Interactive Image Restoration

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Abstract

Machine learning and many of its applications are considered hard to approach due to their complexity and lack of transparency. One mission of human-centric machine learning is to improve algorithm transparency and user satisfaction while ensuring an acceptable task accuracy. In this work, we present an interactive image restoration framework, which exploits both image prior and human painting knowledge in an iterative manner such that they can boost on each other. Additionally, in this system users can repeatedly get feedback of their interactions from the restoration progress. This informs the users about their impact on the restoration results, which leads to better sense of control, which can lead to greater trust and approachability. The positive results of both objective and subjective evaluation indicate that, our interactive approach positively contributes to the approachability of restoration algorithms in terms of algorithm performance and user experience.

1 Introduction

![Image](image1.png)

Figure 1: Left to right: An artificially generated damage mask, the image damaged within the masked area, the image restored by Deep Image Prior [Ulyanov et al. 2018] and the restored image using our interactive approach.

Image inpainting is a process for restoring damaged or missing sections of images, such that the results are visually plausible. Naturally, performance of restoration algorithm degrades when the corrupted sections become dense or large, since more semantic information is missing.

Due to the lack of semantic information, restored images can contain artifacts like areas with inconsistent texture or monotone color as shown in the third image of Fig. 1. Despite this, given those pre-restored images, human beings can easily deduce the semantics in the corrupted regions. Therefore, this awareness can be used to accomplish restoration tasks. Based on this intuition, we extend Deep Image Prior (DIP) [Ulyanov et al. 2018] with Human-Computer Interaction (HCI) and present Interactive Deep Image Prior (iDIP), a collaborative, interactive image restoration framework.

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This framework enables human and algorithms to collaboratively restore images in an iterative manner. With the proposed framework, even people with little painting knowledge can generate plausible images and manage restoration task. Furthermore, frequent feedback promises higher sense of control and better user satisfaction than non-interactive methods.

We then evaluate iDIP-based image restoration system with respect to two research questions:

1. Does the interactive approach produce higher quality images?
2. How do users view such a system regarding user experience and satisfaction?

We answer the first question in Sect. 4 in terms of objective and subjective measurement. To judge user experience and satisfaction, we have conducted a user study as described in Sect. 5.

2 Related Work

Previous research works attempted to fully automate the image restoration process. As one of the state of the art approaches, DIP restores images by exploiting image prior modelled by a Convolution Neural Network (CNN) [Krizhevsky et al. 2012]. DIP minimizes the following loss function for image inpainting:

$$L = \min_\theta ||(f_\theta(z) - x_0) \odot m_0||_2,$$

where $f_\theta$ is a CNN parameterized with $\theta$, $z$ is a fixed input, $x_0$ is a corrupted image, $\odot$ is Hadamard product and $m_0$ is the mask for damage area. DIP overcomes the drawbacks of exemplar-based [Barnes et al. 2009], [Hays and Efros 2007], [Kwatra et al. 2005], [He and Sun 2012] and learning-based methods [Yu et al. 2018], [Iizuka et al. 2017], [Yeh et al. 2017], [Yan et al. 2018], such as difficulties in recovering sophisticated texture and requirement of large training set, respectively. Same as classic machine learning models, training of DIP is non-interactive and will be performed only once. However, DIP cannot use human understanding of textural semantics and leads to poor user satisfaction due to its low transparency. Nonetheless, interactive Machine Learning (iML) Fails and Olsen Jr [2003] increases the sense of control by introducing human intervention into learning loops [Amershi et al. 2014]. The increased sense of control can improve trust and user experience in many scenarios [Amershi et al. 2014], [Cohn et al. 2003], [Holzinger 2016], [Johnson and Johnson 2008].

3 Approach

To our best knowledge, there is no previous work combining DIP with iML. In this work, we extend the DIP with interactivity Fails and Olsen Jr [2003] and bring humans into the training loops of iDIP. The updates of iDIP is iterative, focused and rapid. These properties make the restoration process more transparent and contribute to a user-satisfied approach (Sect. 5).

iDIP restores images by iteratively exploiting image prior and human knowledge via human-in-the-loop intervention. The underlying human involvement could be either creating new mask (correction) or painting on the corrupted regions (guidance).

Training iteration: One training iteration can be visualized in Fig. 2 and it consists of three stages. 1. User is presented with the image $x_n$ restored by iDIP from the last iteration, where $n$ is the current timestamp. 2. User paints on the image $x_n$ to obtain a refined image $x'_n$. 3. iDIP restores image $x'_n$ by minimizing the loss function in Eq. 1 and output the image $x^*_n$. Note, the output image $x^*_n$ of the $n$th iteration is equivalent to the input image $x_{n+1}$ of the $(n+1)$th iteration.

