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Bridging the Knowledge Gap Between Design Requirements and CAD - A Joint Embedding Approach

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Introduction

As artificial intelligence advances manufacturing corporations, this evolution redefines both industrial business model innovation and reforms the manufacturing sector by using big data to drive the manufacturing process and associated decisions. One of the most promising approaches, Model-Based Enterprise (MBE), has shown its potential to drive smart manufacturing (or Industry 4.0) by linking all sources of digital data through the product lifecycle[1]. The global net value of the MBE market has grown from $7.89 billion in 2017[2] to $9.94 billion in 2019[3], and the forecast for the future market performance is set at about $44 billion by 2027. Beyond upgrading manufacturing equipment, companies have sought to develop a digital model-based network for higher production efficiency and a profitable return on investment. Unlike traditional manufacturing, the next generation of manufacturing networks will provide seamless product record-tracking and tracing capabilities for all parties, from customers to government regulatory compliance agents using machine learning (ML) techniques[4,5]. The advances and implementation of MBE in engineering enterprises critically influence the practice of design. As MBE presents a unique opportunity to link all sources of digital data throughout the product lifecycle, we explore how the requirement domain can be linked to the CAD domain. In addition to engineers interested in machine learning implementations in product design, this research can benefit educators in developing ML models for ME students. This would allow engineering changes to be tracked both upstream and downstream for requirements and CAD analysis. For instance, design changes originated from requirements can be implemented in CAD, and vice versa. Further, it is important to consider how requirements and CAD can be visualized and realized during the early stages of the design process to help engineers reduce the risk of project failure. This is particularly pertinent as requirements often serve as the contractual agreement between parties, and thus all changes and decisions must be aligned with the corresponding requirements. However, this is difficult to perform as relationships between requirements and CAD are not formalized nor fully realized. Often, correlations are manually determined by experts based on their heuristic knowledge. By automating this process, engineers and designers would make AI-assisted decisions to provide better designs[6].

In this paper, the purpose is to develop a framework for performing a study to address the requirement analysis challenges associated with engineering education in building digital threads for Industry 4.0. Digital threads in manufacturing can be divided into four domains: design requirements, CAD, computer-aided manufacturing (CAM), and quality inspection[7].Tracing digital information across domains presents unique challenges in complex systems, primarily due to the high volume, complexity of requirements management, and the difficulties in interpreting them resulting from change propagation. Current CAD education primarily focuses on teaching low-level skill sets, whereas Industry 4.0 engineering would require the ability to combine domains such as requirements-CAD and CAD-CAM. Engineering design changes are often derived from requirements documents and propagated to CAD and CAM systems. However, it is also important to emphasize the importance of back propagation of information in design education. As an example, engineers must assess the compatibility of new design parts with existing design requirements efficiently in order to streamline the future design process and use design reuse strategies. The complexity of the data sources makes cross-domain analysis difficult as changes are often observed within each domain. In the initial conceptual design phase (i.e., requirement management), requirement changes have been defined into four categories and studied the different change patterns over time[8] with the likelihood of change propagation[9]. Researchers can further predict the higher-order change propagation for a complex system[10]. In addition, engineering changes can be analyzed on a lexical, syntactic, and structural level[11]. For mechanical modeling (i.e., CAD), most extant literature focused on applications related to graphics, analysis of components, computer numerical control, and manufacturing processes[12], but few research studied how to group CAD components with requirements to jointly represent design knowledge.

Challenges in Model Based Enterprise

Though MBE can offer such significant advantages, admittedly, some obstacles make the transition from current manufacturing practices more difficult[13]. Besides the technical difficulties of implementing MBE in design curriculum[5], it is challenging to synthesize data from multiple sources to formulate new insights and meet educational needs. As a result of geopolitical, economic, and regulatory uncertainty, the major smart manufacturing initiatives have had a limited impact on industrial infrastructure and educational programs.

