Super-Resolution Image Reconstruction Using KL Divergence Optimization

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Abstract

This report discusses the application of Kullback-Leibler (KL) divergence for optimizing high-resolution (HR) image patches from low-resolution (LR) inputs. The process involves histogram-based KL divergence optimization to improve image quality. We also perform hyperparameter tuning using grid search to find the best parameters for reconstruction, including patch size, alpha, bins, and the number of iterations. The results are evaluated using the Structural Similarity Index (SSIM) and Mean Absolute Error (MAE) to measure image quality.

1 Introduction

Super-resolution techniques aim to reconstruct high-resolution images from low-resolution inputs. One of the key challenges in image super-resolution is to preserve image details while scaling up the resolution. Traditional methods such as interpolation provide basic solutions, but they often fail to capture fine details. In this report, we use KL divergence to optimize image patches and perform super-resolution, combining patch-based optimization with histogram-based metrics.

2 Dataset Description

The dataset used in this study consists of low-resolution (LR) rectangular images, size (510, 339 - count: 29), (510, 384 - count: 10) and high-resolution (HR) images, size (2040, 1356 - count: 29), (2040, 1536 - count: 10) and a few others in the same ranges. The dataset includes images of various types, such as natural scenes and objects, with diverse texture and color characteristics.

3 Methodology

3.1 KL Divergence for Optimization

KL divergence is used as a loss function to measure the difference between the probability distributions of pixel intensities in the LR and HR patches. The idea is to iteratively adjust the HR patch such that its histogram distribution closely matches that of the LR patch. This is achieved through the following steps:

- Compute the histogram distribution of the LR patch.
- Initialize the HR patch with bicubic interpolation from the LR patch.
- Iteratively update the HR patch by adjusting pixel values based on the gradient of KL divergence.

3.2 Super-Resolution with KL Divergence

The super-resolution process starts by dividing the LR image into smaller patches. Each patch is then optimized using KL divergence to match its histogram distribution to that of the corresponding HR patch. The HR image is reconstructed by combining the optimized patches. Multiprocessing is used for parallel patch optimization, which speeds up the process.

3.3 Hyperparameter Tuning via Grid Search

We perform a grid search to tune the following hyperparameters:

- Patch size: Affects the granularity of image details.
- Alpha: Learning rate for updating pixel values.
- Bins: Number of bins used for histogram computation.
- Max iterations: Controls the number of optimization steps.

The best parameters are chosen based on the Structural Similarity Index (SSIM) between the reconstructed HR image and the resized LR image.

4 Models and Algorithms

The primary model used is the KL divergence optimization model. The optimization process involves:

- Estimating the distribution of the LR image.
- Iterative gradient-based optimization to match the distributions of HR patches.
- Final reconstruction using the optimized HR patches.

Additionally, the SSIM metric is used to evaluate the quality of the reconstructed images. The SSIM score measures structural similarity and gives an indication of how well the reconstruction preserves the details of the original image.

5 Analysis and Results

5.1 Qualitative Results

The method effectively increases the resolution of the input LR images, producing visually appealing HR images. The optimized HR patches preserve more details compared to basic interpolation methods. Below is an example of a reconstructed HR image using the best hyperparameters found through grid search.

Figure 1: HR Image

Figure 2: Reconstructed HR Image using KL Divergence Optimization

5.2 Quantitative Results

The SSIM scores were calculated for different LR and HR Pairs. Average SSIM is 0.4679 and Average MAE is 166.5047. Table 1 summarizes the SSIM and MAE scores for various images.

IMAGE	SSIM	MAE
(Penguin)	0.540	183.85
(0807x4m worst)	0.17136	135.87
(0843x4m best)	0.8856	111.297

Table 1: SSIM and MAE Scores for Various images

6 Flowchart of the Process

The following flowchart represents the steps involved in the super-resolution image reconstruction process using KL divergence: