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Reading functional requirements using machine learning-based language processing

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Industrial innovation has accumulated *big data* in the form of past design successes and failures. Designers must painstakingly identify, extract, and structure requirements from texts and drawings of archived documents to understand the past and guide future designs. This is not a trivial task for human designers, despite the digitalization of design data. This paper presents a system of "Design Reading" which takes in textual design data and applies a machine learning-based language processing model to extract a structured hierarchy of functional requirements by recursively decomposing text passages. Design Reading will benefit future design practice by learning from the past.

Design, Machine Learning, Natural Language Processing

1. Introduction

Present day designers sit on a wealth of digitally documented design and manufacturing data from the past; evidence of a modern legacy of innovative complex problem-solving to advance the quality of life for society. There exists an overwhelming amount of available information about design successes and failures, and this quantity is only increasing. Some fields, such as biomedicine, see more than 1 million papers published per year, with such figures steadily increasing across all disciplines by 8-9% annually [1]. In manufacturing, most design information exists in the form of documented initial specifications; artifacts of extensive stakeholder research, user feedback, and design revisions throughout the product life cycle. Despite the digitalization of past design information, distilling documentation into learnable outcomes to guide future design practices remains a difficult task in most industries. As a result, when experienced designers and manufacturing engineers switch teams or leave an organization, their successors have difficulty consuming documentation of past work for smooth continuation of a project. When experts are not available, learnings from past designs may not be distilled at all, resulting in perpetuation of past mistakes in future designs.

Keyword searches and other rudimentary processes with text mining tools may be used to organize documented specifications to a degree, but human designers must still conduct a painstaking study of documentation to understand, extract, and structure embedded functional requirements. As a result, a thorough and complete analysis of past design specifications requires time-consuming effort of experienced designers with extensive domain knowledge. This paper presents an approach to enable machines to understand design documents in text form, extract and memorize past designs' key functional requirements (FRs) and tested design parameters, and retrieve them when needed. We call this process "Design Reading" in this paper, which is one of the major modules of the Hybrid Intelligence System we recently proposed [2]. Design Reading can be used to construct databases of detailed FRs addressed in the past that designers can utilize when creating future products, to facilitate rapid innovation.

In the case of engineering design, the task of "Design Reading" involves extracting a hierarchical map of the functional requirements and design parameters of past products. We have developed a novel system which can automate Design Reading by applying state-of-the-art Natural Language Processing (NLP) models and Machine Learning (ML) tools. In this work, we focused on reading design specifications in text form only, excluding graphic data or drawings.

2. Background in AI for Design

2.1. Functional Domain of Design

While terminology may vary among different schools of design research, the importance of identifying requirements in the functional domain, or *what* a design must achieve, is universally recognized as the first priority of early-stage design. CIRP members have demonstrated the necessity and utility of correctly identifying *Functional Requirements* (FRs) [3] as the core design activity of translating *Customer Requirements* into a successful product design [4]. In industry, significant resources are invested to identify and surface FRs via laborious design processes involving stakeholder interviews and intensive domain research. If artifacts from past design research could be leveraged during this early-stage process, a rich history of past design successes and failures in industry could be transformed into a valuable asset to guide future designs. However, a barrier to immediately translating learnings from artifacts of past design data is that they are often expressed in language, meaning that designers themselves must manually read, identify, and extract FRs to understand the core knowledge being represented. How we can apply NLP models to extract and structure FRs from textual design documentation is the core goal of this paper.

The methodology by which a designer may translate requirements in the functional domain to design parameters in the physical domain also varies among schools of design thinking. In Axiomatic Design [3], the decomposition process is applied top-down, starting with the highest-level *Functional Requirement* (FR). This highest-level "what" of the design is paired with a high-level solution or *Design Parameter* (DP), which is "how" the design may achieve "what" the FR defines. This root node FR-DP pair may be decomposed one level lower by first identifying the sub-requirements (FRs) needed to satisfy this high-level "what-how" pair. Subsequently, a DP is paired to each sub-FR, and the process continues recursively until the terminal nodes of the FR-DP tree are identified. Well-documented product specifications should contain such FR-DP information embedded contextually, which engineers may discover if they read carefully. However, it requires significant effort to extract, even for domain experts, if they are unfamiliar with Axiomatic design practices. This work's goal is to allow machines to read the FRs and DPs in design documentation with minimal human intervention. For consistency and clarity, terminology from Axiomatic Design will be borrowed in this paper, where FRs will refer to the "what" of a design, and DPs to the "how."