An urgent need exists for focusing educational and training programs on equipping the future workforce with the necessary knowledge and skills to gather, manage, and improve product information. Many practical challenges remain unsolved to achieve this goal. First, managing an entire information system requires a more efficient business and operating model, which enables the model-based system to manage automation, optimization, and decision-making across different manufacturing infrastructures. Second, every organization utilizes various product lifecycle management (PLM) tools/software to build a fully designed model, and not many companies can afford such integrated software shared with their suppliers. In response, Model-based enterprise (MBE)[*]software (i.e., Syndeia[†]) integrates different domain platforms with various standard-based data, using digital threads. The goals of MBE are data repair, synchronization, and sharing, while digital threads connect the information flow among all phases of the product lifecycle[7]. Moreover, many leaders of major manufacturing sectors accept the MBE concept and envision that MBE can reduce the cost of the technology management process by 50% and reduce time to market by 45%[14,15]. While digital threads as a concept exist, there is still a lack of detailed techniques and formal studies used to support decision-making in data management[16]. This study addresses such issue by providing a method to bridge the information gap between design requirements and CAD models.

Educational Issues and Related Theories

As CAD becomes the essential method to convey and deliver design artifacts, the extent to which a student is equipped with desired representational fluency contributes to the understanding and

[*]Model-based enterprise and model-based engineering are indistinguishable terms. For clarity, MBE is defined as follows[1]:

- Model-based enterprise refers to an organization that uses model-based engineering.
- Model-based engineering is a strategy for product development, manufacturing, and lifecycle while using a network approach (i.e., digital threads) to connect engineering activity.

[†]http://intercax.com/products/syndeia/

quality of their engineering work. The scenario of this work situates in bridging the written design requirement descriptions and the visualized CAD design artifacts. Engineering students in training might find it challenging to map the CAD models and the design requirement due to underdeveloped representational fluency. Scholars have long established the important roles of representational fluency in model development[17,18]. The well-known Lesh Translation Model (LTM) could be used as a framework to articulate the learning challenges presented in this study - students' conceptual understanding of the representations on the design task, and their translations among and within representations around the requirements[19]. LTM proposes the interaction of five forms of representations: 1) Realistic: representation through realistic and lived experiences informed contexts or metaphors; 2) Symbolic: written symbolic representation; 3) Language: spoken or written representations; 4) Pictorial: graphic representation; and 5) Concrete: manipulatable modeling representation[19,20]. The model indicates that to improve students' representational fluency it is critical to support students' ability to understand and translate the concepts and situations via and among the five types of representation[21,19,20]. Thus, the deliverable of this research project could provide a learning tool for students to embody the written design requirements and translate between written and pictorial (CAD drawing) representations.

Research Aims

This study is comprised of a two-stage investigation for requirement management followed by CAD. We aim to answer two research questions for a given product: how to build a model that correlates written requirements with CAD drawings, and how to make sense of these correlations. As a first step in answering these questions, Figure 1 illustrates the association between knowledge representation and CAD requirements. For instance, design requirements might not necessarily describe all of the design details for CAD, and CAD component designs cannot directly translate the design specifications back to requirements. The current literature lacks a descriptive method to define the connectivity among CAD components. Thus, if requirement sentences and CAD data can be represented in vector space, we can develop a model that can learn the association between images of CAD components and corresponding text. To simplify the correlations, we assume that each requirement can be correlated with one CAD image. Using a zero-shot learning algorithm, the results are validated with the judgments of domain experts. By using joint embedding methods, text-image pairs can be learned simultaneously while maintaining functional reasoning from requirements. Further, a proof-of-concept study provides evidence and discusses how CAD can be integrated into engineering education.

RELATED TECHNICAL BACKGROUNDS

This paper discusses how to link requirement management and CAD with engineering education practices through the design of a digital thread. This section introduces the necessary background with the connections among requirement management, CAD models, and joint embedding methods to support future educational needs.

