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User-Centred Product Design with Photorealistic Virtual Prototypes: A Case Study on Process Optimisation for Aesthetic Quality Enhancement

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Abstract

In Industry 4.0, companies must focus on human-centred design for a competitive edge. The 4USER project aims to establish a user-centred design method using an interactive Photorealistic Virtual Prototype (PVP) based on Extended Reality (XR) technology, objectifying customer requirements into technical specifications. The PVP overcomes limitations associated with traditional physical prototypes, serving as a quality benchmark for final products. The research focuses on a case study involving the development of sports rifles, emphasising the importance of aesthetic quality. The proposed semi-automatic process in Blender enables the generation of low-poly PVPs, incorporating hyper-realistic textures and high-frequency details. In particular, the overall process is composed of the following steps: i) wooden texture generation via the Wasserstein Generative Adversarial Network (WGAN); ii) model creation based on a low poly "Shrinkwrap Cage"; iii) integration of generated textures into the UV-mapped model. This approach accelerates the product development cycle, reduces costs, and facilitates efficient quality control.

Keywords: Generative Model; Texture Mapping; 3D Modelling; Virtual Prototyping.

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1. Introduction and literature review

Nowadays, to maintain competitiveness in the Industry 4.0 landscape, companies should emphasise the importance of incorporating the human factor into product design to meet the user's physical, social, and cultural needs, thus increasing the product's perceived value. When developing a new product, several aspects must be considered, such as functionality and operability: the prior analysis of these factors, during the realisation of its prototypes, can be possible using the tools made available by digital manufacturing and virtual technologies, which will allow customer requirements to be objectified and translated into technical specifications in an objectified manner.

In this context, the 4USER project aims to establish a method based on user-centred design so that information about the users and their interaction with the product can be collected and applied to create a safe, comfortable, efficient, and highly valued artefact by the final customer. This method can be achieved by creating an interactive Photorealistic Virtual Prototype (PVP) based on Extended Reality (XR) technology that overcomes the drawbacks and limitations of the various traditional physical prototypes currently required in product development. As a result, the PVP will become the quality benchmark against which the final products must be compared. In this sense, PVP offers manufacturers significant benefits in the quality control process since XR simulation reduces physical prototype costs and speeds up time-to-market.

Among all the product features, hedonic design is another crucial factor that needs to be considered, as it refers to the emotional level associated with choosing a set of geometrical, texture, and colour combinations for its components or the product as a whole. In particular, the 4USER project focuses on a specific case study, namely developing a sports weapon, where an attractive product aesthetic is one of the most sought-after specifications [1]. As a result of the different features that can be configured, such as the choice of materials, XR allows the user to get a sense of what the finished product will look like in terms of aesthetic quality. At the same time, during the design phase, the product development team must adhere to these quality requirements that meet the customer's demands as much as possible.

The research aims to provide a semi-automatic process for turning virtual models produced by 3D CAD systems into low-poly PVPs that can be used in XR applications. The process is implemented in Blender. First, a modelling cage is generated from a low-poly simplified version of the CAD geometry. On the cage, texture mapping is done using textures generated and updated by hyper-realistic texture models. The cage is then projected onto the CAD-imported high-poly model using a combination of the Shrinkwrap, Boolean, and Subdivision Surface modifiers. A low-poly version of the identical external geometry is created as a result. Finally, the Normal Baking process adds high-frequency details (like engravings). Blender can swiftly update the virtual model semi-automatically in case of local changes to the component by creating a UV-Mapped cage around it.

1.1. Generative AI models for creating material textures

The use of Deep Learning (DL) based generative models can be beneficial to generate material textures that satisfy customers' needs. At present, Generative Adversarial Networks (GANs) [2] are widely employed and studied for image synthesis. The main idea behind these models is to train coupled generative and discriminator networks jointly. The goal of the discriminator is to classify between "real" and "fake" generated images. On the other hand, the generator aims to fool the discriminator by generating images that are indistinguishable from real images. Once trained, the generator can synthesise images when fed with a noise vector.

The various applications of GANs have also been used in the literature to generate materials textures. TextureGAN [3] is the first DL method for image synthesis that allows the user to control the textures of objects in the fashion scenario. Specifically, the user can "drag" one or more example textures onto the drawn objects, and the generative network realistically applies these textures to the indicated objects. With TextureGAN, the network learns to propagate textures to relevant object boundaries, implicitly segmenting sketch objects and performing texture synthesis.

