Design Learning: a methodology for the autonomous design and manufacture of customised toys based on Machine Learning

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Abstract: Society is increasingly demanding products with a higher degree of customization and shorter manufacturing phases. This demand is currently conditioned by a context of reduced mobility due to Covid-19. For these reasons, a new methodology called Design Learning is proposed, capable of designing personalized toys autonomously to improve the physical and mental development of children, including those with special needs. This method is based on the automated study of the user through their activity on audio-visual platforms and social networks, and on the application of Machine Learning techniques, Augmented Reality, Mixed Reality, parametric CAD and Additive Manufacturing. The results of the experiment show that children are able to use the proposed method and enjoy using it. It has also been obtained, thanks to the techniques used, in addition to designing and manufacturing toys autonomously and contributing to the development of children, that this tool also favours the competence of small companies and reduces the carbon footprint produced by traditional manufacturing processes.

Keywords: Product Design, Machine Learning, Augmented Reality, Parametric CAD, Covid-19.

1. Introduction

We live in a society where products are demanded more and more frequently and with an ever-increasing burden of personalisation. [1, 2]. To meet this demand, companies are investing large sums of money to adapt their production systems to Industry 4.0 [3] at the same time as they are trying to meet the Horizon 2030 [4–6] where activities that leave a carbon footprint are limited. However, these are not the only challenges, as from the beginning of 2020, both companies and the users of their products have to operate in the context of the Covid-19 pandemic, and therefore their mobility as well as social and work relations are drastically limited. This work and social context has a very direct impact on children, who have limited access to school and other social activities that are essential for their development.

The purpose of this work is to provide a tool that enables children to independently obtain playful and pedagogical material to help them in their natural development, whatever the limitations they are subjected to. Additionally, the aim is to provide a tool that serves as a stimulus for online commerce so that small businesses can develop their work when they do not have a business open to the public.
If solutions are sought for this type of problem, very few bibliographical references can be found on the automatic generation of products based on a mathematical model of autonomous learning. However, the best known model in terms of knowledge of user preferences and its implementation in industry is Kansei Engineering \cite{7-9}, which uses databases and relates concepts to design properties using statistical techniques. However, human support must be constant, since it does not use learning techniques to improve its solutions. As a contribution in this sense, Krahe et al \cite{10} use Deep Learning as an engine to automatically propose objects that the designer can use in their ideation process. This method is intended as a way of freeing the designer from some of his or her routine work, so it is also a methodology that requires supervision by a specialist. On the other hand, Wang et al \cite{11} apply Deep Learning to try to match customer needs with the features capable of satisfying them. A notable qualitative contribution of the previous model is the introduction of the concept of design properties, which is the knowledge base for the generation of a new product concept. Both contributions are pioneering in the application of Deep Learning to product design, although they do not provide a tool capable of operating autonomously. On the other hand, the work of Bickel et al \cite{12} employs Machine Learning for the comparison of three-dimensional CAD models, allowing similar products to be linked with models within a 3D catalogue. It is a tool that introduces the use of CAD models, but it is restricted to a very small number of possible solutions, and like previous works, it requires the supervision of a designer for the generation of the final product.

For these reasons, this paper proposes the Design Learning methodology, a novel technique that allows the automated design and manufacture of toys for recreational and educational purposes or to improve the development of children with special needs. To achieve this goal, the proposed methodology is based on Machine Learning, Augmented Reality (AR), Mixed Reality (MR), parametric CAD and Additive Manufacturing.

2. Design Learning: method overview

Based on the challenges outlined above, a methodology is proposed that can be easily implemented in the market through mobile devices such as tablets or smartphones. Therefore, three modes of toy generation are proposed: pre-designed, customised and designed for special needs. In the first mode, through a database of 3D models, it is possible to generate a new toy according to the specifications deliberately entered by the user, generating a product from offline data. In the second mode, personalised toys, offline data is used, as well as data from the user's Internet activity, allowing for more accurate and varied toy generation. In the third mode, toys for special needs, both offline and online information can be used in addition to a selection of proposals aimed at enriching the model with information related to the type of special need, thus allowing the generation of toys that help to improve the child's development. In all modes, the type of proposal is modulated according to the age of the end user.

The next phase has four modules which, by combining them, make it possible to create the three types of toys from phase 1. Thus, in module 1, information must be entered regarding the design properties preferred by the user: shape, colour and material, to be chosen from a series of options offered. Module 2 shows a series of pre-designed toy typologies modelled in parametric 3D CAD. These models are created in such a way that the geometry can be modified from a numerical database. Thus, it is possible to choose, for example, a construction set and vary the shape of the blocks, as well as the number of different blocks or their colour, generating a different toy for each child.

