# Conceptual Product Development through Parametric Optimization: A Case Study on the Design of an Ophthalmic Instrument

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## Abstract

In this paper, we describe a conceptual product design approach based on variational 3D models, parametric optimization, and rapid prototyping for facilitating the exploration of the solution space for a design problem. We demonstrate the proposed strategy through a case study on the design of an ophthalmic instrument. A template 3D model was manually created and fed to a parametric optimization tool to automatically generate design alternatives based on a set of criteria, which were then exported for 3D printing and testing in both dry and wet lab environments. Our results show that the method facilitates parallel prototyping and enables the exploration of a wider range of solutions more quickly and efficiently, particularly in highly constrained scenarios, but it requires designers to think of the initial models as families of solutions.

## Keywords
Product development, Parametric optimization, Concept design, Design space exploration, and Computer-Aided Design.

## 1. Introduction
Human-machine collaboration technologies have consistently been leveraged to enhance the various stages of the design process, including ideation and concept evaluation (Camburn et al., 2020-1; Camburn et al., 2020-2; Yuan and Moghaddam, 2020). Advanced Computer-Aided Design (CAD) and rapid prototyping tools, in particular, are being introduced earlier into the engineering design process (Marion and Fixson, 2019) to allow designers to create physical models and validate concepts quickly and easily.

Parametric CAD is a widely adopted computer-aided design technology where 3D models are controlled by parameters, which define relationships between different parts of the geometry. Parametric modeling enables the integration of design intent and facilitates model updates by eliminating the need to manually recreate a model every time a dimension changes. If the model is structured and built correctly, when a particular parameter is modified, all the parameters in the model that depend on it will automatically adjust to maintain their relationships. The flexibility of parametric CAD can be leveraged during conceptual design stages by allowing designers to create models that can be easily modified as the design evolves and by enabling the exploration of different design options more quickly and easily than traditional CAD methods.

In this paper, we discuss a conceptual design approach for the exploration of solution spaces based on parametric optimization techniques. We describe a case study involving the design of a novel ophthalmic instrument and a semiautomated process for exploring variations of a single design idea. Instead of modeling each variation individually for rapid prototyping, which can be inefficient and time-consuming, we employed variational geometry and Knowledge-Based CAD techniques to assist in the iterative phases of ideation, prototyping, and testing. Our method allows designers to generate a multitude of design alternatives and physical prototypes by automatically extending a single concept. Furthermore, our approach streamlines data collection, which can inform subsequent iterations of ideas and the selection of the most appropriate design candidate.

### 1.1 Objectives

The primary objective of this research is to facilitate conceptual product development processes by automating tasks in the prototyping phase. In this paper, we describe a case study in which parametric optimization and rapid prototyping methods were leveraged to enhance the concept design process of an instrument for ophthalmic surgery.

## 2. Literature Review

Computer-Aided Design (CAD) tools have been gradually replacing traditional methods of design prototyping and conceptual product development (Kazi et al., 2017; Camba et al., 2018; Marion and Fixson, 2019). They are also used for concept exploration through various automated mechanisms. During the early stages of the design process designers typically ideate a number of different design concepts, and even small interventions such as building on other people's ideas can enhance creativity (Deo et al., 2021; Salvador et al., 2014). Authors Alcaide-Marzal et al. (2020), for example, used sketch transformation rules within CAD software to automatically produce design variations. They employed a conceptual generative model (CGM) built in Grasshopper and Rhinoceros software using both numerical and categorical parameters (Alcaide-Marzal et al., 2020).

