

A Collaborative Filtering Based Movie Recommendation System

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Abstract

This is the abstract

I. INTRODUCTION

Here is the introduction.

II. METHODS

Hello I am figures and algorithms

Input: Image I , mask M , kernel K and threshold ϵ

Result: Reconstructed image I_r

$K \leftarrow \frac{K}{\sum_i \sum_j K_{i,j}}$ (normalize K to preserve energy);

$I_{prev} \leftarrow 0_{size(I)}$;

$I_r \leftarrow I$;

while $\|I_r - I_{prev}\|_F > \epsilon$ **do**

$I_{prev} \leftarrow I_r$;

$I_r \leftarrow \text{convolve}(I_r, K)$;

$I_r \leftarrow I_r \circ \mathbf{1}_{M=0} + I \circ \mathbf{1}_{M \neq 0}$;

end

Algorithm 1: Diffusion algorithm for inpainting. We denote element-wise multiplication with the \circ operator. The $\mathbf{1}_{M=0}$ function represents a matrix with elements (i, j) set to 1 when $M_{i,j} = 0$ and 0 otherwise.

- 1) *Constructing a directional kernel:* I am a subsubsection
- 2) *Per-patch diffusion using K_θ :* I am another subsubsection.

$$K_{\text{diamond}} = \begin{bmatrix} 0 & 0.25 & 0 \\ 0.25 & 0 & 0.25 \\ 0 & 0.25 & 0 \end{bmatrix}$$
$$K_{\text{diag}} = \begin{bmatrix} 0.38 & 0.04 & 0.04 \\ 0.04 & 0 & 0.04 \\ 0.04 & 0.04 & 0.38 \end{bmatrix}$$

Figure 1: Kernels used for diffusion.

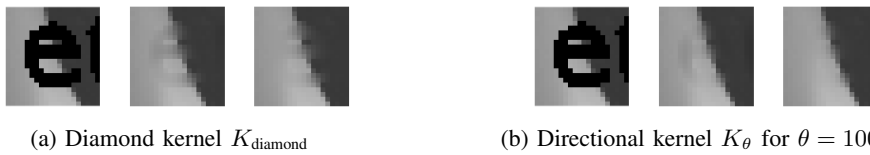


Figure 2: Step-by-step illustration of the diffusion process with different kernels. Each step represent 20 iterations.

Algorithm	MSE	Runtime
Directional Diffusion (16×16)	0.00055 \pm 0.00051	8.7 \pm 2.13
Directional Diffusion (32×32)	0.00057 \pm 0.00053	2.4 \pm 0.04
Diffusion (K_{diamond})	0.00061 \pm 0.00057	0.5 \pm 0.06
Sparse-coding (DCT)	0.0015 \pm 0.0012	12.8 \pm 4.67
Sparse-coding (Haar wavelet)	0.0024 \pm 0.0021	13.0 \pm 3.72
Singular Value Decomposition	0.0019 \pm 0.0018	0.7 \pm 0.09

Table I: Mean squared error and runtime (in seconds) across different algorithms for the text mask. The best result is highlighted in bold.

III. RESULTS

This is results.

Example of list:

- 1) Sparse-coding with a DCT dictionary [1].
- 2) Sparse-coding with a Haar wavelet [2].
- 3) Singular Value Decomposition [3].
- 4) Regular diffusion with a K_{diamond} kernel.
- 5) Directional diffusion with patches of size 16×16 .
- 6) Directional diffusion with patches of size 32×32 .

blabblabla:

$$\text{MSE}(I, I^{\text{rec}}) = \frac{1}{512 \cdot 512} \sum_{i,j} (I_{i,j} - I_{i,j}^{\text{rec}})^2$$

Hello I am a table

IV. DISCUSSION

why?

because sky is high!

V. CONCLUSION

U are close

REFERENCES

- [1] T. Hofmann, B. McWilliams, and J. Buhmann, “Sparse coding, overcomplete dictionaries,” 2015, <http://cil.inf.ethz.ch/material/lecture/lecture09.pdf>.
- [2] —, “Sparse coding, classical methods,” 2015, <http://cil.inf.ethz.ch/material/lecture/lecture08.pdf>.
- [3] T. Hofmann, “Singular value decomposition,” 2015, <http://cil.inf.ethz.ch/material/lecture/lecture03.pdf>.