Module 3 is based on the Image Processing technique, an image analysis tool derived from Machine Learning and based on Feature Extraction. Through this technique, the aim is to determine the feature vector that represents an image, as in the case of the autonomous recognition and classification of plants through their leaves by Sachar et al \cite{13}, who explain how they are able to determine the shape, colour, texture and veins of a leaf. We also find the example of Sharma et al \cite{14} using Feature Extraction in hand image recognition with the aim of understanding sign language. To do so, they use the new ORB edge detection model and the bag of Word technique. These techniques would allow us to know the degree of curvature of the drawings or photographs.
Figure 1 shows an explanatory diagram of the different phases of the method, while Figure 2 shows a diagram of the operation of module 3.
This is based on a software application that collects data via Application Programming Interfaces (APIs) from different Internet-based media such as audiovisual entertainment platforms like YouTube [15] or Netflix [16], or data from user postings on social networks such as Instagram or Facebook [17]. The key words of titles or real/fictional characters that are of interest to the user are obtained from these platforms. From there, these terms are automatically searched for in Google Images. The resulting images are processed using Image Processing and those that correspond to real or fictional characters are chosen. The next step is to extract three design properties from these images: proportion, colour and shape. In proportion, we seek to know the ratio of height and width, in colour, to know the range of RGB colours present in the image, and in shape, we seek to know whether straight or curved lines predominate in the image, this data is tabulated through an average radius of curvature between all the lines of the image. Through this data it is possible to know which of these properties are the most recurrent and in this way a design proposal is generated by modifying the 3D CAD models, thus creating a geometry based on the child's preferences. From this technique it is possible to generate more than one proposal by combining the calculated design properties.

Module 4 is designed to generate proposals for children with special needs. In this module the design properties are generated based on the type of need presented by the child and based on medical recommendations. Therefore, if this module is used, this information takes precedence over the information in modules 1, 2 and 3. This module seeks to present toy proposals that help the child to improve specific aspects of their physical and intellectual development, allowing the size, colour or material of the proposals to be modified at the end of the process so they are better adapted to each user.

It is through the combination of these four modules that the necessary information is collected to modify the geometry of the parametric 3D models. Accordingly, the pre-designed toy mode is made from the combination of modules 1 and 2, personalised toys from modules 1, 2 and 3, and toys for special needs from the four modules. Afterwards, the 3D models are available, 3 proposals are displayed via tablet or smartphone (AR) or via an RM device such as the Oculus Rift [18]. The user is able to see in the play area of his home the proposed toys rendered with colour, material and real scale, being able to choose in a simpler and more direct way his preference. It is then possible to make a second selection using a variation of the design properties selected in the first option. Lastly, the final result of the toy is shown, allowing the user to edit the design properties of module 1: shape, colour and material. If the toy satisfies the user, the CAD file is proposed to be sent to a 3D printing centre for its manufacture and subsequent delivery to the user's home.

3. Materials and Methods
As an example, a case study on the application of the Design Learning method was carried out. For this purpose, a simple version of this technique has been applied in the form of pre-designed toys. Modules 1 and 2 in Figure 1 were used. The toy used in this test was a construction set.
3.1. Participants and Ethical Implications
Two children aged 4 and 6 years, both boys, participated in the case study. As they were minors, the legal guardians were provided with comprehensible information about the experimental procedure and were present at all times during the test, thus informing them that there were no known dangers for the participants. All subjects participated on a voluntary basis and could decide to leave the study at any time without explanation. The data collected in this research are anonymous and their use is governed by the provisions of the current legislation on the Protection of Personal Data.

3.2. Materials
The generation of the virtual toys was carried out with the parametric CAD software Solidworks® (2019 version, Dassault Systèmes SE, Velizy-Villacoublay, France) as it is one of the most widely used 3D drawing software in the industry, in addition to Unity® (October 12 2017, 2. 0f3 version, Unity Technologies, San Francisco, California, U.S.) because it allows for the correct representation of the real perspective of the human eye and the fluid viewing of a rendered version of the 3D object. In turn, the AR software engine used was Vuforia® Engine 8.3 due to its speed in the generation of graphics. Along with this technology, printed QR codes were used to allow users to visualise the toys in their final location at real scale. In addition, a Samsung® Tab A 2016 10.1-inch IPS tablet with a maximum resolution of 1920x1200 was used to eliminate the bias of asking children to use new technology such as MR glasses.

