Computational Parquetry: Fabricated Style Transfer with Wood Pixels

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Parquetry is the art and craft of decorating a surface with a pattern of differently colored veneers of wood, stone or other materials. Traditionally, the process of designing and making parquetry has been driven by color, using the texture found in real wood only for stylization or as a decorative effect. Here, we introduce a computational pipeline that draws from the rich natural structure of strongly textured real-world veneers as a source of detail in order to approximate a target image as faithfully as possible using a manageable number of parts. This challenge is closely related to the established problems of patch-based image synthesis and stylization in some ways, but fundamentally different in others. Most importantly, the limited availability of resources (any piece of wood can only be used once) turns the relatively simple problem of finding the right piece for the target location into the combinatorial problem of finding optimal parts while avoiding resource collisions. We introduce an algorithm that allows to efficiently solve an approximation to the problem. It further addresses challenges like gamut mapping, feature characterization and the search for fabricable cuts. We demonstrate the effectiveness of the system by fabricating a selection of "photo-realistic" pieces of parquetry from different kinds of unstained wood veneer.

1 MOTIVATION

The use of differently colored and structured woods and other materials to form inlay and intarsia has been known at least since ancient Roman and Greek times. In the modern interpretation of this principle, pieces of veneer form a continuous thin layer that covers the surface of an object (marquetry or parquetry) [Jackson et al. 1996]. The techniques denoted by these two terms share many similarities but are not identical. Marquetry usually refers to a process similar to "painting by numbers", where a target image is segmented into mostly homogeneous pieces which are then cut from more or less uniformly colored veneer and assembled to form the final ornament or picture. Parquetry, on the other hand, denotes the (ornamental) covering of a surface using a regular geometric arrangement of differently colored pieces. While most artists in their work embrace the grain and texture found in their source materials, they mostly use it as a stylization device as a decorative effect. Nevertheless, the resulting artworks can attain high levels of detail, depending on the amount of labor and care devoted to the task (Figure 2).

To overcome the "posterized" look of existing woodworking techniques, make use of fine-grained wood structures, and obtain results that are properly shaded, we introduce computational parquetry. Our technique can be considered a novel hybrid of both methods and is vitally driven by a computational design process. The goal of computational parquetry is to make deliberate use of the rich structure present in real woods, using heterogeneities such as knots, grain or other texture as a source of detail for recreating more faithful renditions of target images in wood, using a moderate number of pieces, see Figure 13. Since this goal can only be achieved by exhaustively searching suitable pieces of source material to represent small regions of the target image, the task is absolutely intractable to solve by hand. In the computer graphics world, our technique is closely related to patch-based image synthesis [Barnes and Zhang 2017] or texture synthesis [Wei et al. 2009], a well-explored family of problems for which a multitude of very elaborate and advanced solutions exist today.

Our end-to-end system for fabricated style transfer only uses commonly available real-world materials and can be implemented on hobby-grade hardware (laser cutter and flatbed scanner).
we believe that our method marks the first time that a measured
Ancient Roman and Greek mosaics are probably the best-known
process, explicitly making use of features present in the wood.

The texture of the source material has been used to drive the design
tools, such as posterization, to find image segmentations (Figure 2),
applied to the entire design). While some artists use computational
unaltered in color (except for a final layer of clear varnish that is
refer to two-dimensional arrangements of wood veneer that are
for instance by staining, painting or carving.

Surface (inlay) or covering the entire surface with a continuous layer

technique can be implemented either by carving and filling a wood
broadly aligned with a Cartesian grid.

Fig. 2. Two modern examples of marquetry portraits of different complexity.
Left: Self-portrait by Laszlo Sandor (using two maple specimens, brown
and black walnut, beech, Indian rosewood, okoume and sapele; original size
approx. 10 cm × 10 cm). Right: Portrait of a girl by Rob Milam (using wenge,
Carpathian elm burl, Honduran rosewood, lauan, pear, plaintree, maple and
ash; original size approx. 53 cm × 53 cm).