In contrast to the aesthetic product design approach explored by Alcaide-Marzal et al. (2020), Knowledge-Based Engineering (KBE) techniques aim to reduce costs and time in the product development process by automating repetitive design tasks and reusing engineering knowledge (Gembarski et al., 2017; Verhagen et al., 2012). Knowledge-Based Design (KBD), and more specifically, Knowledge-Based CAD, focus on supporting design processes through the reuse of predefined methods, algorithms, or results and is integrated into the workflows of the design process (Hirz et al., 2013). While the term KBD covers a range of functionalities and applications, authors agree that variational geometry, that is, the parameterization of geometric objects used in the design process, is the common starting point (Hirz et al., 2013). Knowledge-Based Design methods and tools can be implemented at different levels, with various degrees of complexity and sophistication, from the integration of mathematical and logical relations to the development of automated routines for geometry creation or calculation procedures to the implementation of fully interactive applications (Hirz et al., 2013). Knowledge-Based Design integrates parametric and feature-based design with problem-specific solutions, for example, in the form of template models (Kreis et al., 2021). Applications of KBE and KBD have been explored in the aerospace and automotive development contexts, in manufacturing, and in the overall product lifecycle (Cho et al., 2016; Kreis et al., 2021; La Rocca, 2012; Pugliese et al., 2007; Zheng et al., 2022).

Modeling a single idea in a flexible and configurable manner and using this model to automatically generate design variations may similarly enhance creativity and inspire new concepts that were not previously considered. However, the effort required to create template models, algorithms, and routines for KBD and CAD automation can be significant. Furthermore, when using autonomous software tools, designers need to change their workflow and approach so they can make most effective use of the tools. They often must use different mental models, frame design problems differently, and evaluate ideas differently (Seidel et al., 2018).

Additive manufacturing technologies such as 3D printing have greatly enhanced the prototyping phase of the design process. Though some have discussed methods to avoid physical prototyping by using approaches like digital human modeling to simulate interactions with virtual prototypes (Ahmed et al., 2021), these approaches are not suitable for all situations. The combination of CAD and rapid prototyping has been, and continues to be, transformative for innovation across many industries (Marion and Friar, 2019).

Physical prototyping tends to be time consuming due to its iterative and manual nature (Dering et al., 2018). Parallel prototyping, an approach where multiple prototypes are created and evaluated at the same time instead of in a linear manner, has been shown to produce superior results (Dow et al., 2010). This prototyping approach aligns well with the automatic generation of multiple design alternatives described above. In this regard, the combination of these techniques can accelerate design processes and give designers many options to evaluate at once. In this paper, we discuss a novel approach for concept design and prototyping and demonstrate its application to the design of an ophthalmic instrument.

## 3. A Method to Automate the Prototyping Process

The proposed method is best implemented after design requirements and needs have been properly identified and defined. At this point in the design process, designers and engineers work on developing a wide range of possible solutions as well as prototyping and testing those solutions to determine viability.

In this context, manually creating an individual 3D model for each variation in a set of design concepts and then 3D printing each model is certainly possible, but also time consuming, particularly if the number of variations is high. As part of our work, we implemented an approach based on the creation of 3D CAD models of the most promising ideas generated during the initial ideation phase and the subsequent generation of model variations within a predefined range through parametric optimization techniques. These techniques automate the common approach of changing design variables and determining other variables that may be impacted by changing the variable of interest.

The design space exploration process requires an initial model (i.e., a “template” or “seed” model), which must be created manually by the designer. The designer must also indicate which parameters in the model are allowed to change as well as the allowable ranges of variation for these parameters (i.e., the extent to which they are allowed to vary). New configurations are produced by iterating through the various combinations of values for the parameters, verifying that all constraints are within the preestablished ranges, and generating the corresponding geometric combinations within the defined design space. Each configuration becomes a unique model that can be 3D printed for physical testing and analysis. This approach allows for parallel testing, resulting in a faster feedback loop in the iterative design process. For example, a particular design might be produced in a single size, but it may be difficult to determine the exact size until the physical prototype is produced and tested. Instead of creating a new model and producing a new prototype every time a change is made, in our method each prototype is modeled in such a way that multiple features are contained and prototyped within a single configurable model. Additionally, the method facilitates the automatic expansion of each concept or idea proposed by the designer, leading to a broader range of possibilities. The process is illustrated in Figure 1.

