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Original Article

Research and Proposal of 3D Domain Processing Techniques in Woodblock Model Restoration ⋆

Viet Nam Le[1], Thai An Nguyen[1], Duc Hoang Long Nguyen [1], Luu Tu Nguyen [1], Thanh Ha Le[1], Seung-Won Jung[2], Thi Duyen Ngo[1]*

[1] *VNU University of Engineering and Technology, 144 Xuan Thuy, Cau Giay, Hanoi, Vietnam*
[2]*Department of Electrical Engineering, Korea University, Seoul, South Korea*

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Abstract: Vietnamese historical printing woodblock, engraved with Han or Nom characters, have earned UNESCO recognition as World Documentary Heritage. However, after hundreds of years, the number of these woodblocks is gradually diminishing due to loss or damage over time. This poses the challenge of restoring the 3D digital model of these woodblocks based on the remaining imprints on traditional paper. In the execution of this restoration task, 3D processing techniques play a pivotal role, determining the final quality of the restored 3D models. Current 3D processing techniques often fall short when applied to woodblock due to the intricate manual carving process that imparts a distinct cultural essence to each plate. In this work, we delve into the research and propose 3D processing techniques tailored for the restoration of 3D models from 2D imprints. These techniques have been integrated to form a comprehensive 3D processing pipeline for the woodblock restoration task. In our experimentation, we evaluated the effectiveness of our overall process using criteria such as naturalness, background quality, edge and corner quality, and character quality. The average score across these criteria was 3.92, indicating positive results and confirming the suitability of our techniques for addressing the restoration problem.

Keywords: 3D Reconstuction, Vietnamese woodblock, combining 3D, inpainting, meshing

1. Introduction

Woodblocks are pieces of wood carved with characters for printing books, popular in Vietnam during feudal times. They are the "primitive printer", documenting significant events in the country's cultural, literary, political, social, and historical landscape. Moreover, the woodblocks themselves hold artistic value.

*Corresponding author.
E-mail address: duyennt@vnu.edu.vn

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UNESCO acknowledged Vietnam's Nguyen Dynasty woodblocks as a world documentary heritage in 2009, followed by the recognition of the Vinh Nghiem Pagoda scripture woodblocks in 2012 and the Phuc Giang School woodblocks in 2016 through Memory of the World Committee for Asia and the Pacific (MOWCAP) program[1].

After centuries, the number of woodblocks has decreased due to loss or damage. However, the preservation of many imprint copies on "dó" paper presents promise for the restoration. Hand-carving demands ancient-like skills, but it has long ceased so artisans are extremely rare. On the other hand, CNC carving can only produce "printable woodblock" from an imprint 2D images, without preserving the style of engravings. Recently, AI development has introduced a new approach to restoring lost woodblocks by learning from existing ones.

Our team is currently engaged in a project aimed at restoring woodblocks from existing imprint paper. Its main tasks encompass digitizing both the 3D woodblocks and 2D prints, gathering datasets, training generative models, and ultimately applying a sequence of 3D domain processing techniques to completely reconstruct 3D woodblock models.

In this study, our focus is particularly directed towards the final task, where we research and propose 3D domain processing techniques for reconstructing 3D woodblock models from 2D prints. This proposed procedure involves pairing characters into woodblock surfaces, combining 3D elements, and employing surface reconstruction techniques. In the experimentation phase, we reconstructed 3D models of woodblocks following the proposed pipeline. We then evaluated the quality of the generated 3D models, which confirmed the effectiveness of our proposed techniques in addressing the woodblock restoration problem.

The main contributions of the paper include:

- Proposing a 3D processing pipeline to reconstruct complete 3D woodblock models from 2D print data.
- Developing algorithms/models to execute each processing step within the pipeline.
- Conducting MOS evaluation to assess the reconstructed 3D woodblock models, validating the efficacy of our proposed techniques.

In addition to this introduction, the paper is organized as follows:

- *Section 2 - Related Work:* Reviews literature on 3D cultural heritage restoration and techniques specific to woodblocks.
- *Section 3 - Proposed Methodology:* Details our 3D woodblock reconstruction pipeline with a flowchart and detailed explanations.
- *Section 4 - Experiment and Evaluation:* Focuses on experimental reconstruction of 3D woodblock models and evaluation methods used.
- *Section 5 - Conclusion:* Summarizes key contributions, highlighting achievements in 3D processing and positive MOS evaluation outcomes.