In the context of Industry 4.0, generating textures holds significant implications for product design, manufacturing, and customer engagement. Texture generation is crucial in enhancing the realism, aesthetics, and functionality of digital models, virtual prototypes, and XR applications [4]. The work [5] focuses on classifying road pavement textures, generating new samples through a WGAN- GP network architecture, and subsequently testing the accuracy of the images adopting different ML network architectures. The advanced WGAN-GP adopted is a network that can obtain high-quality images. Still, it has to be considered the limited dimension of the samples (80x80 pixels) in respect of other actual cases of study.

Like the proposed application, Lopes et al. [6]demonstrate the feasibility of generating synthetic microscopic cross-sections of hardwood species. The proposed algorithm, StyleGAN, can synthesise realistic, diverse, and meaningful high-resolution microscope cross-section images virtually indistinguishable from real images. Moreover, the StyleGAN includes progressive resolution increase by adding layers to the network, working with images with a high dimensional space (512x512 pixels).

In the 4USER project, the generative task is related to a new and real industrial use case, i.e. the generation of synthetic images related to different aesthetic quality classes of wood used to manufacture sporting rifle parts.

1.2. Virtual prototyping

PVPs, which XR viewer apps need, are polygon-based textured models generated from CAD files. Each modification to the 3D model requires a new, intricate, and time-consuming modelling and texturing process because this is entirely manual. This conventional strategy is unsustainable for customised products where modifications frequently occur. User inputs require adapting the CAD model and, consequently, the PVP. Thus, this approach would require manual execution of all the virtual prototyping phases.

The three critical stages of virtual prototyping are modelling, texturing, and VR programming [7]. Utilising 3D CAD modelling software, the virtual prototype's 3D model is first created. The model is rendered using computer graphics methods, such as texture mapping. This procedure can be carried out immediately using the 3D CAD software application. Otherwise, separate, specialised software can handle texturing and rendering processes. The game engine imports the virtual prototype to produce the XR software and related graphic UV texture maps.

It is customary to mesh the original model and transmit it to a rendering graphics system to use a CAD model in an XR system [8]. Because so many triangles were produced, this method is ineffective for XR systems [9]. Meshes created via tessellation have a high triangular density and transmission load for local viewing.

Tang and Gu proposed a novel technique for CAD model translation and simplification for a VR system [10]in response to these considerations. Harlan et al. [7] recently created an XR-CAD platform to connect a game engine and CAD software effectively. Massive aircraft CAD models can be rendered using a GPU-based compression technique, according to Dunming et al. [11]. Model complexity reduction, animation, and kinematic adoption were used by Lorenz et al. to create an automated CAD-to-XR conversion method [12]. Despite the advantages, the method cannot handle textured models.

Prada et al. [13] provide an intriguing method for transforming CAD models (taking textures into account) for real-time rendering. The authors overcame the issue of UV mapping intricate polygonal models exported in STL format by using the DATASMITH plugin of Unreal Engine. Unfortunately, the cited paper does not describe how to use the method to manage CAD model revisions quickly.

2. Methodology

The overall process to integrate the generated textures, representing various wood classes of the company, with the UV-mapped model produced using the shrinkwrap method can be described as follows:

1. **Texture Generation**: The textures are created using a Wasserstein Generative Adversarial Network (WGAN), trained on a dataset of 3210 images of various wood classes from the company's inventory. These images are captured using a custom-designed quality control bench, specialised for rapid image acquisition of significant wooden parts of rifles [14]. The WGAN model is optimised with various hyperparameters to generate high-quality, realistic textures.
2. **Model Creation**: For each component that must be updated, a "Shrinkwrap Cage" is manually modeled for each rifle component. An STL of the part is imported from the CAD environment as a high poly model. Through the effect of modifiers and detail Baking in Blender software, the Shrinkwrap Cage embodies the high poly model, reproducing its external shape in a simplified but high-quality and UV-mapped version.

3. **Texture Integration**: The generated textures from the WGAN model are then applied to the UV-mapped model. Each pixel in the texture corresponds to a specific point on the 3D model, enabling the realistic representation of the wood classes on the model.

