister	compactor	dehydrator
afterburner	bedstead	cannula	comparator	demodulator
agitator	bell	canoe	compartment	descrambler
ailette	bellows	canopy	compensator	descriptor
airfoil	belt	cantilever	component	designator
airgun	bench	cap	compress	desk
airplane	bicycle	capacitor	compressor	desktop
alarm	bike	capsule	computers	desuperheater
alignment	billard	car	condenser	detector
alternator	bin	carabiner	condensor	detonator
ammunition	bingo	carbine	conditioner	dial
amplifier	biomarker	carburetor	conditioners	dialyzer
analyzer	birdhouse	carburettor	conductor	diaphragm
anchor	bladder	cardia	connector	diffuser
anchorage	blade	carousel	connector	dilator
annulus	block	carpet	conrod	diode
annunciator	board	carriage	console	disk
antenna	boat	carrier	contactor	discriminator
anticipator	body	cart	container	dish
applicator	bogie	cartridge	containers	dishwasher
aquarium	boiler	cartridges	contractor	disk
armature	bolt	case	converter	dispenser
armrest	bone	cassette	conveyor	displacer
arrow	booster	castor	cooker	display
arrowhead	boot	catalyst	cookstove	disruptor
artery	border	catapult	cooktop	distractor
aspirator	bottle	catheter	coordinator	distributor
atomiser	bottles	cathetor	cord	divider
atomizer	bow	catridge	core	dome
atrium	bowl	cavaletti	cork	door
attenuator	bowstring	cavity	cornea	doublet
auditorium	box	ceiling	corset	dowel
autoinjector	brace	cell	cotter	drawstring
automobile	bracelet	centimeter	countermeasure	drier
ax	bracket	centrifuge	countershaft	drill
axle	brake	chain	cover	drum
backbone	branch	chair	cradle	duct
backpack	breadboard	chalk	crankcase	dumbbell
backpack	breech	chamber	crankshaft	durometer
backrest	brewer	channel	cribbage	dynamometer
badge	bridge	chassi	crinoline	economiser
bag	bronchoscope	chimney	crossbar	economizer
bagatelle	brooch	chip	crossbow	editor
ball	brush	circuit	crown	effector
balloon	bucket	clamp	cuff	ejector
band	buckle	classifier	cufflink	electrode
bandage	bulb	cleaner	cup	electroluminescent
bar	bullet	clip	cursor	electromagnet
barbell	bundle	clock	curtain	electronics
barcode	bus	closure	cushion	elevator



eliminator	gate	inflator	luggage	oscillator
emitter	gauge	inhaler	luminaire	oscilloscope
emulsifier	gear	inhibitor	magnet	outlet
encoder	gearbox	initiator	maintainer	oven
endoscope	gears	injector	mandrel	oversleeve
engine	gearset	injector	manifold	oxidizer
enhancer	generator	ink	manipulator	oximeter
envelope	geometrizer	inlet	manometer	pacemaker
equalizer	girdle	installer	mantle	package
equalizer	glove	instance	marker	pad
equipment	glowplug	insulator	mask	paddle
estimator	glue	integrator	mast	paintball
evaluator	goggle	interconnector	mat	pan
evaporator	gown	intercooler	mattress	pane
examiner	graft	interface	mediator	panel
excavator	granulator	interior	membrane	panel
exciter	grease	interrupter	microcomputer	parachute
exhaust	grenade	intestine	microcontroller	parameter
expander	grid	introducer	microlens	parlor
extender	grip	investigator	micrometer	passage
extension	guidewire	isolator	microphone	passageway
extinguisher	guitar	jack	microprocessor	patch
extruder	gum	jacket	microscope	path
eyelet	gun	jaw	microswitch	pawl
eyepiece	handle	jet	midline	pedal
fan	handled	jets	mirror	pedestal
fastener	hardware	joint	missile	peg
fastening	harness	joypad	modifier	pen
femur	harpoon	joystick	modulator	pencil
fence	hat	kernel	module	penetrator
fermenter	headband	key	moisturizer	penis
fermentor	headgear	keyboard	monitor	peppergun
ferrule	headrest	keypad	motherboard	perforation
fertilizer	headset	kit	motor	petticoat
festoon	heart	kite	motorcycle	phone
filament	heel	knife	mouldboard	photodetector
filler	helicopter	knob	mount	photosensitizer
film	helmet	lamp	mounted	pillar
filter	highway	lanyard	mousetrap	pillow
fin	hinge	laser	mouthpiece	pin
fins	hoist	lash	mover	pinion
firearm	holder	latch	mower	pipe
firebridge	hole	layer	muffler	pipeline
fireplace	holster	leaflet	multicylinder	pistol
firmware	homogenizer	leash	multiplate	piston
flameholder	honeycomb	led	multiplier	pitot
flap	hood	leg	multivibrator	planetary
flash	hook	legging	muscle	plasticizer
flashlight	hoop	legs	muscles	plate
flask	hopper	lens	muzzle	platelet
floor	horn	lenslet	nanometer	platform
flue	horseshoe	lever	neck	player
flute	hose	lid	neckband	playhouse
flywheel	hosel	lift	needle	playslip
foil	house	lighter	nerve	pleximeter
footwear	housing	liner	net	plug
forceps	howitzer	lining	neurotransmitter	pocket
forearm	hub	link	nostril	pod
fork	hypotube	linkage	notebook	pointer
frame	identifier	lip	notepad	polarizer
freewheel	idler	liquefin	nozzle	pole
furnace	igniter	lobe	nut	pool
fuze	ignitor	localizer	observer	pore
gaiter	illuminator	locator	obturator	port
gallery	impeller	lock	occluder	portafilter
gamepad	inclinometer	lodge	opacifiers	potentiometer
garland	incubator	longbow	operator	pouch
garter	indicator	loop	ordnance	powertrain
gasket	inducer	loudspeaker	organ	prechamber
gastroscope	inductor	lubricant	orifice	precipitator