Using this technology, a database of toys was created with three types of modular building blocks: one based on parallelepipeds, one based on spheres and one based on pyramids.

3.3. Procedure
21 QR codes corresponding to the 21 different sets of games created were printed in A4 format. Figure 3 shows these sets, as well as the decision tree that was presented to the children.

![Figure 3. Decision tree for construction games.](image-url)

At each decision level they were shown the QR codes corresponding to that level and were given a tablet that allowed them to view the set in AR. At the first decision level they were asked to choose between the three types of pieces described in the previous section, where those pieces formed a set. At
the next level, the shape of some modular elements was altered. At the last decision level, the colour of the elements was evaluated. Thus, Figure 4 shows how the children visualised the sets.

![Figure 4. AR-visioned modular construction kit.](image)

4. Results and Discussion

As a result of the experiment, the two children chose set 2.1 (spheres) and set 2.2 (curved and straight joints). At the next decision level one chose subset 2.4 (monochromatic version) and the other one chose subset 2.5 (polychromatic version). Looking at the children's choice and behavior it can be seen that the type of toy configuration displayed, as well as the color tone of the toy configuration, influences the child's choice. For this reason, it is necessary to show the alternatives with similar layouts and to use the same viewpoints and camera lenses when rendering.

From a user experience point of view, different results have been observed. On the one hand, the test time was 3.55 min on average between the two children. They were asked whether they found the process long and boring or short and fun, with the latter being the preferred option. Also, one of the children spontaneously declared that he not only wanted to have the construction set he had chosen, but also wanted to repeat the process with more toys. For this reason, it can be deduced that some children not only accept this method, but use it as a game in itself.

On the other hand, analyzing the children's behavior during the test, it was observed that they moved the tablet closer and further away to check if the scale of the game changed, while at the same time they rotated around the QR code to see it from other points of view. This also showed that the test users were comfortable with the use of the technology and were not hesitant to use it. Although the process was fun for them, it was observed that they paid attention to the purpose of the test, the toy, rather than the AR technology. For this reason, and based on these data, AR technology is viable as a means of exposing the models for this methodology.

Thus, this experience has allowed the first impressions of two end-users to be obtained. However, the number of users used is small and it is necessary to carry out tests by expanding the sample, as well as programming the autonomous learning module to obtain data closer to a real experience. Nevertheless, from a user experience point of view, this first approach shows promising data.

With regard to the operability of the creation of CAD models, it has been observed that the time taken to create the various toy alternatives within the decision tree can be a problem when it comes to creating a catalogue large enough to satisfy a large number of users without the proposed solutions being frequently repeated. It is proposed as a solution to open this method to the Maker Community [19], so that each member can create different parametric CAD models within the typologies of toys present in a general catalogue.
5. Conclusions
From the experimental test it is concluded that the DL method can be interpreted as a game in itself, improving the use and implementation of the methodology. The AR technology has also been validated as a means of displaying the generated alternatives. However, shortcomings have been detected, making it necessary to standardize and improve the visualization of the 3D renderings, as well as to open the methodology to the Maker Community in order to reduce the creation time of the toy catalogue.

Therefore, through the Design Learning method, the possibility of creating a platform capable of designing toys autonomously is proposed, while making the end user even more involved in the design process, doing so without the need to leave their home. This practice is proposed as a response to the growing demand for personalization by users for both recreational and physical and psychological development purposes. Hence, new techniques in the field of Machine Learning make it possible to create models that learn autonomously from the data coming from our activity on the Internet and use them to create services that would not be possible without them. On the other hand, it should be noted that this new automated methodology does not eliminate the product design phase, but takes the target audience even more into account, to the point of including them in the design process.

On the other hand, using Industrial 4.0 automation systems, it is possible not only to adapt to a confined lifestyle, but also to reduce the carbon footprint that can be produced by marketing products using traditional manufacturing and distribution methods. With this type of techniques, it is possible to manufacture and ship only those products that are in demand, reducing stock and the use of raw materials and energy resources. On the other hand, this type of service can not only be useful for the children's sector, it is also possible to apply this methodology to other areas such as the design and manufacture of furniture, favoring the emergence of small companies that can compete with large manufacturers that mass-produce generic products.

Acknowledgements
On behalf of the authors we would like to thank Macarena Cantero Díaz for her technical support.

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