2. Related Work

The utilization of digital 3D models in cultural heritage restoration has been demonstrated by Matteo Dellepiane et al. [2], seamlessly integrating them with traditional methods and virtual reality technology to achieve highly accurate reconstructions. Their work emphasizes advancements in 3D scanning device technology and processing tools, addressing the complex task of processing raw 3D data to produce clean, usable models using specialized algorithms.

Addressing challenges in classification accuracy and fragment assembly efficiency, Zhao et al. [3] introduce a system rooted in fuzzy logic algorithms for the virtual restoration of 3D cultural heritage artifacts, blending traditional and virtual techniques.

Juho Kim et al. propose a method for depth estimation in historical photos [4], enhancing the quality without relying on ground-truth data. This approach refines pretrained monocular depth networks using stereo depth maps from rendered stereo images.

Although many studies have focused on restoring 3D cultural heritage, as far as we know, no research beyond our group has addressed the specific challenge of reconstructing 3D woodblock from its 2D prints. The primary challenges include the complexity of data collection, the computational demands for high-resolution 3D reconstruction, and the careful evaluation of the research's impact on existing heritage. We have reviewed the methodologies mentioned above to consider building our reconstruction process tailored for woodblocks.

In the realm of woodblock restoration, while no overarching study has been published, there have been publications focusing on individual stages that could be integrated into an overall restoration process. Tuan Dao et al. [5] concentrate on character detection and recognition in woodblock-printed images, crucial for preserving textual elements. Meanwhile, Viet Nam Le et al. [6] introduce an inpainting technique tailored for depth images of woodblocks, simplifying restoration and improving compatibility with modern 2D models. Additionally, Luu Tu Nguyen et al. [7] propose a novel meshing method using Deepfit to reconstruct woodblock surfaces, departing from traditional normal vector estimation methods. Lastly, Thi Duyen Ngo et al. [8] contribute quality assessment methods for 3D digital replicas, providing both objective and subjective criteria to ensure fidelity and authenticity. Together, these studies represent foundational advancements towards establishing a comprehensive woodblock restoration workflow, which can serve as a foundation for further research and contribute to the development of a holistic woodblock restoration process.

3. Proposed Methodology

3.1. Overall pipeline

Figure 1 delineates a comprehensive process for transforming a 2D print into a 3D model. This involves several key steps: First, a dataset comprising both 2D and 3D characters is assembled. Next, a model is developed to restore 3D characters from a lost 2D print. The 3D characters are then combined to form a surface, followed by the integration of various 3D components. Finally, the surface is reconstructed to create a mesh model, which can be utilized in presentations and other applications. Each of these steps is elaborated in the subsequent sections, providing a detailed understanding of the restoration process.

3.2. Pairing characters into woodblock surfaces

This session addresses the task of pairing characters onto woodblock surfaces. The input for this step consists of a set of 3D characters generated by a 3D character generation model (which is not within the scope of this study). The output is a 3D point cloud data representing the woodblock surface. To achieve this, we propose a phase comprising two techniques: "Character placement" and "Filling missing data" However, the first technique does not incorporate any significant advancements in machine learning, so our discussion will focus on the second technique.

The "Filling missing data" technique, also known as "Image Inpainting", presents a significant challenge, particularly when dealing with 3D images. The objective is to interpolate the absent information or pixels with semantically congruent and visually plausible content, thereby augmenting the efficacy of subsequent tasks such

