# Image Super-Resolution Based on Data-Driven Gaussian Process Regression

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**Abstract.** In this paper, we aim at producing the super-resolution image from a single low-resolution image based on Gaussian Process regression. Gaussian Processes provide a framework for deriving regression techniques with explicit uncertainty models. Super resolution can be transformed into a regression problem. We show how Gaussian Processes with covariance functions can be used for image super-resolution. Furthermore, considering that the training data have greatly effect on the super-resolution performance and the unsuitable training data would result in unexpected details, we adopt a data-driven scheme to learn a regression map for each query patch. There are two advantages of our approach: 1) we establish a map between the low-resolution space and the high-resolution space independent of a specified regression function; 2) the data-driven learning scheme improves the super-resolution performance. We estimate our approach on the popular testing images which are used in other super-resolution literatures, and the results demonstrate that our approach is efficient and it manifests a high-quality performance compared with several popular super-resolution methods.

**Keywords:** Super Resolution, Gaussian Process Regression, Covariance Matrix, Data-driven.

## 1 Introduction

Image super-resolution (SR) has been a hot topic in the field of computer vision, and it's widely used in many practical applications, such as satellite imaging and medical image formation where the analysis or diagnosis from low-resolution (LR) images can be very tough. The goal of image SR is to generate a high-resolution (HR) image from one or a set of low-resolution (LR) input images. The SR problem is ill-posed because a low-resolution image can be generated by many different high-resolution images under different transformations. There are many literatures to discuss image super-resolution, which can be divided into three classes: the interpolation based methods, the reconstruction based methods and the learning-based methods. Interpolation-based methods [1] [4] [5] are simple and fast, but the quality of the super-resolution image is very limited, because they cannot recover the high frequency details. Reconstruction based

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methods [2] [6–10] apply various smoothness priors and impose the constraint that makes the HR image reproduce the original LR image when properly downsampled. The limit of these methods is that they require that the smoothed and downsampled version of an HR image should be similar to the original LR image. Their performance relies on the prior information and the compatibility with the given image. Moreover, their performance degrades rapidly with the increase of the magnification factor, or with the decrease of the size of the input image.

Alternatively, the learning based methods [11–14] are promising, where detailed textures are hallucinated by searching through a training set which contains pairs of LR and HR patches. Freeman [11] proposed an example-based learning approach in which the prediction from the low-resolution image to the high-resolution image was learned via a Markov Random Filed (MRF). Yang [15] transformed the super-resolution problem into a sparse representation problem. Instead of dealing with image patches, Sun [3] proposed to use the primal sketch priors to enhance blurred edges.

In learning based SR methods, we are concerned about the regression based SR methods. Ni [16] used support vector regression (SVR) to solve the super-resolution problem in the frequency domain. Kim [19] estimated the high frequency details based on the kernel ridge regression. In these methods, the regression functions were specified. And the super-resolution performance depends on whether a specified regression model is suitable. In this paper, we want to adopt a finer method than those specified regression models, in which the regression function is represented by the data. Thus, we utilize Gaussian Process regression to solve the super-resolution problem, because Gaussian Processes provide a framework for deriving regression techniques with explicit uncertainty models. He [17] showed the feasibility of Gaussian Process regression to solve the SR problem, but in his method, a HR image is produced from a single image without the external training dataset. Our method will use Gaussian Process regression to learn the relationship between the LR space and the HR space from the training data. Furthermore, we investigate the training data selection. In the learning based method, the training data should be selected carefully, otherwise the unexpected details are introduced. Thus, we implement a data-driven scheme to learn a regression map for each query image patch, that is, for a query image patch, we collect its nearest neighbors as the training data.

Our contributions are as follow: 1) we use Gaussian Process regression to solve the super-resolution problem, which avoid specifying a special regression model; 2) we implement a data-driven regression scheme, in which each query image patch has its special training data and its special regression model.

The remainder of this paper is organized as follows: we give a brief overview of Gaussian Process regression and describe our algorithm of our approach in Section 2. Section 3 presents the experimental results, and conclusions are given in Section 4.