How to archive the visual contents of aging analog film holograms?

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We introduce a novel method for the digital preservation of analog film holograms. Our approach uses a machine learning-based approach dubbed Neural Radiance Fields (NeRF). We evaluate the performance of our method with both qualitative and quantitative experiments, showing that analog holograms can be digitally preserved with high quality.

1 Introduction

An analog hologram can record the complete three-dimensional light field of an object on a simple 2D film. Even more than 70 years after the invention of holography, watching an analog film hologram still seems like pure magic. The probably most fascinating feature is the seemingly perfect reconstruction of the recorded object that can be viewed from every possible perspective. Besides its technically intriguing aspect, analog holography has also become a unique form of art over the years, and the works of "holography artists" can be found in major museum collections nowadays. Being "active material," however, these works of art are subject to constant degradation, which raises the question on how the unique impression of watching them can be "digitally preserved" for future generations – ideally without capturing terabytes of data.

In this contribution, we introduce a novel approach for the digital preservation of analog film holograms. We emphasize that we are only interested in preserving the visual appearance of holograms under playback illumination to convey the unique impression and experience to future generations. This means that this work does not seek to produce an exact copy of the holographic film itself, which would require a meticulous scan of the hologram surface to digitize every single fringe in terabytes of data. In contrast, our approach aims for an easy, efficient, and fast capturing procedure that could be performed by non-experts with off-the-shelf hardware (like smart phones). For this purpose, we employ a machine learning based technique dubbed "Neural Radiance Fields" (NeRF) [1]. NeRF was originally developed to synthesize novel viewpoints (from new camera perspectives, see Fig. 1) on a three dimensional scene, using only a sparse set of 2D photographs. In this work, we apply the technique on the virtual playback of analog film holograms.

2 Hologram Preservation using Neural Radiance Fields (NeRF)

"Neural Radiance Fields" (NeRF) [1] is a machine learning-based rendering technique that is capable of generating novel viewpoints on 3D objects/scenes from a sparse set of 2D photographs. Compared to other techniques (e.g., light field rendering), NeRF is known to handle occlusions and high frequencies in the scene particularly well, which makes it a good fit for our purpose.

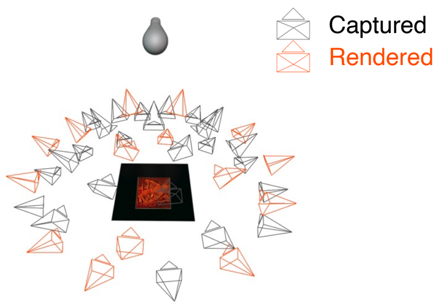

Fig. 1 *Schematic of our approach: The hologram playback is captured with a sparse set of images from multiple viewpoints (black cameras). NeRF renders the novel views from new perspectives (red cameras) to provide a "seamless" viewing experience of the digitized hologram.*

In the following, we will outline our data capture and processing steps: To digitally capture the playback of an analog hologram, we illuminate the hologram at the correct playback angle with a coherent light source. Eventually, we move our camera (DSLR camera or phone camera) roughly on a hemisphere around the hologram and capture the holographic playback from different viewpoints with a sparse set of images (see Fig. 1). As the camera positions during image capture are unknown, we obtain the camera positions from COLMAP, a Structure-from-Motion (SfM) pipeline [2]. COLMAP extracts features

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from the given image, then incrementally adds one camera at a time and estimates corresponding camera parameters. The sparse camera images and respective camera parameters for each captured viewpoint serve as input for NeRF. Eventually, NeRF samples each scene point along each camera ray with its spatial location and viewing direction, and uses these sampled points to train its machine learning model [1].

During the training step, the model predicts the RGB pixel value and the opacity for each point along each camera ray, and the final pixel color is obtained by averaging each point color weighted by its opacity. Once this process is done for all camera pixels, a predicted output image is composed which is compared with the original captured image in an iterative fashion using a loss function.

After the training of the NeRF model for the respective hologram is completed, we can obtain novel views from unseen viewing directions and locations. With this ability, we can provide a "digital" experience of interacting with a captured hologram that is similar to watching a real analog hologram.

3 Experiments and Evaluation

Amongst other holograms from the MIT Museum hologram collection, we used our method to capture Stephen Benton's famous Engine no. 9 hologram ("train") [3]. We captured 18 images of the hologram playback with a DSLR camera (Canon EOS 5D Mark III) mounted on a gantry. In a different experiment, we captured 72 images of a commercially available hologram ("spiderman") in a free hand-guided fashion with a mobile phone camera (Samsung Galaxy Note 8).

We use our pipeline to generate novel viewpoints between the viewpoints of the captured images. When digitally "watching" the rendered hologram, the user can potentially freely cycle through these different viewpoints (e.g., with a mouse or position tracking in a VR headset) to freely watch the digitized hologram playback from every perspective. For the purpose of this paper, we have defined a fixed camera trajectory along the novel viewpoints and export a video of our results while the virtual camera moves along the trajectory. The results can be watched here.

We further analyze the rendering performance of NeRF in a quantitative evaluation: For the captured "spiderman" hologram we train multiple networks while gradually decreasing the number of input images for the training. From the initial dataset of 72 images we take out 5 images for the evaluation ("test images", see below), and eventually randomly select 100% (67 images), 80% (57 images), 50% (36 images), and 10% (7 images) of the remaining dataset for training. After training, we generate synthetic views at exactly those 5 positions where the 5 test images where taken, and compare the rendered results with the ground truth test images. Table 1 shows the RMSE intensity value error of the generated novel viewpoints wrt the test images. Representative images are shown in Fig. 2c-d. It can be seen that (not surprisingly) the largest number of training images provides the best quantitative performance. However, the RMSE values degrade gracefully as the number of trained images decreases, which means that high-quality results can be already reached with a small number of captured images. This is an important finding for potential early adopters of our method, e.g., museum conservators or researchers in the cultural heritage community.

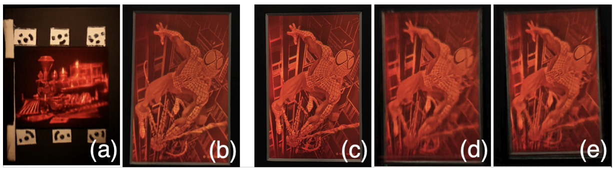

Fig. 2 *Results: (a), (b) Train and spiderman hologram rendered from a novel viewpoint; (c)-(e) Quantitative evaluation: (c) spiderman ground truth; (d), (e) Novel view of spiderman hologram after being trained on 80%, and 50%, of training data respectively.*

100% train (67 imgs)	80% train (57 imgs)	50% train (36 imgs)	10% train (7 imgs)
21.1	22.9	26.5	30.7

Tab. 1 *Averaged RMSE from comparison of 5 novel viewpoint images with the ground truth (see text). The error value (RMSE) increases as the size of training dataset is reduced.*

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