2.2. Natural Language Processing

The field of Natural Language Processing (NLP) has benefitted from the resurgence of research in AI methods. The core goal of NLP, representing language for machines to understand, has been performed using deep neural networks, trained on massive datasets of text. Novel neural network architectures such as the *Transformer* [5], designed specifically for capturing contextual information in a language sequence, have allowed for the development of sophisticated NLP models such as *Bidirectional Encoder Representations from Transformers* (BERT) [6] by Google, which will be applied to design tasks in this paper.

BERT is especially valuable to the scientific community due to the manner in which the model's training is de-coupled. The training process is split into two phases: pre-training and fine-tuning. During pre-training, BERT's internal parameters are trained on 3.3 billion words worth of text. The pre-trained parameters of BERT are made publicly available, so that they may be fine-tuned to perform a specific language task. Tasks in the field of NLP range from sentiment analysis of product reviews, to text generation. A dataset with as few as 10^5 examples may be used to subsequently fine-tune BERT's parameters to perform a wide range of such benchmark NLP tasks.

The NLP-based module in the design reading system proposed by this paper uses BERT, fine-tuned on the task of question-answering. Question-answering involves considering two inputs: a long-form passage of text, and a prompting question. The output is the extracted span of text from the longer passage which contains the answer to the question prompt. The output is obtained *extractively*, where the answer is an unmodified sub-sequence of the context passage. BERT performs question-answering by introducing trainable parameters which can be optimized, using training examples, to identify the start and end position, within the context, having the maximum likelihood of containing the relevant answer information to the question prompt. A common dataset and testing metric for question-answering is the Stanford Question Answering Dataset (SQuAD) [7], a crowd-sourced set of 10^5 example contexts, questions, and correct answers. An implementation of BERT, fine-tuned on SQuAD by the HuggingFace Transformer library [8], is applied in this paper.

2.3. Machine Learning in Design

Previously, we have shown how representations of design documentation, from neural network-based models like BERT, could be applied to quantify metrics of functional coupling in systems design [9]. Because the functional domain in design is reflected in the semantic domain of language, which can be represented as a feature vector, we were able to demonstrate how language descriptions of products could be processed to accurately measure the functional independence of a matrix of FRs and DPs. This confirmed the possibility of applying NLP models to analyze design texts in terms of functional requirements.

We also showed how synthetic data may be generatively created for training an ML model in low-resource design data environments. We demonstrated that generative text models could be applied to effectively auto-complete "seed" design prompts to assemble a dataset of labeled problem and solution statements [10]. A binary classifier was trained on this dataset to identify if an unseen, unlabeled statement described a problem or a solution. We also demonstrated the ability to extract FRs from context through the application of BERT, fine-tuned on question-answering [11]. By posing a succinctly worded "what"-type question, the relevant functional domain information in a passage could be extracted. The following method describes how a design reading system may be built around such a module to scale the design information extraction system to extract complete functional trees from multiple design documents.

3. Method

This section describes how a set of design texts documenting a common problem can (1) be processed to extract their highest-level functional requirement and decomposed to extract a structured FR-DP hierarchy, and (2) all be compiled to create a global map of the functional domain of the problem.

3.1. Extracting FRs

The *Design Reading* analysis is initialized by first extracting the highest-level FR from a given document. This top FR_0 ("what") can be identified as the overarching goal which the design seeks to achieve, which is expected to be explicitly stated in the document. The next task involves mapping the highest-level FR_0 to the highest-level DP_0. The physical domain is mapped from the functional domain by identifying "how" the FR is addressed in the document. After mapping, this "what" and "how" pair is used in the third task: decomposition. The next level of FRs required for the highest-level FR-DP pair are extracted, and the mapping and decomposition process continues recursively until relevant text to extract is exhausted. Figure 1 visualizes this process.

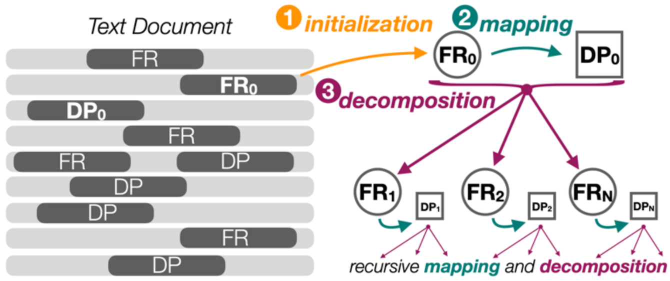

Figure 1. Process for extracting functional structure from text document

Each extractive step in this process is implemented by "question-answering" process using the BERT with fine-tuned on SQuAD as described before. By choosing the correct inputs (context and question) for each task of initialization, mapping, and decomposition, the target answer is returned as an opuput. The input context used is the design document and is updated after each step to remove previously extracted content. The input questions are dynamically updated during recursion and are based on previously extracted content, as summarized in Table 1. Recursion terminates when no output answers are returned or context is exhausted.

Table 1 Question-Answering Inputs for Functional Decomposition

Task	***Initialization***	***Mapping***	***Decomposition***
Description	given a document, identify the key functional requirement (FR_0) being addressed by the design.	given a document, and a functional requirement (FR_N), identify the corresponding "how" (DP_N).	given a document, and a (FR_N-DP_N) pair, identify any sub-requirements ($FR_{N.i}$)
Input Context	Design Document	Design Document	Design Document (extracted content removed)
Input Question	**"What is the aim?"**	**"How does it {FR_N}?"**	**"What is needed for {DP_N} to {FR_N}?"**
Output Answer	**FR_0**	**DP_N**	**$FR_{N.i}$**

Input Text: Vibration energy harvesters based on the resonance of the beam structure work effectively only when the operating frequency window of the beam resonance matches with the available vibration source. None of the resonating MEMS structures can operate with low frequency, low amplitude, and unpredictable ambient vibrations since the resonant frequency goes up very high as the structure gets smaller. Bistable buckled beam energy harvester is therefore developed for lowering the operating frequency window below 100Hz for the first time at the MEMS scale. This design does not rely on the resonance of the MEMS structure but operates with the large snapping motion of the beam at very low frequencies when input energy overcomes an energy threshold. A fully functional piezoelectric MEMS energy harvester is designed, monolithically fabricated, and tested. An electromechanical lumped parameter model is developed to analyze the nonlinear dynamics and to guide the design of the nonlinear oscillator based energy harvester. Multilayer beam structure with residual stress induced buckling is achieved through the progressive residual stress control of the deposition processes along the fabrication steps. Surface profile of the released device shows bistable buckling of 200μm which matches well with the amount of buckling designed. Dynamic testing demonstrates the energy harvester operates with 50% bandwidth under 70Hz at 0.5g input, operating conditions that have not been demonstrated by MEMS vibration energy harvesters before.

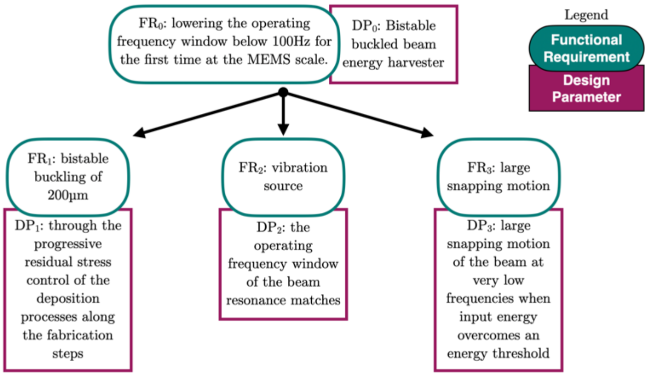

Figure 2. Fully automated functional extraction and structuring of an individual MEMS paper abstract [24], using process from Section 3.1

3.2. Abstraction by Structuring Extracted Design Information

The intermediate result of the recursive decomposition in section 3.1 is an FR-DP tree structure for each design document, like that shown in Figure 2. If multiple documents describe different aspects of a system, it is necessary to compile individual FR-DP trees from them into a global map of the functional domain and to abstract them into a global FR-DP tree.

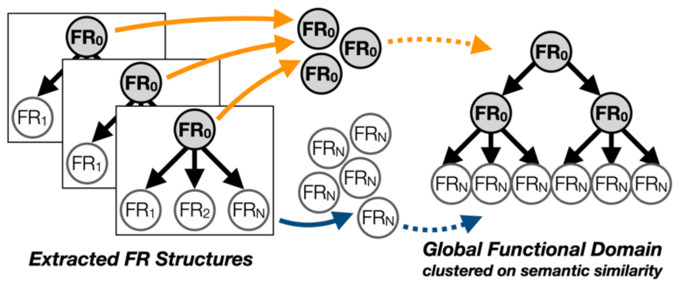

Figure 3. Extracted FRs from individual documents may be compiled into a global structure using clustering based on semantic similarity

K-means clustering, based on semantic similarity, is used to construct a global hierarchical tree of all extracted FRs. Semantic representations (the linguistic meaning of each FR) are obtained by producing vectors for each FR text span using the pre-trained language modeling parameters from BERT. The method by which all extracted FRs are structured is explained in the following and visualized in Figure 3.

1. The highest-level FR$_0$ (one from each document) are K-means clustered. The FR at each cluster's centroid has the most in common with all other FRs in its cluster and is therefore considered a highest-level FR for the new global hierarchy.
2. The other extracted FR$_N$ are assigned to an FR$_0$ group based on semantic similarity such that FRs describing similar requirements are grouped together. Semantic similarity is measured by cosine distance between vector representations.

With this method, multiple artifacts of documentation can be analyzed and compiled creating a searchable structure in the functional domain of a problem. Past design efforts sharing functional requirements may be represented such that designers of new products may easily find similar FRs and matching DPs that have been previously conceived and used, thus facilitating future design with the full knowledge of the past.

4. Case Study: FR Map Construction of MEMS Design

4.1. Background on Low-Frequency Vibrational Energy Harvesting

Due to the low availability of industrial design specifications, published scientific papers are used to demonstrate this *Design Reading* system. These papers focus on solving the problem of Microelectromechanical Systems (MEMS) energy harvesting from low-frequency vibrations. This is a complex challenge if a piezoelectric microscale cantilevered device is considered for this application [12]. From the relationship between natural frequency ω_0, mass, and stiffness k, resonance scales inversely with the scale L from $\omega_0 = \sqrt{k/PL^3}$ where mass is density P multiplied with volume L^3. This relationship results in high linear resonant frequencies for micro-scale cantilever beams. This case study shows the mapping of the functional domain by processing papers published on the designs of two *non-linear* devices to solve this problem, utilizing the oscillation of a clamped-clamped beam array [12-17], and an array of buckled beams [18-24].

4.2. Functional Domain Mapping for MEMS Case

A total of 13 papers [12-24] are identified and processed. Each paper describes a part of the global problem but, together, they collectively solve challenges in developing low frequency MEMS energy harvesting devices. For each paper, the abstract is considered as the high-level summary of the design. First, the FR-DP tree is extracted for each abstract. One of these abstracts [24], and its corresponding extracted tree are presented in Figure 2 as an example of the output of the decomposition process. For the 13 papers, 88 FRs were extracted. The top-level FR$_0$ for each paper are listed in Table 2. The remaining FRs may be viewed in our repository, in [25]. The extracted FRs were structured, using K-means clustering with (K=10) following the method outlined in section 3.2. As a result, a global map of the functional domain is produced, shown in Figure 4. This is the compilation of 13 individual maps such as the one from Figure 2. This is a demonstration of how *Design Reading* may be applied to map the functional space of a complex problem.

Table 2 Highest-Level Functional Requirement from each MEMS paper

Abstract Ref.	Highest-level Functional Requirement (FR$_0$)
[12]	*harvest energy from parasitic vibrational energy sources and convert it to electrical energy*
[13]	*robust power generation*
[14]	*ultra wide - bandwidth energy harvesting applications*
[15]††	*harvests energy from parasitic ambient vibration*
[16]	*energy harvester*
[17]†	*overcomes the limitations of conventional linear resonance beam - based piezoelectric energy harvesters in terms of power bandwidth and power density*
[18]	*generate electric power from ambient vibrations*
[19]	*harvesting small energy from the ambient vibration*
[20]	*increasing the operating frequency bandwidth*
[21]	*stiffens the beam as the beam deflects and transforms the dynamics to a nonlinear regime*
[22]	*to address the challenges of low-frequency , low-g vibration energy harvesting at mems scale*
[23]	*lowering the operating frequency while widening the bandwidth*
[24]*	*lowering the operating frequency window below 100hz for the first time at the mems scale*