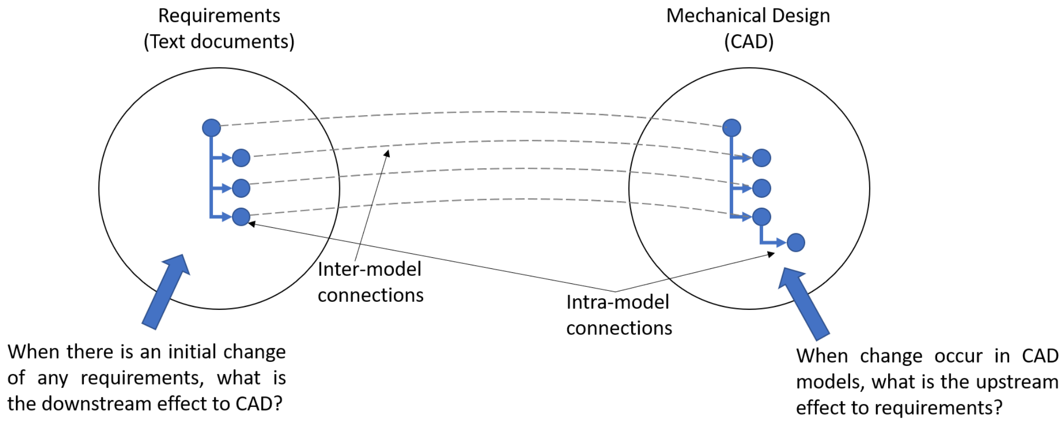

Figure 1: A flow chart of coding process to build digital threads for MBE[7]

Requirement Management

Requirements play a critical role in the conceptual design phase, and they are often presented as a list of documents containing product design specifications/constraints[22,23]. By consulting stakeholders, users, customers, or suppliers, requirements clarify design tasks and record the limitations for product development[24,25,26,27]. For a complex system, it is difficult to test and evaluate the propagation of engineering changes across the entire requirements documentation[8,28,29,30]. Moreover, the design is an iterative process, and any initial changes might result in an unanticipated change propagation due to different representations or insufficient communication among designers[31,32,33]. To predict the most likely consequences, requirement propagation is defined based on their types and purposes[11,34]. Much existing commercial software (i.e. IBM DOORS[35] or JAMA[‡]) and many research tools (i.e., ARCPP[23], ROM Client[11]) can manage requirement repositories[36,37,38,39]. An alternative method is the design structure matrix (DSM) (i.e., affinity matrix, $A \in \mathbb{R}^{n \times n}$), which represents the relationship between the requirements of a complex system for tracing potential changes propagation[40,41,42,43]. Each element of DSM defines a document or unique word. The off-diagonal component reveals the dependency of the pairwise comparison between any two subcomponents. Within DSM, various techniques can analyze and categorize requirements into subgroups/sub-diagonal blocks based on the concepts (words)[44,45,46,47]. DSM can be used to generalize correlations among requirements into a matrix representation, thereby reducing the number of dimensions in subsequent analysis. However, both approaches are incapable of representing the CAD models. To address this challenge, this study describes a scheme that correlates requirements (both functional and non-functional) with images of CAD designs. Upon successful completion, this work will improve the chance of ensuring that the product design meets all specifications, allowing for a more efficient design process. The established correlations allow designers to quickly and accurately modify designs that meet the desired requirements, while also providing the ability to quickly update and refine the design as needed.

[‡]https://www.jamasoftware.com

Computer-aided Modeling

Computer-aided engineering (CAE) refers to the use of CAD software to simulate geometric models. As the 3D CAD model replaced engineering sketches/drawings, digital documents have improved the reusability, accessibility, and quality of engineering model designs[48,49,50]. 3D CAD representation contains a set of distinct parts, such as geometric objects generated in CAD format, including completed product components and assemblies (i.e., product materials and manufacturing information)[15,51]. In industrial practice, engineers interpret system requirements and create CAD models to meet the design goals for every step of the product lifecycle. Any product design modification would result in a time-consuming procedure to increase the potential system failure[10]. In response, our goal is to associate CAD models with corresponding requirements and reduce the liability of changes in a complex system by using joint embedding. Thus, this proposed study would be able to utilize the CAD model in the form of 2D images, then finetuning the model to obtain domain knowledge.

