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GENERATE A HIGHER RESOLUTION IMAGE FROM LOWER RESOLUTION INPUT IMAGE

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Abstract: Super-resolution imaging (SR) is a class of techniques that enhance the resolution of an imaging system. Super-resolution imaging techniques are used in general image processing. Main aim of my project is to construct a high resolution image from low resolution image input. To achieve this goal, I introduce a novel self-learning approach for super resolution imaging. By using this approach, we focus on modeling the relationships between image patches from each scale. Once these models are observed from each scale, we select the best ones to refine each patch into the final output. To produce the final, we calculate the posterior probability for each patch in the target high-resolution image process corresponds to the Bayes decision rule in minimizing the prediction error when assigning the category to the input. The experimental results demonstrate that the proposed approach can generate superior HR images with better visual quality and lower reconstruction error.

Key schema –Super resolutions (SR), high resolution (HR),support vector regression (SVR)

I. INTRODUCTION

Super-resolution imaging (SR) is a class of techniques that enhance the resolution of an imaging system. In some SR techniques—termed *optical* SR—the diffraction limit of systems is transcended, while in others—*geometrical* SR—the resolution of digital imaging sensors is enhanced.Super-resolution imaging techniques are used in general image processing and in super-resolution microscopy.Because some of the ideas surrounding superresolution raise fundamental issues, there is need at the outset to examine the relevant physical and information-theoretical principles.

Diffraction Limit The detail of a physical object that an optical instrument can reproduce in an image has limits that are mandated by laws of physics, whether formulated by the diffraction equations in the wave theory of light[1] or the Uncertainty Principle for photons in quantum mechanics.[2] Information transfer can never be increased beyond this boundary, but packets outside the limits can be cleverly swapped for (or multiplexed with) some inside it.[3] One does not so much "break" as "run around" the diffraction limit. New procedures probing electro-magnetic disturbances at the molecular level (in the so-called near field)[4] remain fully consistent with Maxwell's equations.

A succinct expression of the diffraction limit is given in the spatial-frequency domain. In Fourier optics light distributions are expressed as superpositions of a series of grating light patterns in a range of fringe widths, technically spatial frequencies. It is generally taught that diffraction theory stipulates an upper limit, the cut-off spatial-frequency, beyond which pattern elements fail to be transferred into the optical image, i.e., are not resolved. But in fact what is set by diffraction theory is the width of the passband, not a fixed upper limit. No laws of physics are broken when a spatial frequency band beyond the cut-off spatial frequency is swapped for one inside it: this has long been implemented in dark-field microscopy. Nor are information-theoretical rules broken when superimposing several bands, disentangling them in the received image needs assumptions of object invariance during multiple exposures, i.e., the substitution of one kind of uncertainty for another.

Information When the term superresolution is used in techniques of inferring object details from statistical treatment of the image within standard resolution limits, for example, averaging multiple exposures, it involves an exchange of one kind of information (extracting signal from noise) for another (the assumption that the target has remained invariant).

Resolution and localization True resolution involves the distinction of whether a target, e.g. a star or a spectral line, is single or double, ordinarily requiring separable peaks in the image. When a target is known to be single, its location can be determined with higher precision than the image width by finding the centroid (center of gravity) of its image light distribution. The word *ultra-resolution* had been proposed for this process but it did not catch on, and the high-precision localization procedure is typically referred to as superresolution.

II. SCOPE OF THE PROJECT

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.

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III. RELATED WORK

Reconstruction-Based SR Typically, reconstruction-based SR algorithms require image patches from one or several images (frames) when synthesizing the SR output. This is achieved by registration and alignment of multiple LR image patches of the same scene with sub-pixel level accuracy. For single-image reconstruction-based SR methods, one needs to exploit self-similarity of patches within the target LR image. With this property, one can thus synthesize each patch of the SR image by similar patches in the LR version. However, reconstruction-based methods are known to suffer from ill-conditioned image registration and inappropriate blurring operator assumptions (due to an insufficient number of LR images). Moreover, when an image does not provide sufficient patch self-similarity, single-image reconstruction based methods are not able to produce satisfying SR results. Although some regularization based approaches were proposed to alleviate the above problems, their SR results will still be degraded if only a limited number of low-resolution images/patches are available or if a larger image magnification factor is needed. According to the magnification factor of reconstruction-based SR approaches is limited to be less than 2 for practical applications. A recent approach proposed in alleviates this limitation by learning image prior models via kernel principal component analysis from multiple image frames.