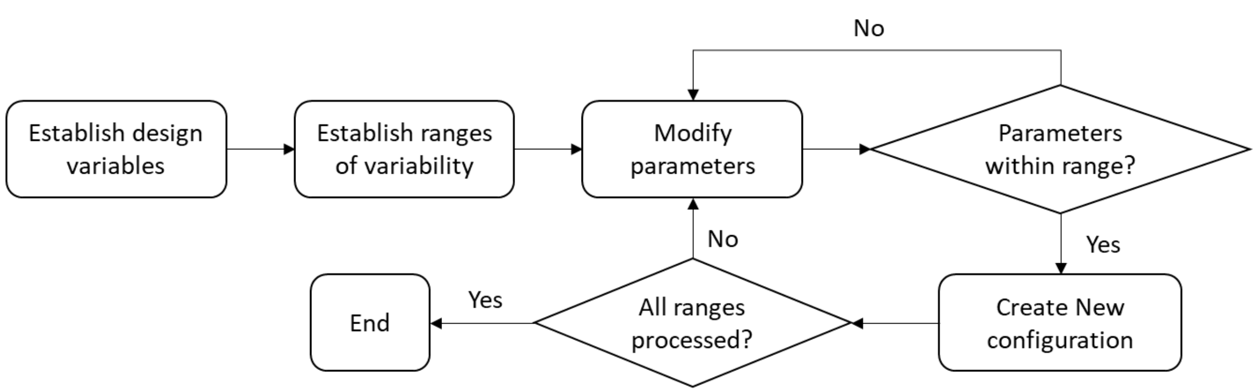



Figure 1. Design space exploration process through parametric optimization.

The quality of the initial template models used to generate the geometric variations is critical for the effectiveness of the method. Model quality in CAD is a multidimensional construct (Contero et al., 2002). In the context of our paper, we focus specifically on parametric quality and reusability (Otey et al., 2014). If the template model does not have a sufficient level of quality, design alternatives may not be created successfully due to regeneration errors (Camba et al., 2014; Aranburu et al., 2022).

The quality of the template model is ultimately the designer's responsibility. While modeling the different ideas, the designers must view the template model as a family of design solutions rather than a single design option and create each model in a configurable manner. Many commercial CAD systems implement tools to facilitate parametric optimization. For example, "Design Studies" in SolidWorks and Creo Parametric, or "Geometry Optimization" in Siemens NX. An example of the design generation process using the Design Studies tool in SolidWorks is shown in Figure 2.

Finally, rather than manually exporting each individual configuration as a standard stereolithography file (STL), a simple automation script can be used to traverse through the different geometric variations that were generated and then export each model automatically to separate files or combine all in a single file to facilitate setup for printing.