2.1. Wasserstein GAN for wooden texture generation

The employed generative model is a Wasserstein GAN (WGAN) [15]. This generative model is a variant of traditional GAN architecture that addresses stability and convergence issues in the traditional GAN training process. The key difference between WGAN and other GAN models is using Wasserstein distance or Earth Mover's Distance (EMD) as the loss function, which provides a more meaningful measure of the distance between the generated and real data distributions. This distance metric encourages the generator to generate samples closer to the real data distribution, resulting in more stable and high-quality image synthesis. In addition, WGAN also introduces a weight clipping technique to ensure that the discriminator is a Lipschitz function, which further improves the stability of the model training. A dataset of 3210 images (270x470 pixels) was used to train the WGAN network, collected using a custom-designed and purpose-built quality control bench consisting of multiple cameras, lighting system, and handling/hooking system, to enable rapid image acquisition of the significant wooden part of the rifles. Regarding hyperparameters, different combinations were performed for batch-size {32,64,128}, latent space {50,80,100,200,500}, number of training epochs {200,500,1000,2000,2500,3500,4000}, beta1 {0.4,0.5}, beta2 {0.9,0.999} and learning rate in {10^-4, 10^-5}. As for optimisers, Adam, SGD and RMSprop were tested once the best hyperparameter configuration was found. Adding too much latent space would not have made much difference to the final images since the range of colours is limited. All GAN training was finally run with a batch size of 64 images, as adopting a larger batch size did not bring effective improvements and, at the same time, caused the training process to slow down due to the increase in computational demand. The final adopted hyperparameter settings are summarised in Table 1.

Table 1. Hyperparameters for WGAN generative model.

Optimizer	Batch_size	Latent_space	Epochs	Beta1	Beta2	Learn_rate
Adam	64	100	3500	0.5	0.9	10^−4

2.2. Shrinkwrap procedure for modelling and texturing

The method allows recreating a low poly textured version of the CAD model to apply the material on it and achieve photorealism. The virtual prototype can be obtained semi-automatic through an optimised procedure in the software Blender.

The method relies on modifiers: automatic algorithms for non-destructive operations on polygonal meshes. A low poly "Shrinkwrap Cage" must be obtained just once for each component by manual modelling, to be used in every update cycle, which can be summarised in the following steps:

1. From the CAD environment, an STL of the component is imported as a high poly.
2. The modelled Shrinkwrap Cage embodies the high poly. Through the effect of modifiers, it reproduces its external shape at a medium level of detail.
3. Normal Baking is performed on the low poly to obtain a normal map on which high-frequency details of the high poly external surface are transferred and replicated as material information.

The output of the process is a lightweight low-poly model to be used in combination with a normal map, exported as a 16-bit raster image that must be applied to the material to create the high-frequency detail on the external surface of the model.

Through the action of the Shrinkwrap modifier, the simplified model, shown in Fig. 1 as a wireframe, adheres to the high poly model, reproducing its external surface. The modifier's algorithm omits the high-frequency details because of their dimension concerning the topology of the low poly model.

Holes and sharp edges are not reproduced correctly by the algorithm because of a bridge mesh effect: so the Boolean Modifier, in combination with the Shrinkwrap, is needed to refine the cage before wrapping, as shown in Fig. 2.

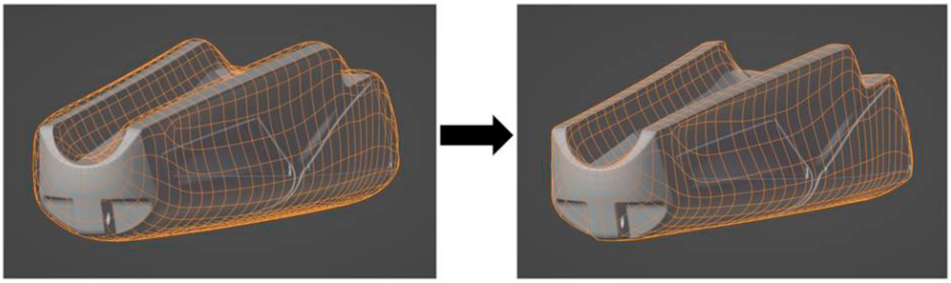


Fig. 1. Shrinkwrap modifier the simplified model.