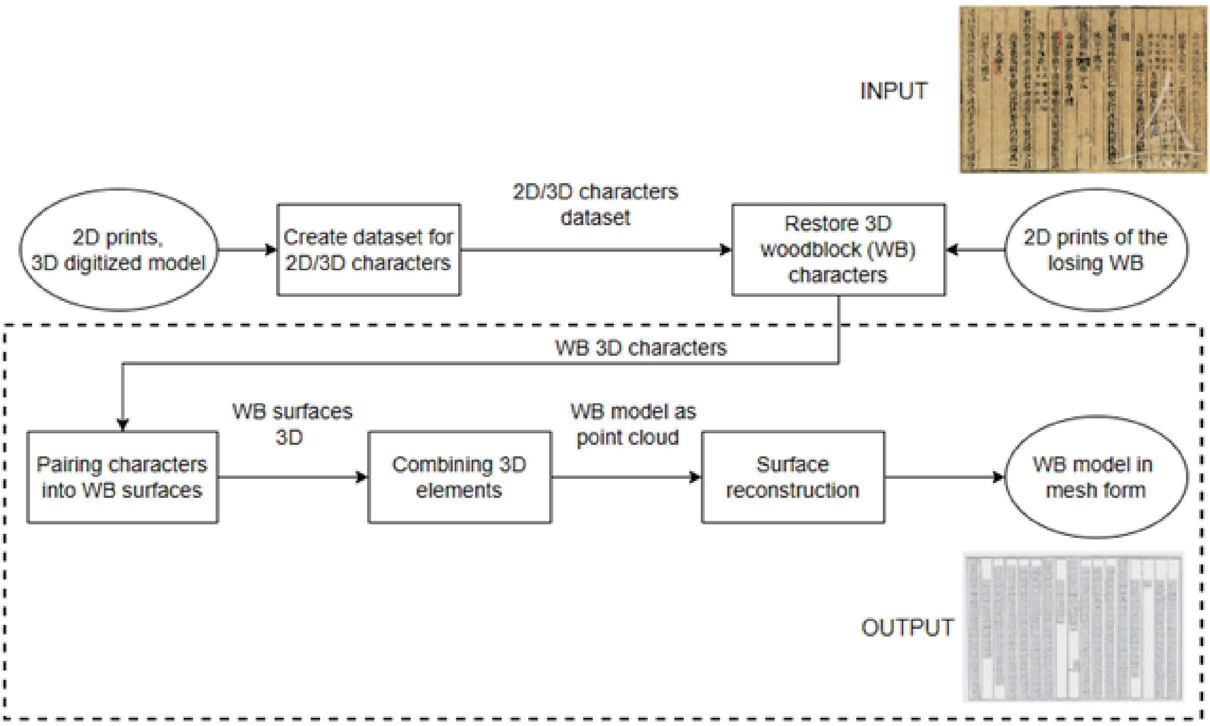


Figure 1. 3D woodblock recovery process.

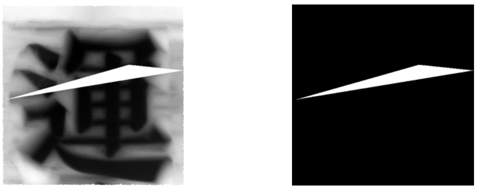
as classification, detection, and segmentation[9]. Image inpainting is a pivotal issue in the realm of computer vision and serves as an indispensable feature in a multitude of imaging and graphics applications, including but not limited to: object removal, image restoration, manipulation, re-targeting, compositing, and image-based rendering [10][11][12].

Figure 2. Illustration of missing section on Nguyen Dynasty Woodblocks.

Data preprocessing

The process of character placement on the surface may result in gaps between the characters themselves or between the characters and the frames. The task of the data filling process is to estimate the missing data to fill in these empty areas. To fill these sections, it is crucial to first identify them. This can be achieved by cropping and enlarging the missing areas, making them easier to recognize for both human observers and machines. This stage is particularly important as the image will be resized to a dimension of 512x512 pixels, with each pixel describing the depth of the image point, and in the absence of cropping the missing region, it will diminish to a size too minuscule to be detected and masked.

Proposed Solutions model for inpainting The primary approach we adopt is based on deep learning, specifically utilizing the “Free-form image inpainting with gated convolution” method, originally tailored for 2D color images.



(a) Image has missing area.

(b) Mask after detect and draw.

Figure 3. Pre-process data for inpainting.

This method, as proposed by Yu et al. [13], presents an advanced solution for image completion. It employs a gated convolution model to select soft features for each channel and spatial position. The gated convolution, learned automatically from data, facilitates more flexible feature selection compared to conventional convolution [14]. This approach significantly contributes to reducing ambiguity and generating high-quality inpainted images.