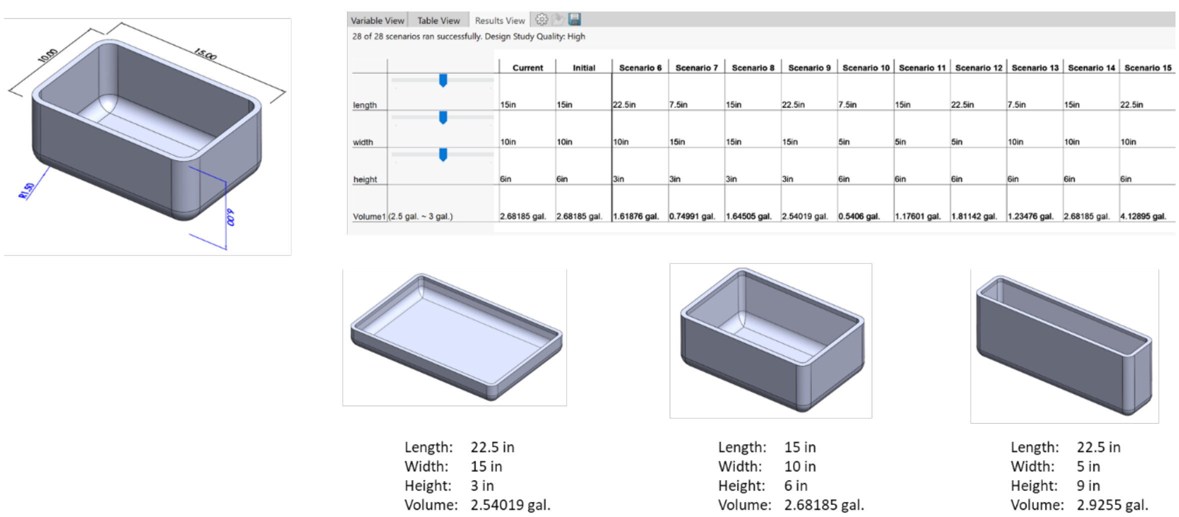



Figure 2. Example of variations generated by parametric optimization in SolidWorks.

## 4. Case Study: Ophthalmic Instrument Design

To test our approach, we developed an improved method for extracting defective or otherwise unneeded previously implanted intraocular lens (IOL) from the eye during a surgery called intraocular lens exchange. Previously, the standard of care was to cut the implanted IOL in two parts with tiny scissors to make it removable through a smaller incision in the eye. However, this technique poses risks to the eye (Lee and Webster, 2016). Our goal was to instead explore the possibility of removing the IOL by folding it into a tube-like device to extract it from the eye. This approach could potentially reduce risks during the procedure. The problem involved a high degree of uncertainty regarding the shapes of the device which would best facilitate IOL folding, and regarding which dimensions of the device would be optimal to fit the IOL inside the device while also minimizing the size of the incision needed. Sub-millimeter dimensions are considered critical in the context of eye surgery, and surgeons aim to reduce the size of all incisions made during operating procedures.

Because IOLs coming in varying shapes, materials, and thicknesses (Bellucci, 2013), it was determined that physically testing prototypes with the IOLs would be the best way to evaluate designs. However, the uncertainty regarding which designs and dimensions would be more effective called for the creation of a wide variety of prototypes for testing.

Based on the recommendations of an expert ophthalmologist as well as the relative dimensions of other instruments involved in the procedure (e.g., IOLs and forceps), a set of template models was created and the specific ranges of parametric dimensions for each concept were established. An example of the parameters (inner tube diameter, curvature profile of the opening, and length of the opening) used to control the variations for a particular concept is shown in Figure 3.

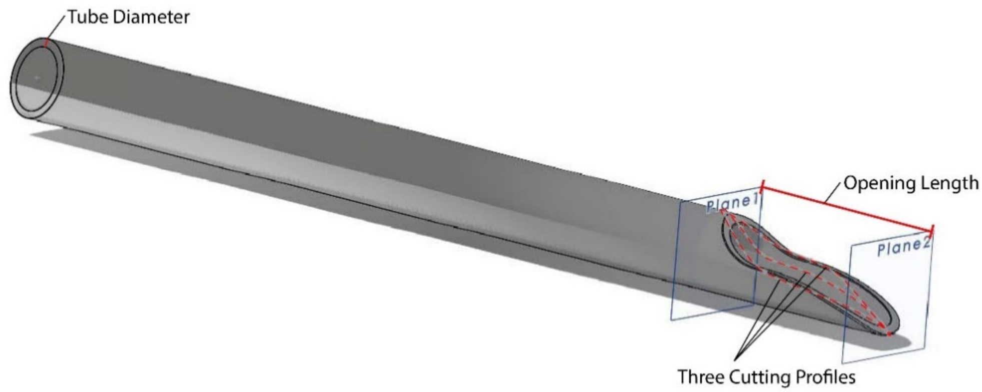



Figure 3. Parameters used to generate design variations.

Throughout multiple rounds of prototyping and testing, nine different concept families were manually generated, from which multiple design variations were produced automatically using the method described above, as illustrated in Figure 4. In Figure 4, 12 different design variations are generated from the single model. This saved a lot of time for the design team, who otherwise would have had to create new files and models for each of these 12 different configurations.