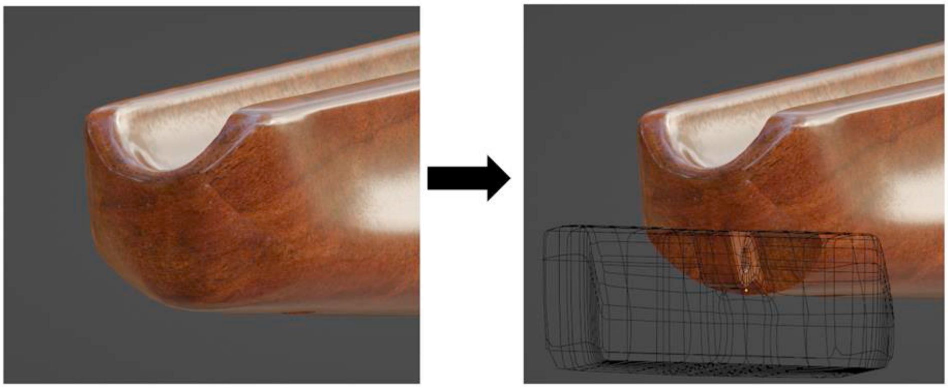


Fig. 2. Boolean Modifier to refine the cage before wrapping.

2.3. Texture integration

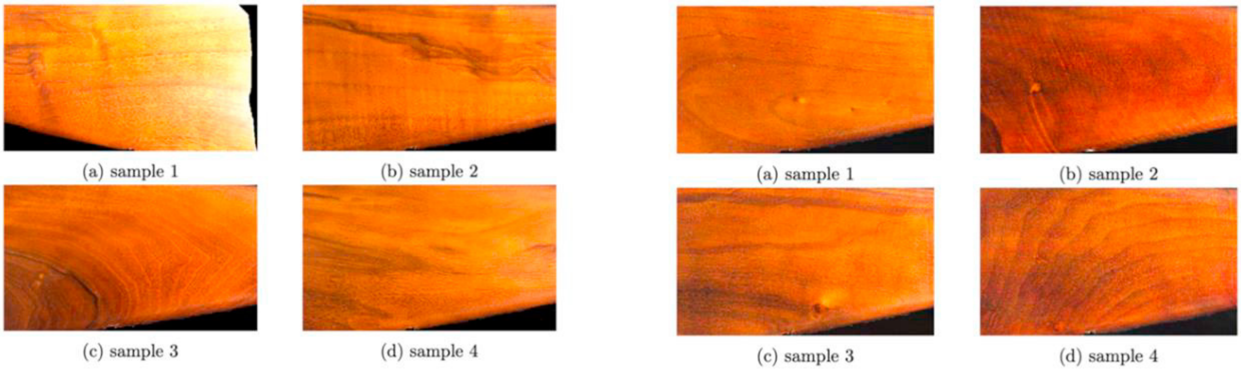
Once the colour texture of the wood is generated, it must be applied to the low poly geometry obtained by the Shrinkwrap methodology.

To maintain a high level of realism in the virtual model, the resolution of the texture applied must be carefully calibrated relative to the physical space of the model. This activity ensures that the texture does not appear pixelated or granulated when applied to the model. The texture resolution should be selected to reflect the scale and level of detail required on the model's surface. High-resolution textures are advised for close-up views or models with intricate details. One common approach is to select a texture resolution that aligns with the natural granularity of the material being represented, in this case, the wood grain. In doing so, the texture will maintain an accurate and realistic appearance across the model's surface, closely mimicking the material properties of the wood classes.

Given that the texture generated by the GAN corresponds to a limited area relative to the model's surface extension, tiling is necessary to preserve the scale of the surface pattern of the wood. This involves spatially repeating a crop of the texture across the model's surface. One technique to achieve seamless tiling is to symmetrise the crop of the image, creating a pattern that can be repeated without visible seams. This method allows the realistic representation of the texture over large surfaces, preserving the continuity and consistency of the material properties. However, careful attention must be given to ensure the repeated pattern does not result in an unnatural or overly repetitive appearance. Techniques like random offsets, rotation, or scaling of the tiled texture can help increase the surface's perceived variety and naturalness.