Fig. 3. Examples for intarsia and ancient mosaics: The intarsia from the
year 1776 depicts the adoration of St. Theodulf of Trier and a landscape with
plowing farmers and St. Theodulf (left). The mosaic from the 2nd century
AD depicts a scene from the Odyssey (right).

includes approaches for the simulation of different painting me-
dia such as paints, charcoal and watercolor [Chen et al. 2015; Lu
et al. 2013; Panotopoulou et al. 2018]. In recent years, the potential
of deep learning has been revealed for rendering a given content
image in different artistic styles [Jing et al. 2017]. Inspired by
the ancient mosaics and the application of mosaics for arts (see e.g. Sal-
vador Dali’s lithograph Lincoln in Dalivision [1991] or Self Portrait
I by Chuck Close [1995]), a lot of effort has been spent on non-
photorealistic rendering in mosaic-style. The original photo mosaic
approach [Silvers 1997] creates a mosaic by matching and stitching
images from a database. Further work focused on the application to
non-rectangular grids and color correction [Finkelstein and Range
1998] and tiles of arbitrary shape (jigsaw image mosaics or puzzle
image mosaics) [Di Blasi et al. 2005; Kim and Pellacini 2002; Pavić
et al. 2009], the adjustment of the tiles in order to emphasize image
features within the resulting mosaic [Battistato et al. 2012; Elber
and Wolberg 2003; Hauser 2001; Liu et al. 2010] as well as speed-ups of
the involved search process [Blasi and Petitralia 2005; Di Blasi et al.
2005; Kang et al. 2011]. More recently, texture mosaics have also been
generated with the aid of deep learning techniques (e.g. [Jetchev
et al. 2017]). We refer to respective surveys [Battistato et al. 2006,
2007] for a more detailed discussion of the underlying principles.
Furthermore, panoramic image mosaics [Szeliski and Shum 1997]
have been introduced where photos taken from different views are
stitched based on correspondences within the individual images
and a final image blending.

Example-based synthesis. Pixel-based synthesis techniques [Efros
and Leung 1999; Hertzmann et al. 2001; Paget and Longstaff 1998;
Wei and Levoy 2000] rely on copying single pixels from an exem-
plar to the desired output image while matching neighborhood
constraints.

In contrast, patch-based or stitching-based texture synthesis ap-
proaches [Efros and Freeman 2001; Kwatra et al. 2003; Prant et al.
2000] involve copying entire patches from given exemplars. One
major challenge of these approaches is the generation of correspon-
dences between locations in the exemplar image and locations in
the generated output image to copy the locally most suitable patches
from the exemplar to the output image. For this purpose, common
strategies include arranging patches in raster scan order and subse-
sequently selecting several patch candidates that best fit to the already
copied patches. As this matching process becomes computationally
challenging for larger images, several investigations focused on

2 RELATED WORK

History of the craft. History knows a rich tradition of techniques
that use patches of material for the purpose of composing images.
Ancient Roman and Greek mosaics are probably the best-known
early instances of this idea. An exemplary mosaic from the second
century AD is shown in Figure 3. Often, such mosaics consist of
largely uniformly shaped primitive shapes (e.g., square tiles) that
are aligned with important structures, such as object boundaries,
found in the target image. A modern counterpart of mosaics is pixel
artwork, which has played a similarly ubiquitous role predominantly
through video games in the 80s and 90s. Here, the design pattern is
generally aligned with a Cartesian grid.

Marquetry can be considered a generalization of mosaic. This
art of forming decorative images by covering object surfaces with
fragments of materials such as wood, bone, ivory, mother of pearl
or metal, has also been known at least since Roman times [Ulrich
2007], see Figure 3. The appearance of the resulting image, however,
is mostly dominated by the choice of materials and the shape of
fragments. The closely related term parquetry refers to the assem-
ly of wooden pieces to obtain decorative floor coverings. Either
technique can be implemented either by carving and filling a wood
surface (inlay) or covering the entire surface with a continuous layer
of thin veneer pieces. The materials can be altered in appearance,
for instance by staining, painting or carving.

In this paper, we use the term parquetry more restrictively to
refer to two-dimensional arrangements of wood veneer that are
unaltered in color (except for a final layer of clear varnish that is
applied to the entire design). While some artists use computational
tools, such as posterization, to find image segmentations (Figure 2),
we believe that our method marks the first time that a measured
texture of the source material has been used to drive the design
process, explicitly making use of features present in the wood.