Given pre-restored image $x_n$, users can come up more easily with textural semantics in the damage region than only given $x_0$. Furthermore, iDIP exploits its restoration performance by distilling the reconstructed textual information in the refined image $x'_n$. In this way, iDIP and human knowledge can jointly boost on each other.

Besides, this iterative approach endows users with better control of their impact through trial-and-error. Therefore, users can better determine their involvement intensity in next iterations. Frequent interaction contributes to better user satisfaction and system transparency. What’s more, early
stopping can be applied on time since users continuously observe the textural consistency and can terminate the process in any interaction to avoid overfitting.

User interface (UI): Fig. 3 shows the UI for iDIP. The image in center is the pre-restored one with the mask as red overlay. Users were supposed to pick appropriate color and paint in the masked region.

4 Experiment

We conducted experiments to answer the first research questions in this section: Does the interactive approach produce higher quality images?

Dataset: We used the Dunhuang Grottoes Painting Dataset [Yu et al. 2019] for the experiments. The dataset contains 500 full frame paintings with artificially generated masks for damage region, of which we randomly picked ten.

Metrics: As performance measurement, we computed Dissimilarity Structural Similarity Index Measure (DSSIM) [Wang et al. 2004] and Local Mean Squared Error (LMSE) [Grosse et al. 2009] between restored and ground truth images. Mean Squared Error (MSE) and Structural Similarity Index Measure (SSIM) are common and easy-to-compute measures of the perceived quality of digital images or videos in computer vision. In this paper, we compute MSE and equalize it to LMSE by setting $k = 1$. By using $DSSIM = 1 - \frac{SSIM}{2}$ we let the DSSIM also be inversely proportional to restoration quality as LMSE.

Baselines: To show the effectiveness, we compared our approach with five state of the art baselines. For learning based methods, we used their pre-trained model on Places2 [Zhou et al. 2017], because it is one of the widely-used scene recognition dataset.

- **EdgeConnect**: EdgeConnect [Nazeri et al. 2019] proposed a two-stage adversarial model and can deal with irregular masks.
- **PartialConv**: PartialConv [Liu et al. 2018] used partial convolutions with an automatic mask update step.
- **PatchMatch**: PatchMatch [Barnes et al. 2009] can quickly find approximate nearest-neighbor matches between image patches and was adopted by Photoshop.
- **PatchOffset**: PatchOffset [He and Sun 2012] minimizes an energy function to find patches with dominant offsets.
- **Deep Image Prior**: DIP [Ulyanov et al. 2018] exploits the image prior by minimizing Mean Squared Error (MSE) in the unmasked region.

For objective evaluation, we compared images restored by all six algorithms on ten randomly picked corrupted images using two metrics. The images generated by iDIP for the objective evaluation were recovered by domain expert. Each image was completed within 1200 iterations (600 iterations before
Table 1: Comparison on restoration metrics

| Method      | DSSIM    | LMSE    |
|-------------|----------|---------|
| EdgeConnect | 0.2803   | 629.65  |
| PartialConv | 0.2816   | 2550.02 |
| PatchMatch  | 0.2423   | 185.68  |
| PatchOffset | 0.2246   | 558.05  |
| DIP         | 0.2228   | 214.23  |
| iDIP        | 0.2227*  | 207.37  |

Objective evaluation: In the Tab. 1 we can see that, although we initialized the networks with pre-trained weights, two learning-based methods still have the worst performance. Style transfer failed because the image style of Dunhuang dataset varied too much from the training set. PatchMatch has the best LMSE score by a large margin. However, our approach slightly outperformed all non-interactive methods on DSSIM and has the second smallest LSME score. This suggests that interactivity positively contributes to output quality.

Subjective evaluation: Fig. 4 shows the probability of one algorithm being picked as top two algorithm in the subjective evaluation. We left out learning-based methods, since they had not been picked. The two DIP-variants significantly outperformed other methods, even though PatchMatch demonstrated the best result on LMSE. Compared to DIP, iDIP still showed a considerable improvement, which indicates interactivity introduced in iDIP added to the output quality.

The difference between the two evaluations is also noteworthy: While PatchMatch has the lowest LMSE score, subjectively it appears far inferior to the DIP-based methods. This may be an indicator that simple similarity measures are insufficient to account for human perception.

To summarize, introducing interactivity in iDIP positively affected the restoration performance. Therefore, we confidently give a positive answer to the first research question.

5 User Study

With iDIP outperforming the other baselines in the subjective perception and being not far off with respect to objective measures, it remains whether an iML approach is attractive from a usage point of view. We evaluated this in a user study and via a questionnaire.