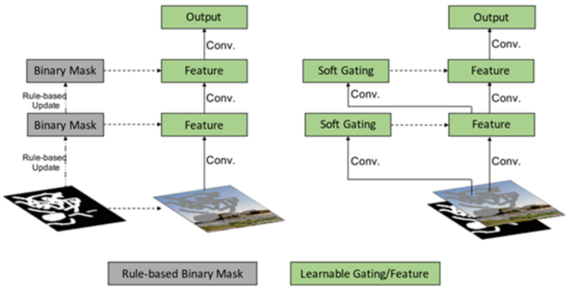


Figure 4. Illustration of partial convolution (left) and gated convolution (right)[13].

This method applies the Generative Adversarial Networks (GAN) strategy to achieve natural and realistic inpainted images. The GAN loss function enables a generator module that produces the most suitable inpainted image, while a discriminator module strives to differentiate the inpainted images from the original ones. This combination boosts the quality of the inpainting results. The gating convolution is expressed as:

$$\text{Gating}_{y,x} = \sum_{i,j} \mathbf{W}_g \cdot \mathbf{I} \quad (1)$$

$Gating_{y,x}$: Represents the gating mechanism at position (y,x). It is calculated as the sum of the products of weights W_g and input I, summed over indices i and j. The feature equation can be represented as:

$$\text{Feature}_{y,x} = \sum_{i,j} \mathbf{W}_f \cdot \mathbf{I} \quad (2)$$

$Feature_{y,x}$: Denotes the features at position (y,x). Similar to the gating mechanism, it is the sum of the products of weights W_f and input I, summed over i and j. And the output equation is given by:

$$\mathbf{O}_{y,x} = \phi(\text{Feature}_{y,x}) \odot \sigma(\text{Gating}_{y,x}) \quad (3)$$

$O_{y,x}$: This is the output at position (y,z), obtained by applying an activation function ϕ to the element-wise product of "$Feature_{y,x}$" and "$Gating_{y,x}$". SN-PatchGAN [15] as a solution for inpainting tasks involving free-form masks that can appear anywhere in images with various shapes. Unlike existing global and local GANs that are designed for rectangular masks, SN-PatchGAN demonstrates improved performance and stability[13].

Inpainting model

Among the state-of-the-art deep learning models for image inpainting, such as DeepFillv2 [13] or MAT inpainting [16], we have chosen the gated convolution method based on the DeepFillv2 model for several reasons. One important thing to think about is that MAT requires a big training dataset with complete context. If the training dataset lacks sufficient context, the results may deviate from reality. This poses a risk since the number of digitized woodblocks available is still relatively small. Given the limited availability of fully contextualized training data, utilizing MAT inpainting may not yield satisfactory results in our specific scenario [16].

DeepFillv2, however, has shown its ability to produce high-quality inpainting results with a more adaptable training method. It does not depend largely on a big training dataset with complete contextual information. Instead, it leverages the power of deep learning and sophisticated inpainting techniques to produce coherent and visually pleasing results even with a relatively limited number of training samples[13].

Original DeepFillv2 model consists of two stages: coarse network and refinement network. The coarse network takes a masked image as input and generates a coarse prediction of the missing regions using partial convolution layers [17], which are defined as:

$$y = W \odot x + b \tag{4}$$

where W is the convolution filter, x is the input feature map, b is the bias term, and $\odot$ is the element-wise multiplication. The output feature map y is then normalized by the number of valid input values in the convolution window. The refinement network takes both the masked image and the coarse prediction as input and generates a refined prediction with more details and sharpness using gated convolution layers [13], which are defined as:

$$y = (W_f \odot x + b_f) \otimes \sigma(W_g \odot x + b_g) \tag{5}$$

where Wf and Wg are the feature and gate convolution filters, respectively, bf and bg are the corresponding bias terms, sigma is the sigmoid function, and otimes is the Hadamard product. The output feature map y is then gated by a learnable mask that controls the information flow. Both networks use partial convolutions to handle irregular masks and gated convolutions to learn dynamic feature selection.