Stylization. With the goal of non-photorealistic rendering, nu-
merous techniques have been proposed to transform 2D inputs
into artistically stylized renderings [Kyprianidis et al. 2013]. This
The main objective of this work is the development of a computational pipeline for creating faithful renditions of a target image \( I_T \) from wood samples by exploiting the rich structures in wood as a source of detail. The pipeline devised in this work takes \( n_{\text{samples}} \) physical, wooden material samples and a target image as inputs and consists of three major steps: data acquisition, data analysis and cut pattern generation (i.e. tile generation, arrangement, and boundary shape optimization), and the final fabrication of the real-world counterpart (Figure 4).

In the first step, the wooden samples are prepared before they can be scanned with a flatbed scanner. This is followed by extracting local features in the input images and by detecting corresponding patches between the source textures and the target image, yielding a stylized, digital wood parquetry of the target image. Finally, the patches are converted to cut instructions (taking into account that the cuts have to be fabricable by a laser cutter), specified pieces are cut with a laser cutter, and assembled to a physical sample of parquetry. We discuss details in the following sections.

3.1 Data acquisition

Before the scanning can be conducted, we first prepare the wood samples. Whereas thicker veneers can be utilized directly, standard veneers (0.6 mm to 0.8 mm thick) are glued to a substrate of 1.5 mm birch plywood in order to improve stability and minimize waviness. Especially burl veneers tend to be very brittle and assume strongly
The images depict the intensity filter response of a wooden veneer panel (left) and the respective responses obtained for the target image without histogram matching (middle left) and with histogram matching (right), as well as their interpolation (middle right).

The output of this step is a set of \( n_{\text{samples}} \times n_{\text{rot}} \) filter responses

\[
F(I_S) = \left\{ F(I_{S,i,j}) : i \in \{1, \ldots, n_{\text{samples}}\}, j \in \{1, \ldots, n_{\text{rot}}\} \right\}.
\]

for the source textures, and one filter response \( F(I_T) \) for the target image. We typically used \( n_{\text{rot}} = 15 \) source texture rotations for our experiments.

3.3 Cut pattern optimization

After evaluating the filter responses, the next step is to find corresponding patches between target image and source textures. To this end we divide the target image into a regular, axis-aligned grid of square patches that overlap by 1/4 of their size with their respective neighbors. By choosing overlapping patches, we are able to align the cut pattern to a data term (Section 3.4), which in turn allows the cuts to follow image features. The patch size depends on the desired size and appearance of the fabricated output.

Given a target patch \( P_T \subset I_T \) containing \( n_P \times n_P \) pixels, we determine a corresponding source patch \( P_S \) by a dense template matching using the sum of squared differences,

\[
d_{i,j}(x,y) = \sum_{u,v=1}^{n_P} \left( F(P_T(u,v)) - F(I_{S,i,j}(x+u,y+v)) \right)^2.
\]

\[
P_S = \arg \min_{i,j,x,y} d_{i,j}(x,y).
\]

Due to the decreasing number of available wood patches, the probability of finding good patch correspondences also decreases as the algorithm advances. For many classes of photos, e.g. portraits or pictures of animals, salient regions usually occur in the image center. To take this into account, we store the target patches \( P_T \) in a priority queue, sorted by their distance to the center of the photo. We avoid the multiple usage of already matched veneer sample regions by carrying along a binary mask for each source texture.
Target image regions with less salient features can be represented by larger patches. To exploit this, we implemented an adaptive patch matching step, where we subdivide a patch into four smaller patches if their associated cost is lower than the cost of the larger patch multiplied by a factor \( w_{\text{adaptive}} \). The factor \( w_{\text{adaptive}} \) can be used to control the artistic balance between larger and smaller patches. We apply this step \( n_{\text{adaptive}} \) (typ. 0 to 2) times.

At the end of this step, we have covered the reconstructed image plane with partially overlapping square patches.