Participants in this study (n = 19; 9 male, 9 female, 1 other; 20-29 years old: 10, 30-39 years old: 7, 40-49 years old: 2) were people medium expertise with image manipulation (mean: 2.68/5, std: 1.25) and low expertise with image reconstruction (mean: 1.74/5, std: 1.19). We presented to them the UI and asked them to reconstruct two images. Due to practical reasons, we limited their working time to seven minutes per image. We then asked the participants to fill out the questionnaire regarding general satisfaction with the process using the System Usability Scale (SUS) and workload using NASA TLX as well as questions regarding the benefits of our interactive approach.

Results from the SUS and TLX were very positive (average score SUS: 86/100, TLX: 3.4/10). Measured on a 5-point Likert scale, the opinion of the participants regarding iML being suitable for image reconstruction (4.5/5) and in general (4.0/5) were also very positive. Participants also did not believe that a non-interactive ML process (0.9/5) or a manual approach (1.8/5) would perform better.
The fact that all participants stated that they liked the combination of interactivity and machine learning, as well as other feedback, led us to conclude that iML can make machine learning more approachable. Whether it is an actual boost to expert-productivity remains to be seen in future work.

6 Conclusion and Future Work

In this paper we have outlined our framework for interactive image restoration. This framework allows users to interactively contribute to DIP-based image restoration process so that both image prior and human knowledge can be well leveraged in an iML fashion. Our experiments show that the designed interactions positively affected the output quality as iDIP outperformed all five state of the art baselines. Meanwhile, good user satisfaction has been achieved according to the user study, as participants stated their appreciation and confidence of the proposed method. In summary, the positive answers of two research questions indicate that our goal of human-centric machine learning have been fulfilled for image restoration tasks.

As human-in-the-loop approach demonstrated its effectiveness in terms of algorithm performance and user satisfaction, we remain the interpretation of rich interactions forms in image restoration as future work.

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7 Supplementary Material

As supplementary materials, we provide the subjective evaluation record of restoration performance, the questionnaire used in the user study and the statistical summary of user study.
PM: PatchMatch, PO: PatchOffset, DIP: Deep Image Prior, IDIP: Interactive Deep Image Prior
1. Please answer how you agree with the following statements *
Mark only one oval per row.

| Statement                                                   | Fully disagree | Somewhat disagree | Neutral | Somewhat agree | Fully agree |
|--------------------------------------------------------------|----------------|-------------------|---------|----------------|-------------|
| I can draw                                                  |                |                   |         |                |             |
| I have experience with machine learning                     |                |                   |         |                |             |
| I consider myself skilled in image manipulation              |                |                   |         |                |             |
| I have previous experience with image manipulation software  |                |                   |         |                |             |
| I consider myself skilled with technology                    |                |                   |         |                |             |
| I am open towards new technology                              |                |                   |         |                |             |
| I have experience with image reconstruction                  |                |                   |         |                |             |

Machine Learning Support
In the following section you will answer some questions regarding the task you have performed and the tool you have used.

2. Please answer how you agree with the following statements *
Mark only one oval per row.

| Statement                                                   | Fully disagree | Somewhat disagree | Neutral | Somewhat agree | Fully agree |
|--------------------------------------------------------------|----------------|-------------------|---------|----------------|-------------|
| A human can perform Image reconstruction better than a machine|                |                   |         |                |             |
| Tools using machine learning are more efficient              |                |                   |         |                |             |
| Machine learning should only be used where necessary          |                |                   |         |                |             |
| Tools using machine learning are more effective              |                |                   |         |                |             |
| Machine learning is a good support mechanism in tools         |                |                   |         |                |             |
| I want more machine learning support in tools                |                |                   |         |                |             |
| Machine learning is helpful for image reconstruction          |                |                   |         |                |             |
| Machine learning should be used more frequently              |                |                   |         |                |             |
| Tools using machine learning help me complete my work faster  |                |                   |         |                |             |
| Machine learning takes a long time                            |                |                   |         |                |             |
3. Please answer how you agree with the following statements *
Mark only one oval per row.

| Statement                                                                 | Fully disagree | Somewhat disagree | Neutral | Somewhat agree | Fully agree |
|---------------------------------------------------------------------------|----------------|-------------------|---------|----------------|-------------|
| I like the combination of interactive and automated elements for image reconstruction | ☐              | ☐                 | ☐       | ☐              | ☐           |
| I am satisfied with the result                                            | ☐              | ☐                 | ☐       | ☐              | ☐           |
| I was in control of how the output turned out                             | ☐              | ☐                 | ☐       | ☐              | ☐           |
| Image reconstruction should be more automated                            | ☐              | ☐                 | ☐       | ☐              | ☐           |
| The interactive part of the image reconstruction worked well              | ☐              | ☐                 | ☐       | ☐              | ☐           |
| The image turned out the way I expected it to                             | ☐              | ☐                 | ☐       | ☐              | ☐           |
| The automated part of the image reconstruction worked well                | ☐              | ☐                 | ☐       | ☐              | ☐           |
| Machine learning without interactivity would create a better image       | ☐              | ☐                 | ☐       | ☐              | ☐           |
| Manual image reconstruction would create a better image                   | ☐              | ☐                 | ☐       | ☐              | ☐           |
| Image reconstruction should be done manually                              | ☐              | ☐                 | ☐       | ☐              | ☐           |