We developed a model based on the DeepFillv2 model by optimizing parameters and adjusting it to fit the 3D problem [6]. We modified the input channels from 4 (RGB + mask) to 2 (depth + mask) and reduced the output from 3 channels (RGB) to a single depth chanel.

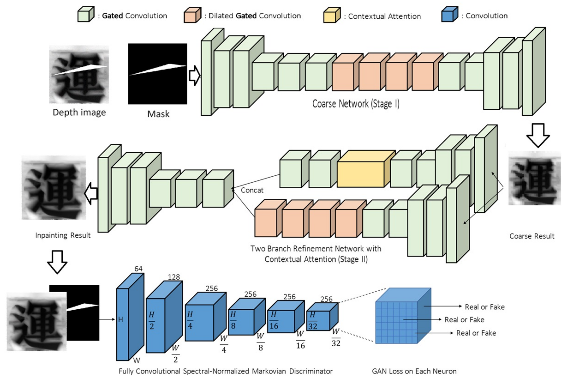


Figure 5. Deepfill [13] based model with gated convolution and SN-PatchGAN for free-form image inpainting.

For our experiments, we trained the model on an Nvidia 3090 GPU for 50 epochs, using a learning rate of 0.0001 and a batch size of 4. We used a dataset of depth images of woodblocks, with each depth image having a resolution of 512x512. The training process involved employing the Adam optimizer for both the generator and discriminator networks, along with a combination of Spectral Normalization PatchGAN (SN-PatchGAN) loss and L1 loss in a 1:1 ratio.

This adaptation allowed the input to include a depth image, capturing the geometric information of the woodblocks, along with a mask image indicating the locations of missing regions. The output was the reconstructed depth image with accurately filled-in missing regions.

3.3. Combining 3D elements

The combining procedure is divided into two main steps: handle standardization and surface realignment. The input data for this stage consists of two woodblock surfaces generated in the preceding processing steps and a high-quality handle model collected from the scanning device. The objective of the task is to generate a point cloud woodblock model, encompassing all details and the natural shape of the object. The following sub sections describe the specific steps in the combining workflow.

Handle standardization

The generated woodblock surfaces initially share a common characteristic: standardized to lie directly on the XY plane and considered perpendicular to the Z-axis. However, the position and direction of the woodblock handle model remain unknown. Therefore, the pivotal objective is to standardize the handle, aligning it with the surface intended for woodblock attachment. The algorithm is detailed as follows:

1. Standardize the woodblock handle to the first surface
2. Realign the first woodblock surface to match the handle
3. Standardize the woodblock handle to the second surface
4. Realign the second woodblock surface to match the handle

The standardization of the woodblock handle's plane involves determining the equation of the plane for the two surfaces intended for attachment. Using the GOM Inspect tool, points within the background region of the woodblock surface are selectively chosen to establish this plane. The Ordinary Least Squares (OLS) algorithm [18] is then employed to derive the coefficients (a, b, and c) characterizing a three-dimensional plane $z = ax + by + c$. This optimization aims to achieve the best fit to the data points by minimizing the Residual Sum of Squares (RSS) [19] which is calculated by Equation 9. OLS achieves this by solving a normal equation, represented in our study by Equation 7. Once the optimal plane is determined, a 4x4 transformation matrix is computed in 3D space to convert the plane to the XY plane with $z = 0$. This matrix serves the crucial purpose of standardizing the woodblock handle to each surface.

$$RSS = \sum_{i=1}^{n} (z_i - \hat{z}_i)^2 \tag{6}$$

$$\begin{bmatrix} \sum x_i^2 & \sum x_i y_i & \sum x_i \\ \sum x_i y_i & \sum y_i^2 & \sum y_i \\ \sum x_i & \sum y_i & n \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \sum x_i z_i \\ \sum y_i z_i \\ \sum z_i \end{bmatrix} \tag{7}$$

Surface realignment

In the surface realignment phase, aligning the four corner points of the handle plane with the corresponding points on the woodblock surface is crucial. For the handle, this task is straightforward as we utilize the GOM tool to select these corner points. Conversely, for the woodblock surface, we leverage Principal Component Analysis (PCA) [20], implemented in the open3d library. The algorithm then constructs an oriented bounding box for the woodblock surface from which we extract the four necessary bottom corner points.