3.4 Dynamic programming
Arranging the previously matched patches according to the target image results in overlapping regions. We resolve these (non-fabricable) overlaps by finding optimal cuts according to the target image reproduction cost

\[
\sum_{x,y} (F(R(x, y)) - F(I_T(x, y)))^2,
\]

where \( R \) denotes the reconstructed wood parquetry image. For image regions with only two overlapping source patches, we obtain an optimum solution using dynamic programming. For details regarding the implementation of axis-aligned patch merging using dynamic programming see e.g. [Efros and Freeman 2001]. As we enforce our cuts to be guided by features in the target image, the corresponding, local cost \( c(x, y) \) for merging two horizontally neighboring patches \( P_{S,1(1,2)} \) along pixel \( x \) is given by

\[
c(x, y) = \sum_{x'=x}^{x-1} (F(P_{S,1}(x', y)) - F(P_T(x', y)))^2 + \sum_{x'=x}^{n-1} (F(P_{S,1}(x', y)) - F(P_T(x', y)))^2,
\]

where \( P_T \subset I_T \) and \( n \) is the size of the overlap. We assign patch \( P_{S,1} \) to the region left of the cut and \( P_{S,2} \) to the remaining region. By approaching this problem using dynamic programming, we enforce \( \ell \)-connectivity of the cut and in turn physical fabricability. Vertically neighboring patches can be aligned in an analogous manner.

In regions where four patches overlap, we have to find two intersecting cuts, one for the horizontal and one for the vertical direction. This prevents cut optimization via dynamic programming. Instead, we find an approximate solution by alternating optimizations for one cut direction while keeping the other direction fixed. We experimentally observed two repetitions of this process to be sufficient.

In order to generate a representation that is laser-cuttable, we fit cubic Bézier curve segments to the cuts. The user can choose between \( \text{G0} \) continuous and \( \text{G1} \) continuous curve segments, or to skip this process entirely and generate axis-aligned cuts. Finally, the output of this step is a vector graphics file containing cut instructions which can be directly executed by the laser cutter.

3.5 Fabrication
In the next step, the optimized, still digital piece of parquetry is physically fabricated. To this end, we use a laser cutter for cutting the veneer boards from the back side and for engraving IDs which facilitate the identification of individual patches during their assembly. For other materials, this step could also be conducted using a CNC mill or a water jet cutter. The patches are separated from the rest of the veneer and laid out in a frame. To fix the patches, we attach a back plate using wood putty. After the putty has dried, we sand the veneers and finish them with clear coat or hard wax oil.

3.6 Implementation details
The method was implemented in C++ using the OpenCV library [Bradski 2000] and parallelized with OpenMP. Fitting a single patch typically takes 0.5 s to 3 s on an Intel Core i7-5820K CPU, where the runtime is dominated by template matching. Thus, the runtime primarily depends on the number of pixels per patch, and on the size of the wood samples tested.

During our experiments, we used a Plustek OpticPro A360 Plus flatbed scanner for A3-sized veneer boards, and a Cruse Synchron Table Scanner 4.0 for scanning larger panels. The fabrication (cutting) was performed on a Trotec Rayjet with a 12 W CO\(_2\) laser and an Epilog Fusion 40 M2 engraver with a 75 W CO\(_2\) laser.

4. RESULTS
We begin our evaluation with the analysis of user-controllable design choices in the optimization, such as the effect of different energy terms, different sizes and shapes of the individual patches. This is followed by an ablation study, where we investigate the gradual decline in quality that occurs when repeatedly producing the same target image from the same wood veneer panel. We further demonstrate a few examples of fabricated parquetry obtained from different woods and under different conditions. Finally, we show the robustness of our method with respect to different target images by presenting synthetic results for different targets, each optimized using the default parameter set.

| Symbol       | Parameter                        | Default |
|--------------|----------------------------------|---------|
| \( w_{\text{intensity}} \) | Intensity priority weight | 0.5     |
| \( w_{\text{edge}} \)     | Edge priority weight             | 0.5     |
| \( w_{\text{hist}} \)     | Histogram matching weight        | 0.5     |
| \( \text{image size} \)   | Reconstructed image size (shorter axis) | 360 mm  |
| \( \text{patch size} \)   | Patch size                       | 14 mm   |
| \( \text{adaptive} \)     | Adaptive patch levels            | 0       |
| \( \text{adaptive quality factor} \) | Adaptive patch quality factor | 1.2     |

Table 1. User-controllable stylization parameters and their default values.