3. Results and discussion

In Fig. 3, examples of generated images are shown along with a batch of real images for visual comparison. The overall quality is very high despite the small dimension of this dataset for this type of generative task, achieving samples that are close to the real ones. However, it is possible to notice some generation noise due to the GAN model, and the color intensity is often more emphasised than real images. Moreover, sometimes there are flaws at the edges of the generated wood piece. As a result of applying the super-resolution algorithm to the texture generation process using the GAN model, 720 pixels per 100 millimetres were achieved as the final resolution. This resolution is deemed of good quality, providing considerable detail and realism to the rendered textures. In Fig. 4, one can observe representative renderings illustrating how a component of the carbine appears when the textures generated by the GAN employed within the project are applied. The captions below indicate that the four images pertain to different wood classes.


(a) sample 1 (b) sample 2 (c) sample 3 (d) sample 4

(a) sample 1 (b) sample 2 (c) sample 3 (d) sample 4

Fig. 3. Examples of real dataset images (left) and generated images (right).


Class 1 Class 2 Class 3 Class 4

Fig. 4. Renders of models to which textures, generated by the GAN, corresponding to various classes of wood have been applied

Looking ahead, future developments will focus on the reduction of noise in the generated textures to further enhance their visual quality. In particular, this is because, during the inference process, some images are created with a lot of noise, as shown in Fig. 5. This could be a symptom that the employed WGAN model is not well stable, leading to the implementation of a more efficient architecture in future work.

Fig. 5. Noisy sample generated by WGAN.

Additionally, efforts will be made towards creating a normal and roughness texture. These textures are fundamental components in a Physically-Based Rendering (PBR) workflow, which aims to achieve a higher degree of photorealism by simulating the material's physical properties. This will allow for a more accurate and visually compelling representation of the wood classes in the virtual environment.

As for the Shrinkwrap methodology, the implemented procedure significantly reduces the update time of the model during the prototyping phase compared to a standard manual modeling methodology. The main issue lies in the difficulty of fully automating the process due to instabilities in the operation of modifier algorithms, which do not always guarantee an optimal result and almost always require manual repair interventions. Although these interventions are quickly accomplished by someone experienced with the utilized software, they may not be easily replicable by less experienced personnel.

4. Conclusions

In the context of Industry 4.0, understanding and accommodating the nuanced preferences and needs of end-users hold the key to unlocking unparalleled success. In this way, companies can engineer products that offer superior functionality and resonate on emotional and cultural levels. In conjunction with this human-centred attention, integrating digital manufacturing and virtual technologies emerges as a transformative force, enabling real-time user interactions and feedback.

The paper presented a semi-automatic process for quickly updating photorealistic virtual prototypes (PVPs) employed in XR applications during product design. First, high-quality textures are created using a WGAN generative model, trained with images acquired through a custom bench. Second, textures are used in Blender for UV mapping. The virtual prototyping process, implemented in Blender, is based on a textured shrinkwrap cage. The latter, larger than the model, permits automatic UV-mapping on 3D models that differ from the original version for generating the cage. This method speeds up the modelling procedure (after a design revision). Furthermore, most of the UV-mapping activities are automatically carried out by Blender without manually iterating the entire virtual prototyping process.

The proposed semi-automatic process underpins the agility that Industry 4.0 claims. The accelerated update of PVPs aligns seamlessly with agile product development methodologies. Design cycles can become more dynamic and iterative, curtailing the temporal and financial investments traditionally associated with physical prototyping.

Significantly, the advantages of this approach extend beyond the design phase. PVP offers manufacturers considerable benefits in the quality control process, with pragmatic implications regarding cost and resource efficiency, aligning seamlessly with the pursuit of sustainability of Industry 4.0. The marked reduction in physical prototype costs and streamlined design iterations underpin cost-effectiveness and resource conservation. Additionally, the inherent agility of the process bolsters market responsiveness, endowing companies to tailor products to shifting market dynamics and emerging trends.

Limitations of this work are related to the texture generation process and the complete automation of the procedure. Although the generated textures are of good quality, there might be a weakness in the realism of the textures, which could affect the overall visual experience of XR application. In addition, there is not possible to distinguish different wood quality classes in generation. There may still be room for further improvements regarding process automation since some aspects of the procedure still require manual intervention or iterations.

Future activities will follow two pathways. Reducing the noise in the generated textures is requested for texture generation. Furthermore, generative models for normal and roughness textures need to be conceived. For virtual prototyping, the procedure should be further automated in Blender by using scripting.

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