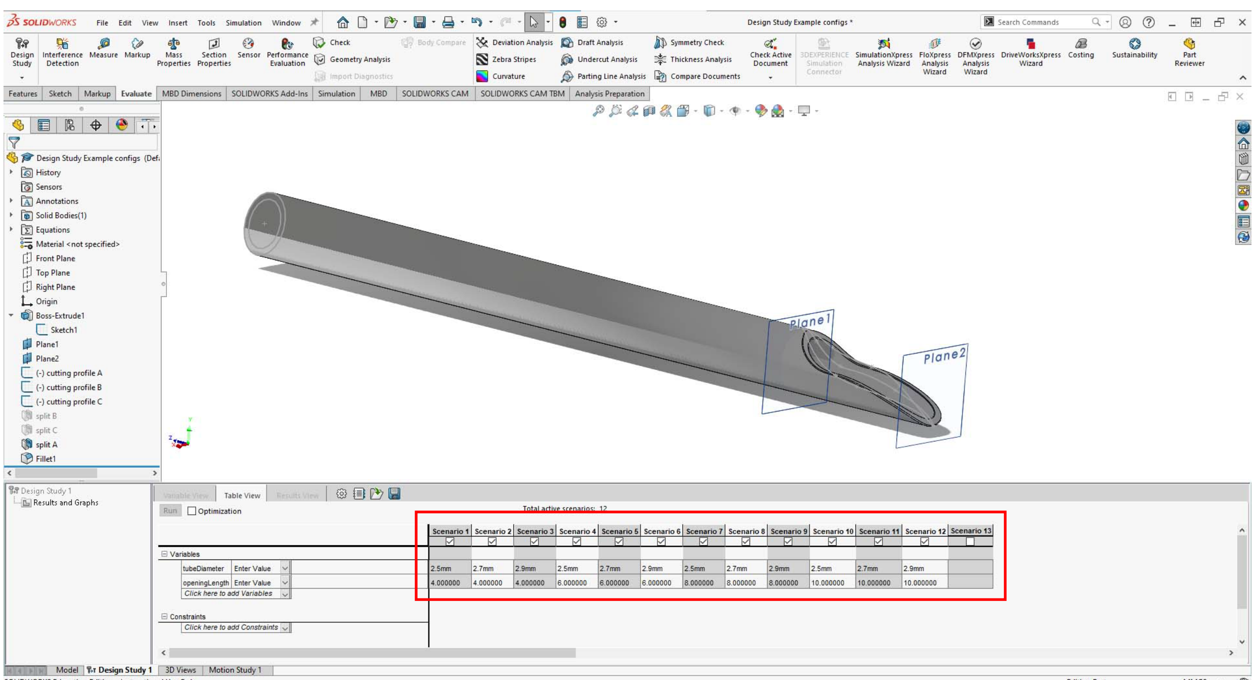



Figure 4. Parameters for the variations created from a single model using SolidWorks Design Studies.

In total, the team went through twelve rounds of ideation and prototyping, testing 150 different 3D-printed prototypes. Example models from the nine different concept families are shown in Figure 5. An example of some of the variation models within a single concept family is shown in Figure 6.

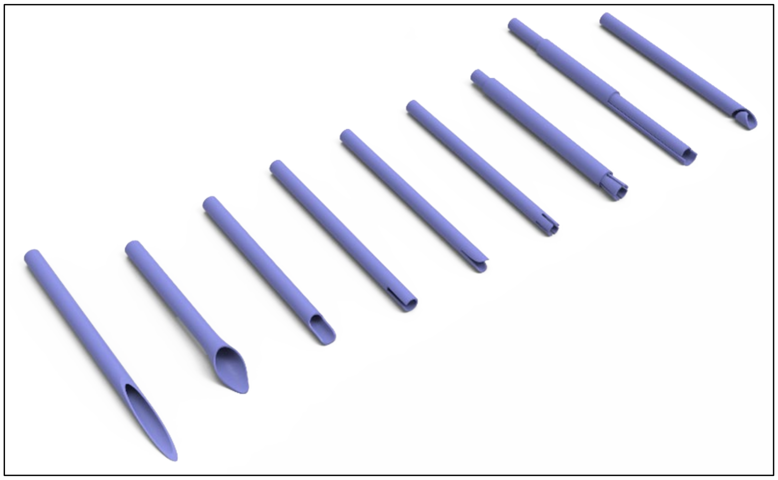


Figure 5. Nine concept families explored during the prototyping and testing process.