4.1 User-controlled stylization
Our method allows the stylization of the generated renditions of target images based on user guidance. Before discussing the effect of individual user-controllable parameter choices on the style of the generated renditions, we first provide insights regarding the involved physical materials. We found an image of a human eye (Figure 10) to be a good target for quality assessment, because it contains features with different frequencies, as well as rounded structures. An overview over the user-controllable parameters related to stylization can be found in Table 1 and a more detailed description in Section 3.
Fig. 6. Effect of different resolutions on the reconstruction quality. We show reconstructions obtained with our framework (top row) and a “baseline” where high frequency features are removed and each patch is replaced by its mean color (bottom row). With decreasing resolution (from left to right), we observe that the structurally aware filters are important for reconstruction quality. The reconstruction quality obtained with our proposed technique gracefully declines with patch resolution and still produces visually pleasing results for very coarse patches.

Fig. 7. Scan of the wooden veneer panel used for the results in Section 4. The panel has physical dimensions of 1500 mm × 1000 mm and contains veneer samples from various wood types. The fiducial markers facilitate optical calibration on suitably equipped cutting systems.

Materials. For the purpose of a better comparability, we generated synthetic renderings using the same scan of a wooden veneer panel as input for all results in this section (unless otherwise noted). The panel has a size of 1500 mm × 1000 mm and contains veneer samples from various wood types. The woods used in our experiments are not protected under CITES. They include maple burl, ash burl, poplar burl, buckeye burl, elm burl, birch burl, walnut burl, pine, wenge, santos rosewood, olive tree, makassar ebony, apple tree, and zebrawood. We sanded the panel and applied a layer of clear coat to enhance the contrast of the individual fiber strands. The physical sample was scanned at 300 dpi using a Cruse Synchron Table Scanner 4.0. A downscaled version of the scan can be found in Figure 7.

Histogram matching. The target image gamut is generally larger than the gamut of the wood textures. Without taking this into account, the template matching step will generally draw patches from the gamut boundaries, which results in reproductions with high contrasts, but flat shading. By matching the target image histogram to the wood texture histogram, we compress the target image gamut to match the wood textures. This reduces the overall contrast, but puts more emphasis on shading nuances, see Figures 5 and 8. We found a simple interpolation between the matched and the unmatched input image to effectively improve contrast while preserving the original style of the image (Figure 5).

Patch size. We evaluated the influence of the patch size on the style of the resulting target image renditions. Figure 6 shows rendered results for different patch sizes ranging from 7.7 mm to 31.0 mm. Our experiments suggest that patches with 5 mm edge length are the lower bound for physical producibility using our pipeline. Smaller patches could easily get lost and would be difficult to assemble. The reconstruction quality improves as the patch size decreases and approaches an almost photorealistic appearance for very small patches. In contrast, reconstructions with coarse patch sizes exhibit a different, more sketch-like style.

As demonstrated in Figure 6, exploiting the structures inherent to the wooden materials greatly enhances the visual quality on all resolutions, thereby providing evidence for the effectiveness of our structurally aware template matching step. The perceived resolution of any image depends on the image size, resolution, and viewing distance. In order to give the reader an impression about the amount
Fig. 9. Effect of different adaptive reconstruction parameters. From left to right: \((n_{\text{adaptive}} = 1, w_{\text{adaptive}} = 1.2), (n_{\text{adaptive}} = 2, w_{\text{adaptive}} = 1.2), (n_{\text{adaptive}} = 1, w_{\text{adaptive}} = 1.5)\). As expected, high-frequency image structures are only touched for large values of \(w_{\text{quality}}\) (e.g., we accept a large decline in reconstruction quality). Nonetheless, we find the effect to be visually pleasing in all images and subject to personal preferences.

Fig. 10. Effect of intensity vs. edge filter. The highlighted zoom-ins depict the respective reconstructed regions for weights \((w_{\text{intens}}, w_{\text{edge}})\): \((1.0, 0.0), (0.5, 0.5),\) and \((0.2, 0.8)\) from left to right. Using only intensity penalty enforces the stylization to match intensity. Structural details become increasingly well preserved with an increasing weight of the edge term.

Fig. 11. The effect of the boundary shape optimization using dynamic programming. Without dynamic programming (left), the generated rendition of the target image has a pixelized style. With dynamic programming (right), the cuts are optimized according to the underlying data term and the rendition exhibits a smoother, more organic style.

of additional perceived resolution introduced by the wood pixels, we include a comparison to a “baseline” that discards the wood structure and instead replaces each patch by its mean color.