precursor	robot	skirt	synchronizer	trimmer
predictor	rocket	sleeve	synthesizer	trocar
prefilter	rod	slide	syringe	trolley
pressurizer	rodlink	sling	table	trommel
preventer	roller	slot	tablet	trough
probe	roof	slug	tack	truck
processor	room	sluice	tail	trunk
progenitor	root	snare	tampon	tub
projector	rope	sock	tank	tube
promoter	rotary	socket	tape	tubes
propeller	rotator	socles	tappet	tunnel
protector	rotor	solenoid	target	turbine
protrusion	sack	solubilizer	tassel	turbo
provider	saddle	speaker	teaspoon	turbocharger
puck	sandbox	spear	teeth	turboexpander
pulley	satellite	speargun	telemetry	turbofan
pump	scaffold	spectrometer	telemotor	turbomachine
puttee	scale	sphincter	telephone	turbomachinery
puzzle	scattergun	spigot	television	turbopump
rack	scene	spindle	tendon	turf
racket	scheme	spine	terminal	turnbuckle
radar	scissors	spinner	tether	turntable
radiator	scooter	spittoon	thermister	turret
radio	scope	spool	thermistor	ultrafilter
rail	screen	spoon	thermocouple	umbrella
railroad	screw	spray	thermometer	ureter
ramp	screwdriver	spring	thermosensor	vacuum
ratchet	scroll	sprocket	thermoset	valance
razor	seal	stabilizer	thermostat	valve
reactor	seat	stand	thorax	vane
reboiler	sector	staple	thread	vaporizer
receiver	see-saw	station	throttle	vault
receptor	segment	stator	thyristor	vehicle
rectifier	segments	stem	ticket	vein
reducer	selector	stent	tie	velcro
reel	semiconductor	stents	tile	vent
reflector	sensor	stethoscope	timer	ventilator
refrigerant	separator	stiffener	tip	venturi
refrigerator	servomotor	stile	tire	vessel
regenerator	sewer	stimulator	tissue	vibrator
regulator	shack	stock	tongue	visor
repeater	shackle	stool	tooth	wagon
resectoscope	shaft	storage	toothbrush	wall
reservoir	shank	stove	torch	wand
resistor	shaver	straightener	toupée	warhead
respirator	sheath	strap	towel	washer
restorer	shelf	stratifier	toy	watch
restrictor	shell	straw	tracheal	watercraft
restrictor	shield	streamline	track	weapon
resuscitator	ship	string	trackball	wedge
retainer	shoe	stroke	tractor	wheel
retina	shoelace	stud	trail	wheelchair
retractor	shooter	subchamber	transceivera	whiteout
rib	shotgun	subsoiler	transducer	window
ribbon	shredder	suction	transformer	wing
riblet	shuttle	sulky	transistor	wire
ribs	sidewall	supercharger	transmission	wrench
rifle	sieve	suppressor	transmitter	yoke
riflescope	silencer	suspension	transometer	zipper
rille	simulator	suture	transponder	
rim	sink	swashplate	trap	
ring	siren	swing	tray	
rips	ski	switch	trebuchet	
rivet	skin	swivel	trigger	