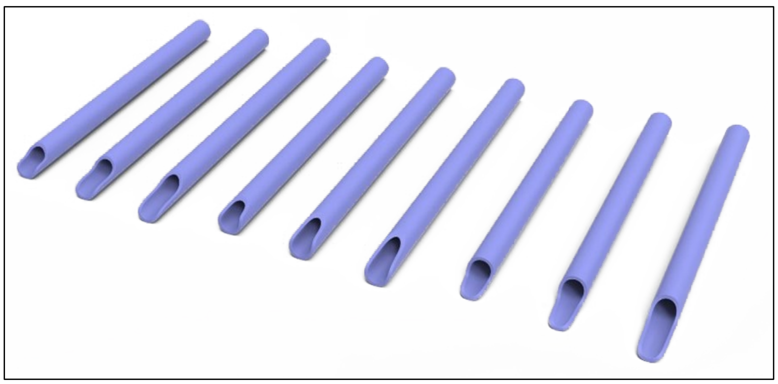


Figure 6. Variations produced within a single concept family.

The prototypes were 3D printed in acrylic using material jetting 3D printing technology. Our material and technology choices were deemed the most suitable for creating small, highly detailed models at a low cost. Semi-transparent acrylic was used in order to be able to see how the IOL was folding up inside the device. All the prototypes were ordered from the commercial 3D printing company Shapeways using their material "Fine Detail Plastic." For this material and method, the minimum wall thickness for supported walls is 0.3 mm, which was ideal to minimize the size of our prototypes. Some of the physical prototypes produced during our process are shown in Figure 7.

Finally, the models were initially tested outside the eye, and then the most promising models were further tested in sheep eyes in the wet lab. To test outside the eye, the researchers used one hand to hold a lubricated IOL with forceps and held the prototype in the other hand. They then attempted to insert the IOL into the receiving end of the prototype. If the IOL was able to fit in completely without requiring excessive force, the prototype was considered acceptable. If the IOL did not fit inside, or if the IOL tore into two pieces during the insertion process, the prototype was considered unacceptable. Ideally, the receiving end of the prototype should be as small as possible in order to require a smaller incision in the cornea of the eye for insertion. Thus, the prototype evaluation and refinement process focused on finding the design that optimized for a small incision while also being able to insert the IOL easily. Testing images are shown in Figure 8.