Finally, we evaluate the effect of adaptive patch sizes in Figure 9. Analogous to adaptive grid methods, this allows us to reduce the total number of wood patches without sacrificing reconstruction quality. Regarding stylization, the larger patches result in an overall smoother appearance with fewer cuts.

**Feature vector weights.** To analyze the effect of differently weighted feature vectors in the template matching step (Equation 4) on the wood puzzle appearance, we show results obtained for various parameter choices in Figure 10. The obtained renditions for the highlighted regions of the eyelid (top row) and the iris (lower row) show that high weights for the intensity penalty \(w_{\text{intens}}\) enforce the matching regarding the intensity features. Finer structures, such as eyelashes, become better preserved by increasing the penalty \(w_{\text{edge}}\) on the edge filter responses.

**Boundary shape optimization.** We also show the respective results before and after cut optimization. As demonstrated in Figure 11, the use of square patches on a regular grid results in a pixel-like rendition of the target image. Merging neighboring patches according to the data term reduces the pixelation effect, thereby putting more emphasis onto the underlying image structures. We found that the representation of rounded, high-contrast image features specifically benefits from the dynamic programming step.

### 4.2 Ablation study

Our approach is inherently resource constrained. Thus we expect the reconstruction quality to scale with the area of available wood samples. To evaluate this effect, we applied our pipeline several times to generate renditions of the same target image under a decreasing availability (and quality) of source patches. The respective results are shown in Figure 12. We observe that the reconstruction quality decreases gracefully and the target image stays recognizable until the very last reconstruction. After the last reconstruction (partially) finished, there was no space left on the veneer panel that was large enough for another patch.

We noticed two types of degradation: intensity and high-frequency detail degradation. Most noticeable is the degradation in overall intensity matching after the panel runs out of dark patches (iteration 5). Less noticeable is the degradation of high-frequency content, e.g., around the eyes after iteration 3. These types of degradations could be alleviated by reconstructing target images with different intensity distributions or by “interlacing” the reconstruction runs.
Fig. 12. From left to right: target image, renditions of a target image generated under a decreasing amount, and quality, of available patches from a single wood sample. The last reconstruction did not complete because there were no patches left on the wood sample. Please zoom in to see image details.

Fig. 13. A fabricated piece of wood parquetry made from four different quarter-cut thick veneers (bottom left corner, from top to bottom: oak, zebrawood, fir, American walnut). The target image is a human eye (bottom right corner). The veneer puzzle consists of 28 × 17 wooden pixels and has a total size of approx. 28 cm × 17 cm.

Fig. 14. Exemplary results of fabricated parquetries using the same target image (bottom center), but different wood types and finish. The left image was fabricated using zebrawood with an oil finish. The right image was produced using poplar burl veneer with clear coating, resulting in a highly specular appearance with limited contrast. The samples consist of 20 × 19 and 23 × 22 wooden pixels respectively and their physical dimensions are about 15 cm × 15 cm. The left puzzle has optimized patch boundaries, the right puzzle consists of square patches.

4.3 Fabricated results
We present exemplary results of physically produced veneer puzzles in Figures 1, 13 and 14. The veneer puzzles in Figures 1 and 13 have been fabricated using multiple wood types. Since different wood types can differ vastly in color and grain structure, these results show a high contrast and perceived resolution. Fine details, such as hair, eyebrows, or eyelashes are faithfully reproduced.

The results in Figure 14 have each been produced using a different single wood type. The amount and quality of detail within a pixel is inherently limited to the features present in the original material. Woods with a limited feature gamut thus lead to a strongly stylized outcome, which we imagine could also be utilized as an artistic tool.

We decided to finish most of the pieces using hard wax oil in order to accomplish a natural look. A clear coat finish (Figure 14, right) results in a highly specular appearance.

With row/column labels engraved on the back side, it takes about 1 h to 2 h for a single person to assemble a 500-piece parquetry inside a suitably dimensioned frame. Although somewhat repetitive, the authors found this activity to be satisfying and relaxing. For thin veneers that are laminated onto a plywood substrate, the final image remains hidden until the finished composition is turned around.