## Appendix D: Wordlist of Behaviors

abdominal	compressed	fetal	invasive	proximal	spinous
absorbable	compressive	fibrous	inverted	pure	stabilized
absorbent	condensed	fitting	invertible	pyrotechnic	stable
accessible	conductive	flammable	irregular	quick	stackable
acetabular	conjoint	flex	irreversible	radiant	stainless
acid	consistent	flexural	isolate	radioactive	static
acidic	controllable	floatable	latent	rapid	stationary
actuatable	controlled	floating	light	rechargeable	steady
actuated	convective	floral	lubricant	recombinant	steerable
adaptable	cool	fluidic	lumbar	recyclable	sterile
adaptive	coronary	fluorescent	luminous	reflective	sticky
adherable	cosmetic	fragile	magnetic	refractory	stiff
adhesive	cryogenic	fresh	magnetizable	regenerative	stretch
adverse	curable	frictional	malleable	releasable	strong
aerodynamic	decorative	fungicidal	mechanic	reliable	sturdy
agricultural	deflectable	fusible	medial	remote	submersible
alignable	deformable	gaseous	medical	repellent	supporting
alternative	dismountable	gastrointestinal	metallic	repetitive	surgical
anatomic	dense	genetic	miscible	replaceable	susceptible
anhydrous	dental	hard	mixed	reproducible	sustained
aqueous	deployable	harmonic	mobile	residual	swivelable
aromatic	detachable	healthy	modular	resilient	symmetric
arterial	detectable	heavy	molten	resistant	synchronous
artificial	diffuse	hemispheric	mountable	resonant	synergistic
asymmetric	discrete	hemostatic	movable	responsive	synthetic
atmospheric	displaceable	hot	moveable	resting	systolic
attachable	disposable	hybrid	muscular	reusable	tangential
audible	dissolvable	hydraulic	myocardial	reverse	therapeutic
automated	distal	hydrodynamic	nasal	reversible	thermal
automatic	divisional	hydrophilic	nestable	revolving	thermodynamic
automotive	downward	hydrophobic	neutral	rigid	tight
auxiliary	dry	hydrostatic	noncombustible	robotic	tiltable
bacterial	durable	hypodermic	nonionic	rollable	torsional
ballistic	dynamic	idle	nonrotatable	rolling	toxic
bendable	edible	ignitable	nuclear	rotary	transluminal
bimetallic	elastic	immovable	nucleic	rotatable	transparent
bioabsorbable	elastomeric	immune	ocular	rough	transportable
biocompatible	electric	impermeable	opposing	rugged	turbulent
biodegrade	electromagnetic	implantable	optic	safe	ultrasonic
biologic	electronic	inbred	optimal	saline	underwater
bipolar	electrostatic	incompressible	orbital	saturated	unstable
bloated	electrosurgical	indicative	organic	seal	variable
bodily	elevated	inducible	periodic	sectional	vascular
breathable	elevational	inductive	peripheral	securable	vehicular
buoyant	endless	inelastic	permanent	secure	ventricular
cardiac	engageable	inert	permeable	semipermeable	vertebral
cellular	enlarged	inertial	pharmaceutical	sensible	virtual
ceramic	environmental	inexpensive	pharmacologic	sensitive	viscous
cervical	equivalent	inflammatory	physical	shiftable	visible
chemical	evaporative	inflexible	piercing	shrinkable	volatile
chronic	exchangeable	infrared	pivotable	slidable	warm
clean	expandable	injectable	pivotal	slideable	waterproof
clinic	expanded	inorganic	planetary	sliding	waxy
coated	explosive	insertable	pneumatic	slow	weak
cold	extendable	insoluble	polymeric	smooth	wearable
collapsible	extended	instant	positionable	soft	wet
combustible	extendible	instantaneous	precise	solar	wheeled
compact	extracellular	insulative	premature	sole	
compatible	fast	interchangeable	programmable	soluble	
complementary	fastenable	interconnecting	programmed	spatial	
complex	fatty	intravenous	prolonged	spinal	
composite	femoral	intricate	propelled	spinning	