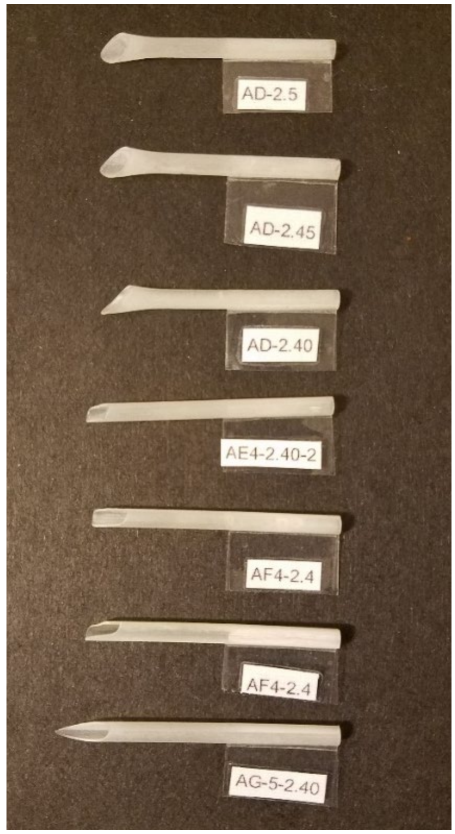
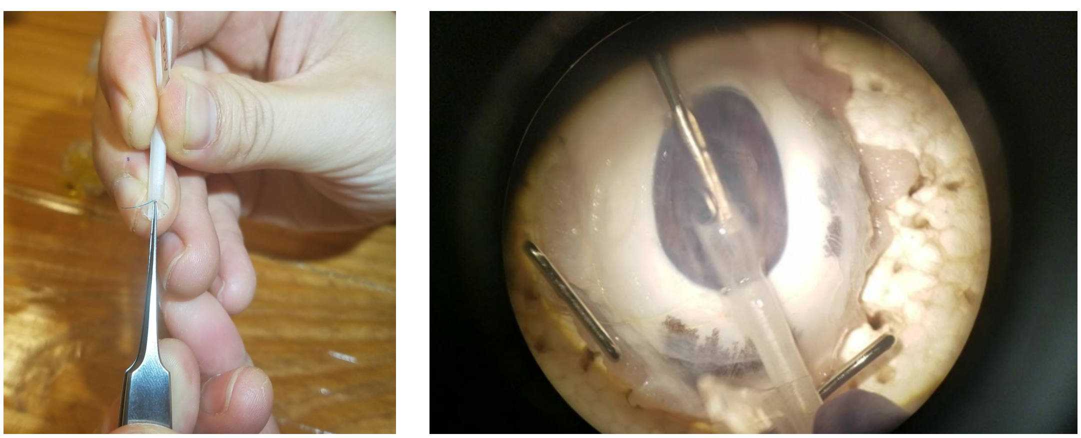



Figure 7. A selection of the prototypes produced during the design and evaluation process.



A B

Figure 8. Prototype testing outside (A) and inside (B) the eye.

## 5. Conclusion

A typical approach in engineering design is to brainstorm a solution and then prototype and test that solution. Three-dimensional parametric solid modeling is often used to create prototypes. In this context, the quality and flexibility of the models is paramount. If models are not designed in a flexible manner, it can be difficult to make changes following the learnings from testing, which hinders the overall creative process.

This project makes a unique contribution to conceptual product development by laying out a method in which many unique variations can be automatically generated and produced from a single model, facilitating the exploration of the solution space for prototyping and testing. While generative design and other non-parametric approaches are becoming increasingly common in product design, at present these strategies often produce forms that are irregular and organic in shape, which can be difficult or even impossible to manufacture using traditional manufacturing processes. Other methods appear to be better suited for generating aesthetic variations. Our approach is focused on functional solutions for engineering design.

The proposed method was validated through the design, prototyping, and testing of a novel ophthalmic instrument. Rather than modeling variations of the same idea individually, we were able to build a flexible and configurable model for each unique idea, and then use parametric optimization to generate variations within that unique idea, expanding the solution space. These variations were finally exported as 3D-print-ready files and sent for 3D printing in batches, to facilitate parallel prototyping and testing.

In general, we found the proposed method to be effective and timesaving for our purpose. That said, the method is best suited for situations where physical prototyping is preferred over digital prototyping or simulation, especially where 3D printing is used. However, some aspects can still be effective in cases where simulation or digital prototyping is viable. Our method is also ideal for situations that require precision in the final design solution, such as this case of the surgical instrument design.

Here we have described a conceptual product design approach based on variational 3D models, parametric optimization, and rapid prototyping which aims to facilitate the exploration of the solution space for a design problem. We carried out a case study on the design of an ophthalmic instrument to demonstrate the proposed strategy. We manually created a template 3D model which was then fed to a parametric optimization tool to automatically generate design alternatives based on a set of criteria. These models were then exported for 3D printing to create prototypes which were tested in both dry and wet lab environments. Our results show that the design approach facilitates parallel prototyping and enables the exploration of a wider range of solutions more quickly and efficiently than a traditional approach in which each design concept would have been modeled individually.

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