Since single-image SR does not require multiple LR images as inputs, it attracts the interest from researchers and engineers due to practical applications. As discussed above, methods assuming the existence of image patch self-similarity need to search for similar patches from an input image when synthesizing the SR output. However, the assumption of self-similarity might not always hold, and the associated SR performance varies with the similarity between different categories of image patches. The nonlocal means (NLM) method is one of the representatives which advocate such a property in image related applications.

IV. SYSTEM ANALYSIS

In broadsense, a general methodology (not a fixed set of techniques) that applies a 'systems' or 'holistic' perspective by taking all aspects of the situation into account, and by concentrating on the interactions between its different elements.It provides a framework in which judgments of the experts in different fields can be combined to determine what must be done, and what is the best way to accomplish it in light of current and future needs. Although closely associated with data or information processing, the practice of SA has been existence since long before computers were invented.

In a narrow sense, analysis of the current and future roles of proposed computer system in an organization, the system analyst (usually software engineer or programmer) examines the flow of documents, information, and material to design a system that best meets the cost, performance and scheduling objectives.

4.1 EXISITING WORK

Require image patches from one or several images (frames) when synthesizing the output.Reconstruction-based methods are known to suffer from ill-conditioned image registration and inappropriate blurring operator assumptionsMore-over, when an image does

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not provide sufficient patch self-similarity, single-image reconstruction based methods are not able to produce satisfying results.

4.2 DRAWBACKS OF EXISTING SYSTEM:

- Require image patches from one or several images (frames) when synthesizing the output.
- Reconstruction-based methods are known to suffer from ill-conditioned image registration and inappropriate blurring operator assumptions
- More-over, when an image does not provide sufficient patch self-similarity, single-image reconstruction based methods are not able to produce satisfying results

4.3 PROPOSED WORK

In our proposed framework, we advance support vector regression (SVR) with image sparse representation, which offers excellent generalization in modeling the relationship between images and their associated SR versions.

Unlike most prior SR methods, our proposed framework does not require the collection of training low and high-resolution image data in advance,

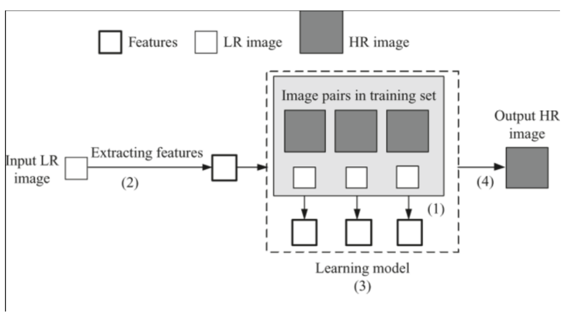
And we do not assume the reoccurrence (or self-similarity) of image patches within an image or across image scales.

4.4 ADVANTAGES OF PROPOSED SYSTEM

- Very unique since we do not require training low and high-resolution image data
- Robustness and effectiveness
- Obtain very promising results
- We need not collect training data from other low and high-resolution image
- Pairs, and we do not require the reoccurrence of image patches either

V. SYSTEM ARCHITECTURE

System architecture is a conceptual model that defines the structure, behavior, and more views of a system. An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviors of the system.



VI. CONCLUSION

Super-resolution imaging (SR) is a class of techniques that enhance the resolution of an imaging system. In some SR techniques—termed *optical* SR—the diffraction limit of systems is transcended, while in others—*geometrical* SR—the resolution of digital imaging sensors is enhanced.

Super-resolution imaging techniques are used in general image processing and in super-resolution microscopy.

The goal of single image super-resolution is to construct a high resolution (HR) image from a low resolution (LR) image input. This problem is an classical and active topic in image processing, which is also a crucial step in many practical situations, e.g. image display, remote sensing, medical imaging and so on. However, image super-resolution problem is an inherently ill-posed problem, where many HR images may produce the same LR image when down-sampled.

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