As the woodblock handle is standardized, we assume a shared height of $z = 0$ for both the four corners of the woodblock handle plane and the four corners of the woodblock surface. Therefore, instead of employing a 3D transformation matrix, we utilize a 2D homography matrix to realign the woodblock surface into an optimal position within the woodblock handle. To establish the tomography matrix between these two sets of points, we deploy Direct Linear Transform [21]. DLT assembles each point correspondence to get the matrix equation $Ah = 0$, where A is a 2nx9 matrix (n = number of point pairs, in our case, n=4), h is a 9x1 vector of the flattened homography matrix elements, and 0 is a 2nx1 zero vector. Employing Singular Value Decomposition (SVD) [22] to decompose A into three vectors, U containing the left singular vectors, Σ containing the singular values, and V containing the right singular vectors, as expressed in Equation 8. Then we select the last singular vector of V as the solution to h. Following the combination with the first surface, we repeat the process of handle standardization and surface realignment for the second woodblock surface.

$$A = U\Sigma V^T \tag{8}$$

3.4. Surface reconstruction

Following the completion of step 3.3, we obtain a woodblock model in point cloud format. However, for practical purposes such as 3D printing or interactive visualization, it is essential to convert the woodblock model into mesh format. This transformation is achieved through the surface reconstruction phase, which processes the point cloud input to produce the woodblock model in mesh format.. This methodology entails two distinct stages: data preprocessing and surface reconstruction utilizing the Poisson surface reconstruction algorithm.

Data preprocessing

To prepare the data for the selected method, it is imperative to compute normals for each point in the point cloud. The calculation of normal vectors is a prerequisite for employing the Poisson Surface Reconstruction algorithm. This preprocessing step ensures that the input data is well-suited for the subsequent meshing process, enhancing the overall quality and accuracy of the reconstructed surface.

The computation of normals for each point in the point cloud is critical for subsequent surface reconstruction, especially when utilizing the Poisson Surface Reconstruction algorithm. Normals provide essential directional information, guiding the algorithm in the creation of a coherent and accurate surface mesh. The accuracy of the normals directly impacts the fidelity of the reconstructed surface to the original historical printing woodblock. In our recent publication, we demonstrated that the choice of the normals computation method holds particular significance for the restoration of Vietnamese historical printing woodblocks. We proposed a novel data preprocessing procedure for the surface reconstruction process, specifically integrating the DeepFit model, as described in Figure 6, into normal vector estimation to enhance efficiency compared to traditional methods [7]. The DeepFit model effectively computes normal vectors directly from the input point cloud [23].

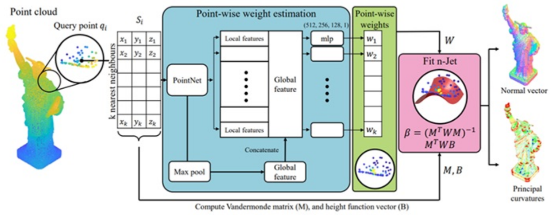


Figure 6. Architecture of the DeepFit model [23].

The model was trained with a dataset for training and testing, utilizing the PCPNet dataset. The training dataset comprises eight shapes: four CAD objects (fandisk, boxunion, flower, cup) and four high-quality scanned models of objects (bunny, armadillo, dragon, and turtle). All shapes are represented as triangle meshes and sampled at a density with 100,000 points. The data is augmented by introducing i.i.d. Gaussian noise to the spatial position of each point with standard deviations of 0.012, 0.006, and 0.00125 relative to the bounding box size. This results in a dataset with 3.2 million training examples. The test set includes 22 shapes, encompassing statues, CAD objects, and analytical shapes [23].