†FR1 and ††FR2 shown in Figure 4
*Full decomposition of which shown in Figure 2

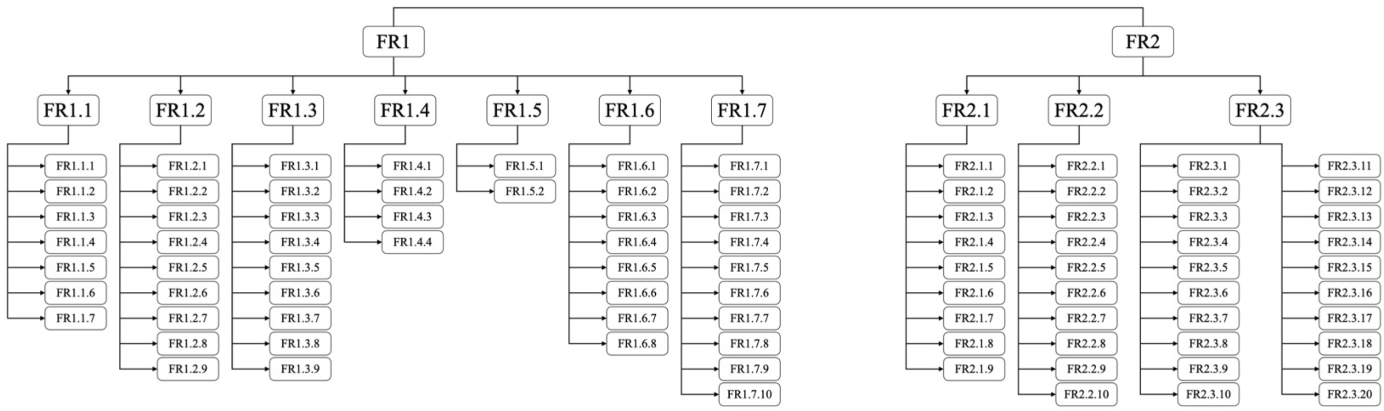

Figure 4. Hierarchical structure of all extracted FRs from [12-24]. Each of the 88 FRs could not be explicitly included in this paper but may be viewed in our online repository in [25]; the highest-level FRs extracted from each document are shown in Table 2.

5. Discussion

The value of the design reading system demonstrated with the case study lies in its speed and thoroughness, even when compared to those (such as the authors) with both product design and MEMS domain expertise. Results are obtained nearly instantaneously, and efficiently produce a hierarchy of design information simply from unprocessed text documents. In an ongoing study [26], we are comparing the NLP model results to those of human practitioners of product design and MEMS, with early results showing good agreement between experts and the AI. The implications of deploying this process on a much larger scale are suggestive of how design knowledge may be managed using AI-powered NLP models, constantly updating and restructuring large functional spaces based on published news.

The automated decomposition of textual data at the highest level of FR-DP space may be expanded to detailed levels of design to include graphics and 3D models in the future, applying similar algorithms to map design, utilizing ML-based image-processing models in the place of NLP, to extract functional features for AI-assisted process planning (AAPP), assembly modeling, and other manufacturing operations. The massive amount of knowledge from past product development would enable designers to identify structured functional requirements of a design inherited from the process domain. This information can be called as "genes" of product design, with an analogy to the translation of DNA to protein production. In the future, "Design Reading" will enable mapping of a "Product Genome" which will elevate the current Industry 4.0 to the next level. Industry will be able to construct large databases of their products from past product development. Such a transformative shift for the production industry will be akin to how sequencing genetic information has revolutionized the rapid development of novel, customizable drugs and vaccines in the pharmaceutical industry. For junior engineers, this design reading system provides a tool for utilizing their design capability to address complex problems in highly specialized technical fields.

6. Conclusion

Motivated by the goal of applying artificially intelligent models to transform the practice of design, we developed a design reading system where question-answering, powered by neural-network based language model BERT, was used to recursively extract a map of the "whats" and "hows" of a design from existing specifications. Design reading presents a step towards enabling Hybrid Intelligence of machines and humans in the practice of high-performance design as well as towards immediate applications such as industrial big data processing, digital threading and intelligent knowledge conservation and transfer.

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