## Appendix E: Wordlist of Materials

acetate	bronze	elastomer	huperzine	mixture
acid	bubble	elastomeric	hydride	molecule
acridine	bur	electrolyte	hydrocarbon	mollusk
adhesive	calcium	enamel	hydrochloride	mud
adsorbent	cancer	enantiomer	hydrogel	myocardium
agent	canvas	endocardium	hydrogen	natural
air	carbide	enzyme	hydromorphone	nickel
albumin	carbohydrate	epoxy	hydroxide	niobium
alcohol	carbon	espresso	hydroxyethyl	nitro
algae	carbonate	ester	hydroxyl	nitrogen
alkali	carboxyl	ethanol	ice	nitrous
alkaline	cast iron	ether	ingredient	nucleotide
alkaloid	castor	ethyl	ink	nut
alkenyl	cellulose	ethylene	insect	nylon
alkoxy	cement	fabric	insecticide	object
alkyl	ceramic	fat	insulin	oil
alkylcarboxamide	chalk	feedstuff	interbody	oligonucleotide
alkylene	charcoal	fenugreek	iodidea	ore
allantoin	chemical	fiber	ion	organ
alloy	chloride	fiberglass	iron	organic
alum	chlorine	fiber	item	organism
alumina	chocolate	fir	ivory	oxide
aluminum	chromium	fish	juice	oxygen
aluminum	claudin	flour	keratin	paclitaxel
amide	clay	fluid	keratinocyte	paint
amine	cloth	fluoride	kernel	paper
aminoalkyl	coal	fluorine	kerosene	particle
ammonium	cobalt	fluorite	ketone	particulate
animal	coffee	foam	lactose	pathogen
antibacterial	collagen	food	lamina	peanut
antibiotic	composite	foodstuff	latex	pearl
antibody	compost	fructose	leaf	peel
arrhythmia	compound	fruit	leather	peptide
arrow	concentrate	fuel	lime	pet
arthropod	concrete	fungicide	limestone	phosphate
aryl	condensate	galactosyl	linoleum	phosphite
ash	coolant	gas	lipid	phospholipid
asphalt	copolymer	gasoline	liquid	photograph
atom	copper	gel	lubricant	piperazine
bacterium	corn	gem	luggage	pith
bait	cotton	gemstone	lye	planet
ball	crab	gene	lyophilizate	plant
bamboo	cream	glass	lysine	plasma
banana	crystal	glucose	magnesium	plaster
bark	curd	glyceryl	mannitol	plastic
baseball	cycloalkyl	glycol	manure	platinum
bauxite	daub	gold	marble	plaything
bead	dextran	grain	martensite	plenum
bean	dialysate	granite	meat	plywood
beeswax	diamond	graphite	medicament	pollen
benzotriazole	diesel	gravel	medicine	polyamino
benzyl	dimethyl	hair	membrane	polycarbonate
beryllium	diode	halogen	mesalamine	polyester
beverage	dioxide	hay	metal	polyethylene
biodiesel	disulfide	hemoglobin	methane	polyglycolide
biopolymer	dough	hemp	methanol	polymer
blood	drug	herbal	methyl	polynucleotide
book	duroplastic	herbicide	methylbenzyl	polypeptide
borax	dye	heteroaryl	methylene	polyphosphate
brass	dynamite	honey	microorganism	polyphosphite
brick	earth	honeycomb	milk	polystyrene
bromide	egg	humectant	mineral	polyurethane



porcelain	silicone	sweetener	warp
potassium	silver	syrup	waste
poultry	slag	tantalum	water
powder	slate	tarpaulin	wax
primer	sludge	tea	weed
prodrug	slurry	termite	wheat
progeny	slush	tetracycline	whiteout
propane	smoke	textile	wire
propellant	soap	thatch	wood
propylene	sodium	thermoplastic	wool
protein	soil	thread	yarn
pulp	solid	tile	yeast
pvc	solute	timber	zinc
quartz	solvent	time	
quinacrine	soy	tin	
rebaudioside	soybean	tissue	
reed	specimen	titanium	
refrigerant	spider	tobacco	
render	sponge	transferase	
resin	starch	tree	
reticulocyte	steam	triethylamine	
rock	steel	trifluoromethyl	
root	stem	triglyceride	
rubber	steroid	tuft	
saline	stockpile	tungsten	
salt	stone	uranium	
sand	stream	urethane	
sap	substance	urine	
sash	substrate	vaccine	
sawdust	sucrose	vantablack	
seawater	sugar	vapor	
seed	sulfate	vegetable	
shampoo	sulfide	veneer	
sheet	sulfur	vinyl	
silica	sunlight	waffle	
silicon	surfactant	wallpaper	

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