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IMAGE RECONSTRUCTION WITH SUPER RESOLUTION

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Abstract: - Subject identification from surveillance imagery has become an important task for forensic investigation. Good quality images of the subjects are essential for the surveillance footage to be useful. However, surveillance videos are of low resolution due to data storage requirements. In addition, subjects typically occupy a small portion of a camera's field of view. Faces, which are of primary interest, occupy an even smaller array of pixels. For reliable face recognition from surveillance video, there is a need to generate higher resolution images of the subject's face from low-resolution video. Super-resolution image reconstruction is a signal processing based approach that aims to reconstruct a high-resolution image by combining a number of low-resolution images. Super-resolution imaging (SR) is a class of techniques that enhance the resolution of an imaging system. Super-resolution image reconstruction is a signal processing based approach that aims to reconstruct a high-resolution image by combining a number of low-resolution images. Super-resolution improves image fidelity, and hence should improve the ability to distinguish between faces and consequently automatic face recognition accuracy.

Keywords: Introduction, LR, Resizing image, Image Reconstruction, Super Resolution, Markov Algorithm

Introduction

This is the first study to comprehensively investigate the effect of super-resolution on face recognition. Since super-resolution is a computationally intensive process it is important to understand the benefits in relation to the trade-off in computations. The low-resolution images that differ by a sub-pixel shift contain complementary information as they are different "snapshots" of the same scene. Once geometrically registered onto a common high-resolution grid, they can be merged into a single image with higher resolution. The attractiveness of the simple idea, that collecting under sampled frames and applying sampling theory one can obtain a decent image quality video, has led to explosive development of multi-frame super-resolution processing. The observed images could be taken from one or multiple cameras or could be frames of a video sequence. These images need to be mapped to a common reference frame. This process is registration. The super-resolution procedure can then be applied to a region of interest in the aligned composite image. The key to successful super-resolution consists of accurate alignment i.e. registration and

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formulation of an appropriate forward image model. Super-resolution is a computationally intensive process, traditional reconstruction-based super-resolution methods simplify the problem by restricting the correspondence between low-resolution frames to global motion such as translational and affine transformation. Surveillance footage however, consists of independently moving non-rigid objects such as faces. Applying global registration methods result in registration errors that lead to artefacts that adversely affect recognition. The human face also presents additional problems such as self-occlusion and reflectance variation that even local registration methods find difficult to model. In this dissertation, a robust optical flow-based super-resolution technique was proposed to overcome these difficulties. Real surveillance footage and the Terra scope database were used to compare the reconstruction quality of the proposed method against interpolation and existing super-resolution algorithms. Results show that the proposed robust optical flow-based method consistently produced more accurate reconstructions.

Increase Resolution

Possible ways for increasing an image resolution:

- Reducing pixel size. Increase the number of pixels per unit area. Advantage: Increases spatial resolution. Disadvantage: Noise introduced. As the pixel size decreases, the amount of light decreases.
- Super-resolution. Process of combining multiple low resolution images to form a high resolution image. Advantages: Cost less than comparable approaches, LR imaging systems can still be utilized.

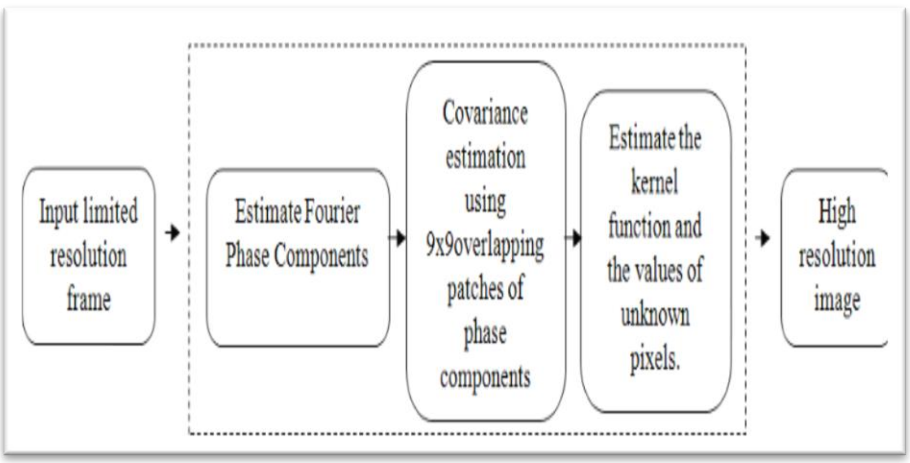


Fig-1

Resizing image

Image resizing is necessary when you need to increase or decrease the total number of pixels, whereas remapping can occur when you are correcting for lens distortion or rotating an image. Zooming refers to increase the quantity of pixels, so that when you zoom an image, you will see more detail. Interpolation works by using known data to estimate values at unknown points. Image interpolation works in two directions, and tries to achieve a best approximation of a pixel's intensity based on the values at surrounding pixels. Common interpolation algorithms can be grouped into two categories: adaptive and non-adaptive. Adaptive methods change depending on what they are interpolating, whereas non-adaptive methods treat all pixels equally. Non-adaptive algorithms include: nearest neighbour, bilinear, bicubic, spline, sinc, lanczos and others. Adaptive algorithms include many proprietary algorithms in licensed software such as: Q image, Photo Zoom Pro and Genuine Fractals.