4. Did anything during the task not work the way you would have wanted it to?

________________________________________________________________________
________________________________________________________________________
________________________________________________________________________
________________________________________________________________________

5. What would you change in the interactive image reconstruction process?

________________________________________________________________________
________________________________________________________________________
________________________________________________________________________
________________________________________________________________________

**General System Usability**
In the following section you will answer some questions regarding the usability of the system we have presented to you.
6. Please answer how you agree with the following statements * 
Mark only one oval per row.

| Statement                                                                 | Fully disagree | Somewhat disagree | Neutral | Somewhat agree | Fully agree |
|---------------------------------------------------------------------------|----------------|-------------------|---------|----------------|-------------|
| I need to learn a lot of things before I could get going with the system |               |                   |         |                |             |
| I found the system very cumbersome to use                                |               |                   |         |                |             |
| I felt very confident using the system                                   |               |                   |         |                |             |
| I thought there was too much inconsistency in this system                |               |                   |         |                |             |
| I think I would like to use this system frequently                       |               |                   |         |                |             |
| I found the system unnecessarily complex                                  |               |                   |         |                |             |
| I found the various functions in the system well integrated              |               |                   |         |                |             |
| I would imagine that most people would learn to use this system very quickly |            |                   |         |                |             |
| I thought the system was easy to use                                     |               |                   |         |                |             |
| I think that I would need support of a technical person to be able to use the system |   |                   |         |                |             |

**Workload**

In the following section you will answer some questions on the perceived workload for the task.
You can give a score from 1 to 10 where 1 means "low" or "not much" while 10 means "high" or "a lot".

7. How mentally demanding was the task?

8. How physically demanding was the task?

9. How hurried or rushed was the pace of the task?

10. How successful were you in accomplishing what you were asked to do?

11. How hard did you have to work to accomplish your level of performance?

12. How insecure, discourage, irritated, stressed and annoyed were you?
**Demographics**
Lastly we ask you for some general information about yourself

13. **How old are you?**
   *Mark only one oval.*
   - [ ] Younger than 20
   - [ ] 20-29
   - [ ] 30-39
   - [ ] 40-49
   - [ ] 50-59
   - [ ] 60 or older

14. **What is your gender?**
   *Mark only one oval.*
   - [ ] Female
   - [ ] Male
   - [ ] Prefer not to say
   - [ ] Other: ____________________________
Survey - Image Reconstruction

21 responses

Data Protection

Expertise

Please answer how you agree with the following statements

Machine Learning Support

Please answer how you agree with the following statements
Please answer how you agree with the following statements

Did anything during the task not work the way you would have wanted it to?
8 responses

No

- Sometimes the pen tool gets automatically deselected when switching between pipette and pen.
- I thought that the algorithm could also reconstruct sharp edges but it didn't.
- No, everything worked well
- when you moved the mouse outside the image while painting on the edges it continued drawing
- I would like to use the pen firstly draw a boundary, and fill it with the color. The ColorPicker is sometime not sensitive enough to pick up the small area color.
What would you change in the interactive image reconstruction process?

11 responses

Let the automated process run in parallel and in background, so you have to wait less.
comparing some images with similar ones (pattern recognition, duplicated elements,...)
maybe more professional drawing brushes that I can give more details.
size of the tool could be symbolized
Shorter processing time.
for now nothing
Nothing
Introduce instructions by voice
Adding zoom functions.
The mouse for a finer pencil-like item
Copy patch instead of only one color

General System Usability

Please answer how you agree with the following statements
Workload

How mentally demanding was the task?
21 responses

![Mental Demand Chart]

How physically demanding was the task?
21 responses

![Physical Demand Chart]

How hurried or rushed was the pace of the task?
21 responses

![Rush Chart]
How successful were you in accomplishing what you were asked to do?

21 responses

How hard did you have to work to accomplish your level of performance?

21 responses
How insecure, discourage, irritated, stressed and annoyed were you?
21 responses

Demographics

How old are you?
21 responses
What is your gender?
21 responses

- Female: 52.4%
- Male: 42.9%
- Prefer not to say: 5.7%

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