Joint Embedding

With the advances of image processing techniques, joint embedding has become one of the merging research area for engineers to develop and implement[52]. In design education, joint embedding can learn the correlations of different types data representations in a latent space. By either training or finetuning models, students can build an AI and explore the different approaches to learn domain specific knowledge. During the learning process, the goal of joint embedding loss function is to make the positive pairs closer while avoiding trivial solution. The most popular training methods are contrastive methods[53], non-contrastive methods[54], and cluster methods. To evaluate model's performance, different classification or clustering techniques are developed for various purposes. One of the biggest challenges in real-world applications is predicting conditions that a ML model has not yet encountered. To overcome these issues, zero-shot learning is often used to predict the case using a model that has never been seen before. A good model would be able to provide the most likely prediction based on the learned patterns. The next generation of engineers must learn how to perform such tasks and build models that combine different types of knowledge to solve unforeseen problems.

CLIP is a contrastive learning model trained on 400 million image and text pairs from a combined dataset, WebImageText (WIT). Aside from the large amount of training datasets, the architecture of this model allows the interchange of different types of image and text encoders, which maintains the ability to switch between pre-trained models. To identify the correlation between words and images, image classification tasks and zero-shot predictions are often used to evaluate model performance. Unlike standard image classification tasks, real-life tasks may contain more diverse instances than training data. Often, zero-shot learning is used to evaluate the performance of a model to overcome these unforeseen challenges.

Requirement Datasets

In this paper, an in-house industrial requirement dataset is used to demonstrate how domain-specific tasks can be performed through joint embedding. Project A is designed for a manufacturing company to design, program, and install threading line equipment. It contains seventeen general sections varying from general descriptions to technical specifications. The total number of requirements is 350 and a simple data preprocessing procedure is used to eliminate non-alphanumeric characters (e.g., “-”).

Cleaning Text Data: Text preprocess is an operation to transform every text into its canonical form. A standard preprocess is necessary for certain models which are sensitive to inputs due to the presence of many stop words in the requirement documents. Lowercase, tokenization, lemmatization, and punctuation have been included in this preprocessing step using Python Spacy Package. Since some of the high-frequency words might still offer some values in representing the structure of requirements, only certain stop words have been eliminated under scrutiny. We also assume nouns, verbs, adverbs, and adjectives have equally important roles in capturing the semantic representations among requirements. For instance, Table 1 shows the difference before and after this preprocessing.

Table 1: One example of requirements from the Project A

Original Requirement:
2.2. Each station shall be able to accomodate casing length of API Range Three from thirty four feet to forty eight feet.
After Pre-process:
station able accomodate case length api range three thirty four foot forty eight foot

Methods

The purpose of this section is to discuss how to finetune a pre-trained model using both industrial requirements documents and synthetic image datasets.

Fine tune CLIP model: As part of this study, we provide insights into how to integrate different types of techniques into a data science project to teach future engineers how to enhance the capabilities of MBE. To implement a joint embedding model, such as CLIP, both text and images must be paired for training or fine-tuning. Certain industrial projects are always challenged by a lack of data. Different synthetic image generation methods can be implemented to fill in the gaps in the image datasets. The availability of many variations of design products on the Internet makes it possible to find similar images using keywords to capture the main features of the products. Image retrieval is one of the techniques adopted to collect online images based on search queries generated by each requirement. Each query contains several phrases or keywords derived from the requirements. Various approaches exist for determining the number of appropriate keywords to represent the semantic meaning of each requirement. It is necessary for designers to apply and compare a variety of approaches depending on the specific requirements of each project. Part of speech (POS) tagging is the most common approach to extracting keywords. Once keywords have been generated, designers can send search queries to image search engines to retrieve online images. Depending on the quality of the keywords, the returned image may have a variety of representations. Filtering out or replacing irrelevant images may require a manual process. We can then feed data to a pre-trained model for finetuning for all 350 requirement sentence-image pairs.