Poisson surface reconstruction

Following the meticulous computation of normal vectors on the point cloud, we advance to employ the Poisson Surface Reconstruction algorithm to create a continuous surface. This meshed surface then serves as the foundation for the subsequent evaluation phase. [24]

In our approach, we employ the traditional Poisson Surface Reconstruction method, as depicted in the illustrative pipeline presented in Figure 7. This method is chosen for its established efficacy in generating high-quality surfaces and preserving intricate details, crucial

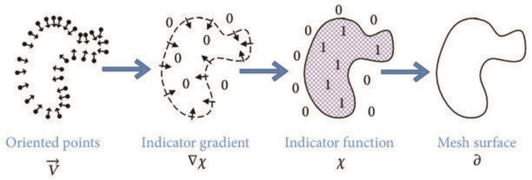


Figure 7. Intuitive illustration of Poisson Reconstruction in 2D. [24]

for the faithful restoration woodblocks.

A key step in the Poisson Surface Reconstruction pipeline involves the computation of the indicator gradient. This gradient is derived from an indicator function, characterizing the presence or absence of geometry within the designated space based on the oriented points. The indicator gradient effectively quantifies the likelihood and strength of surface existence at different points in the 3D space.

With the indicator gradient computed, an indicator function is established. This function serves as a crucial descriptor, articulating the probability distribution of surface presence across the woodblock's spatial representation. It offers valuable insights into the spatial variations in surface characteristics and aids in creating a more accurate and detailed mesh.

Subsequently, the culmination of the Poisson Surface Reconstruction process is the generation of a mesh. This mesh represents a continuous and smooth reconstruction of the object's surface, seamlessly capturing the intricacies and nuances of the historical printing woodblock. The meshed surface becomes the basis for further assessments in the subsequent phases of our study.

4. Experiment and Evaluation

Following our proposed methodology, we successfully reconstructed the complete 3D models of Nguyen dynasty woodblocks, as illustrated in Figure 8.

Our next step is to assess the quality of the woodblocks produced through our proposed approach. In this section, we focus on addressing the evaluation methodology, the implementation of assessments, and the outcomes.

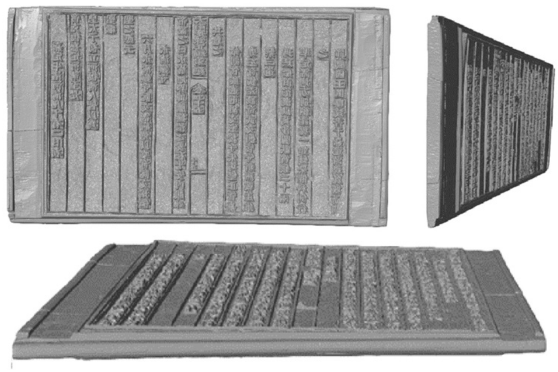


Figure 8. A reconstructed 3D woodblock from our proposed process viewed from multiple perspectives.

4.1. Evaluation Methods

This sub section delves into analyzing the methodology of the evaluation process, with a preliminary focus on understanding the performance of individual stages previously conducted before addressing the overall evaluation method conducted in this study.

4.1.1. Individual Stage Evaluation

Evaluating each component to ensure effective operation of separate techniques is crucial in a system. Inpainting utilizes measurable metrics like such as Mean Squared Error (MSE), Structural Similarity Index Mesure (SSIM), and Peak Signal-to-Noise Ratio (PSNR) to assess performance [6]. Surface reconstruction stage, however, due to its subjective nature, often relies on qualitative evaluation [7].

Our inpainting method was assessed using various mask types, as illustrated in Table 1. Notably, the bounding box mask exhibited the lowest MSE and the highest PSNR, indicating superior performance in preserving image quality compared to other masks.

Table 1. Evaluation of depth map inpainting method with various mask types [6]

Mask type	MSE↓	FID(%)	PSNR↑	SSIM↑
Randomly	0.00098	23.05	39.76	0.9580
Bounding-box	0.00050	12.92	42.51	0.9589
Free-form	0.00135	40.50	38.53	0.9576
Polygon	0.00152	25.87	35.49	0.9566

Furthermore, our surface reconstruction method was compared to traditional meshing techniques, detailed in Table 2, indicating significant improvements in reconstructing the woodblock surface. The detailed results of stages have been published in [6] and [7]

Table 2. Surface reconstruction stage evaluation results[7]

	Traditional Est. Meshing	Ours (DeepFit Est.)
Mean value	3.46	3.63
Standard deviation	0.89	0.39

4.1.2. Overall Quality Assessment

After evaluating each stage individually, it's important to conduct a comprehensive assessment of the overall integration process. We have chosen to employ the Mean Opinion Score (MOS) method[25], to evaluate key aspects of the woodblock, including its naturalness and preservation value in relation to cultural heritage.