Super-resolution Techniques

- Multi-frame Super-resolution
- Single-frame Super-resolution

Multi-frame image super-resolution

Multi-frame image super-resolution (SR) aims to utilize information from a set of low-resolution (LR) images to compose a high-resolution (HR) one. As it is desirable or essential in many real applications, recent years have witnessed the growing interest in the problem of multi-frame SR reconstruction. This set of algorithms commonly utilizes a linear observation model to construct the relationship between the recorded LR images to the unknown reconstructed HR image estimates. Recently, regularization-based schemes have been demonstrated to be effective because SR reconstruction is actually an ill-posed problem. Working within this promising framework, this paper first proposes two new regularization items, termed as locally adaptive bilateral total variation and consistency of gradients, to keep edges and flat regions, which are implicitly described in LR images, sharp and smooth, respectively. Thereafter, the combination of the proposed regularization items is superior to existing regularization items because it considers both edges and flat regions while existing ones consider only edges. Thorough experimental results show the effectiveness of the new algorithm for SR reconstruction.

Single-frame SR

In Single-frame SR– Estimate missing high-resolution detail that isn’t present in the original image, and which we can’t make visible by simple sharpening. Algorithm uses a training set to learn the fine details of an image at low-resolution. It then uses those learned relationships to predict fine details in other images.
– Markov network
– One pass algorithm

Markov Random Fields for Super-Resolution

Algorithm

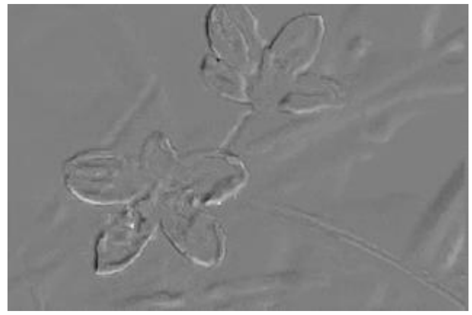
The core of the algorithm is based on [1]. We collect pairs of low-res and high-res image patches from a set of images as training. An input low-res image is decomposed to overlapping patches on a grid, and the inference problem is to find the high-res patches from the training database for each low-res patch. We use the kd-tree algorithm, which has been used for real-time texture synthesis [2], to retrieve a set of high-res, k-nearest neighbors for each low-res patch. Lastly, we run a max-product belief propagation (BP) algorithm to minimize an objective function that balances both local compatibility and spatial smoothness.

We first apply bicubic sampling to enlarge the input image (a) by a factor of 4 (b), where image details are missing. If we use the nearest neighbor for each low-res patch independently, we obtain high-res but noisy results in (c). To address this issue, we incorporating spatial smoothness into a Markov Random Fields formulation by enforcing the synthesized neighboring patches to agree on the overlapped areas. Max-product belief propagation is used to obtain high-res images in (d). The inferred high-frequency images are shown in (e), and the original high-res are shown in (f).

(a) Input

(b) Bicubic upsampling x 4

(c) Independent NN



(e) Inferred high frequency

(f) Original high-res

Technical Implementation

There are both single-frame and multiple-frame variants of SR. Multiple-frame SR uses the sub-pixel shifts between multiple low resolution images of the same scene. It creates an improved resolution image fusing information from all low resolution images, and the created higher resolution images are better descriptions of the scene. Single-frame SR methods attempt to magnify the image without introducing blur. These methods use other parts of the low resolution images, or other unrelated images, to *guess* what the high-resolution image should look like. Algorithms can also be divided by their domain: frequency or space domain. Originally, super-resolution methods worked well only on grayscale images, [15] but researchers have found methods to adapt them to colour camera images. [14]

Conclusion:

Current SR approaches are effective to some extent.SR considering registration error: Use total least squares method to minimize the error. Use channel adaptive regularization: SR images with large registration error should be less contributed to the estimate of the HR. Blind SR Image Reconstruction: when blurring process is unknown. Need blur identification. Computationally efficient SR Algorithm.

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