4.4 Synthetic results
In addition to the evaluation of different parameter choices, we show renditions for several target images depicting portraits and animals in Figure 15. To demonstrate the robustness of our approach with respect to different target images, each of these results has been produced using the default parameters shown in Table 1. The depicted results demonstrate the potential of computational parquetry for fine arts. Portraits and animal pictures can be easily recognized as their characteristic appearance is preserved in the stylized result.

Please see the supplemental material for additional results.

5 DISCUSSION AND FUTURE WORK
A practical drawback of our method is that it requires a surface finish to be applied to the wood two times, once before scanning and then again after the final assembly of the finished puzzle. The first application is important, since this step changes the appearance of the wood samples significantly. For the algorithm, it is crucial to choose suitable patches based on their final appearance. We apply the sanding/finishing procedure a second time in order to flatten out small height variations, which are inevitable after puzzling. For a large-scale, automatic production of custom, wooden parquetry puzzles, we would like to minimize the amount of manual interaction. Thus, we conducted initial experiments on training a model to predict the change of appearance from unfinished to finished veneers. Using these predictions, it might become possible to defer the application of surface finish until after the final puzzle has been assembled. To this end, we trained a U-Net [Ronneberger et al. 2015]
Fig. 15. Exemplary synthetic renditions of portraits and animals. Each of these results has been composed using the veneer sample panel shown in Figure 7 and the default parameters listed in Table 1. Our algorithm is able to handle a wide range of input including color photographs, black and white photographs, drawings, and paintings. The images show, from left to right, top to bottom: Grace Hopper, Eileen Collins, Felix Hausdorff, Katherine Johnson, Ludwig van Beethoven, Whoopi Goldberg, Hedy Lamarr, Alan Turing, a piglet, a penguin, a Corgi, and a flamingo.

Our approach allowed us to produce visually pleasing pieces of wood parquetry, even without having a professional wood-working background. However, we expect that certain technical imprecisions (such as sub-perfectly applied clear coating) would be mitigated with
more experience. Also, we expect that cut clearances and discolorations will be improved with further fine tuning of the cutting equipment.

Here, we treat wood as being a diffuse reflector and ignore any directional effects. Real wood exhibits anisotropic BRDF characteristics, which means that rotation of a part could be used to modulate its intensity. This might also enable the generation of new types of puzzles, where a hidden pattern is revealed by the right permutation and rotation of some parts.

In our experiments, we restricted ourselves to fabricating parquetry based on wood veneers, since they are commonly available and can be cut using a laser cutter. Generally, our pipeline is not restricted to this type of material. Using a water jet cutter, other materials like marble or brushed metal could be processed as well. The process could also be extended to multi-material parquetry.

Parquetry generation is inherently resource-constrained and in the scope of our work, the amount of available source samples was limited. Having access to a larger database of veneers (either by increasing the number of samples per wood type, or by introducing new wood types) would certainly improve the reconstruction quality. However, since this is an artistic process reaching the highest reconstruction quality might not always be the goal. Using only a single type of wood, or a selection of wood samples with a particular structure, can lead to equally interesting and fascinating results, see e.g. Figure 14.

When preparing our puzzle for assembly as a game, various degrees of difficulty could be imagined. As all pieces are made from wood, semantic labels are not immediately accessible as they sometimes are in regular puzzles (water, buildings, skin, foliage, sky/clouds, etc.). Given a bag of identically-shaped (square) pieces, it would seem extremely challenging to arrive at the one “correct” solution: at the same time, there would be numerous mechanically valid “approximate” solutions, or permutations between sets of similar-looking parts. Here, the cuts generated by the dynamic programming step offer a welcome cue for assembly, as they cause adjacent pieces to snap into place.

6 CONCLUSIONS

We approached the fabrication of structure-aware parquetry based on a novel end-to-end pipeline that takes wood samples and a target image as inputs and generates a cut pattern for parquetry puzzles. To the best of our knowledge, there is no prior work that addresses the challenges inherent to the task of producing a physical sample of wood parquetry using commodity hardware from minimal input (a target image). The challenges include the single use of individual pieces of input material without being deformed, scaled, blended, or filtered, as well as keeping track of resource use in order to prevent source patches from colliding with each other, while still faithfully reproducing the target image. Practical aspects regarding the fabricability have also been taken into account. The varying structural details within the wood samples lead to unique and fascinating artworks, and the design of the overall process allows even users without a particular woodworking background to experience producing pieces of this new type of art.

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