Table 3. Survey Results for Overall Quality Assessment

Criteria	Mean	Std. dev
Degree of naturalness	4.05	0.74
Accuracy of the woodblock surface position	4.00	0.77
Quality of edges and corners	3.95	0.80
Presence of irregular protrusions	3.71	0.96
Average	3.93	0.82

MOS is described by a rational number, usually from 1 to 5, where 1 is the lowest quality and 5 is the highest. Then the results are aggregated and evaluated according to formula 9, where *R* is the individual assessment for a system by *N* people.

$$MOS = \frac{\sum_{n=1}^{N} R_n}{N} \quad (9)$$

4.2. Evaluation with MOS

Scenario

We formulated a customized evaluation scenario wherein assessors were furnished with comprehensive details about a scanned 3D woodblock of high quality, intended as the ground truth for our methodology. Participants are instructed to position themselves from 2 to 2.5 meters away from a 55-inch 4K screen to ensure the utmost accuracy in observation. Subsequently, evaluators were asked to compare the 3D-scanned woodblock and the woodblock model reconstructed using the proposed methods.

Participants

The survey was conducted with 15 participants aged between 22 and 40, with diverse levels of expertise, encompassing those unfamiliar with woodblocks and those who had previous exposure.

Evaluation criteria

To assess and evaluate the performance of the woodblock processing solution in 3D space, we conducted experiments on a number of Nguyen dynasty woodblocks. The evaluation criteria formulated in the process of evaluating the woodblock processing solution in 3D space include: the naturalness, the quality of background, the quality of edges and corners and the quality of characters.

Results

Figure 9 summarizes the evaluation results we obtained. The results were quite good, with an overall average score for all criteria from all evaluators of 3.92. Among them, the two criteria for naturalness and background quality were highly rated at 4.05 and 4.00, respectively. The criterion with the lowest rating was character quality at 3.67. This indicates that the reconstructed woodblock meets the overall quality and integrity criteria well, but still needs improvement in character level.

Another aspect, the average standard deviation is relatively low at 0.73, indicating that opinions among evaluators are not significantly different, increasing the reliability of the scores provided.

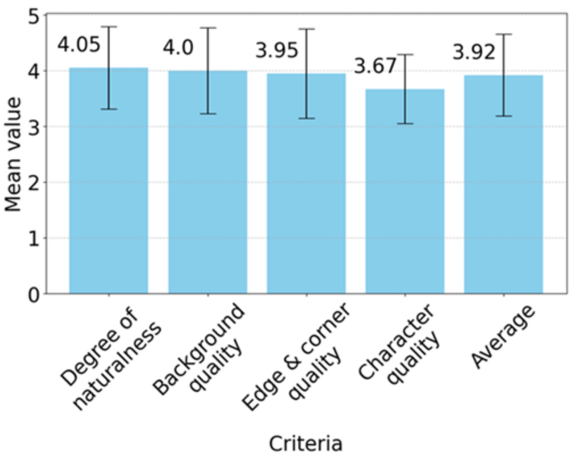


Figure 9. MOS evaluation results for our proposed 3D woodblock reconstruction pipeline.

5. Conclusion

In this work, we have proposed a process involving three 3D processing techniques for reconstructing woodblocks. Firstly, we have utilized a character stitching technique to form the woodblock surface, employing a deep learning model to rectify surface errors and fill blank gaps. Following that, we have merged woodblock surfaces with handles, standardizing and combining them into complete woodblock models represented as point clouds. Lastly, we have enhanced the Poisson Surface Reconstruction algorithm by improving the normal vector estimation method, particularly suitable for woodblock surface reconstruction. These three techniques constitute a complete 3D processing pipeline for the task of reconstructing models of woodblock. Subsequently, the results have been evaluated by experts in woodblock, yielding positive outcomes through MOS evaluations.

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