Often, engineers use pre-trained models to perform downstream tasks in a real-world system. The ability to transfer existing knowledge into a different domain becomes increasingly important for developing applications in MBE. This study uses images of variation design products as inputs to fine-tune the model. Taking a picture of a system from a random angle and mapping out the relevant requirements contains numerous practical challenges in a real-world application. In certain cases, requirements documents may only pertain to a few key components in a system, resulting in many-to-many correlations. One of the challenges in computer vision is to solve this problem. We are testing whether the model can learn patterns from training data by implementing images with certain similarity. Following the fine-tuning of the CLIP model, the testing image will be used to compute the cosine similarity among 350 requirements in terms of probability values. A comparison of predicted results can be made between pre-trained and fine-tuned models based on heuristic knowledge from engineers. As the pre-trained model has accumulated extensive knowledge of the world, training a pre-existing model on a new dataset might provide additional insight. To determine the performance of a model, designers can analyze the quality and quantity of the most relevant requirements based on their heuristic knowledge.

Results

This section describes the performance of the fine-tuned model with respect to its educational purposes. To build future MBE applications, engineers must develop their own models and perform a variety of downstream analyses. In Figure 2, we present a conceptual illustration based on the model's prediction and the most relevant requirement documents. This background image is selected to test the zero shot prediction for a new conveyor system that has never been seen before by the model. Top three requirement predictions are selected and evaluated based on the heuristic knowledge of designers. As requirements are sorted according to their relevance, gradients can range from green to red, indicating the degree of relevance. The final result is only disclosed as keywords due to reasons of confidentiality.

Figure 2: Conceptual user interface for generating results based on joint embedding to correlate existing requirements with CAD images

Building a new product from scratch can be a time-consuming and costly process. Many industries reduce costs by transferring an existing design to a new product or modifying an existing product to meet additional design needs. A further application of this result can provide designers with a knowledge system to help develop projects in a preliminary design phase. In the process of redesigning, engineers could scan images of product defects or CAD models to identify the system's weakest link or determine which requirements should be modified to increase the design buffer. The use of a pre-trained model can facilitate the transfer of knowledge from previous products to new ones when building new designs. With the continued complexity of future products, the future of decision-making will be dependent on collaboration between engineers and AI. In the field of design and manufacturing, this step is critical to the preparation of future engineers.

Joint embedding models coupled with an interface would enable engineers to modify designs more efficiently. Rather than reviewing a large text document and manually determining the most pertinent requirements, a future application will integrate an AI assistant to assist the designer in identifying the most vital functional requirements. Since the cost of making changes for functional requirements increases exponentially over time, identifying and controlling engineering changes at an early stage will be crucial to reducing the failure rate of a product. A knowledge system like this could help private sectors improve their cost-efficiency and increase their productivity in the design process.

Limitations: Several technical limitations of this work and how we assessed the future of work are discussed. Joint embedding is a prominent technique to transfer knowledge from previous designs to the new tasks. However, this study only explore CLIP model with its potential applications. Further exploration of important factors affecting the quality of fine tuning a model and transferring knowledge to a new domain is still not well understood. A variety of industrial requirement datasets, as well as different joint embedding methods, should be evaluated for comparing and testing model performance.

Discussion

Design pedagogy at present does not place enough emphasis on bridging requirements and CAD into the design curriculum to improve students' representational fluency - students are taught how to build correlations manually. As the future of work deals with complex design, building model-based enterprises becomes increasingly imperative for performing inter-domain analysis. This study provides general instruction on how to implement joint embedding on a pre-trained model to fine-tune for a domain specific design task. The results demonstrate improved correlations between requirements and mechanical designs. By implementing joint embedding in engineering complex design, the future application of this study can enhance students' representational fluency, especially between language and pictorial representations, and improve design productivity and efficiency.

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