BIHAR SHODH SAMAAGAM, VOL. 1, ISSUE 4, p.p 20-23 (2023)

SUPER RESOLUTION

ATUL ROHIYA

ABSTRACT:
A variety of super-resolution algorithms have been described till today. Most of them are based on the same source of information however that the super-resolution image should generate the lower resolution input images when appropriately warped and down-sampled to model image formation. (This information is usually incorporated into super-resolution algorithms in the form of reconstruction constraints which are frequently combined with smoothnessprior to regularize their solution.) In this paper, how much extra information is actually added by having more than one image forsuper-resolution is discussed. This paper also reviews single image super-resolution methods considering drawbacks associated withmulti-frame/image super resolution methods.Keyword:Super-resolution, High-resolution, Multi-frame, Hallucination Algorithm, Polygon Based InterpolationI. INTRODUCTIONSuper-resolution (SR) is an inverse process of producing a high-resolution (HR) image from a single or multiple lowresolution(LR) inputs. Conventional reconstruction-basedSR methods require alignment and registration of several LRimages in sub-pixel accuracy [1, 2]; however, ill-conditionedregistration and inappropriate blurring operator assumptionslimit the scalability of this type of approach. While methodswhich introduce additional regularization alleviate the aboveproblems [1, 2, 3], their performance will still be limited bythe number of LR images/patches available.

As pointed out in[4, 5], the magnification factor is typically limited to be lessthan 2 for this type of approach.Single-image SR is more practical for real-world applications,since it only requires one LR input to determine itsHR version. The nonlocal-means (NLM) is a representativesingle-image SR technique, which utilizes the reoccurrence(i.e. self-similarity) of image patches for synthesizing its HRversion. Much attention has also been directed to exampleor learning-based single-image SR approaches (e.g., [6, 7]).For a LR input, example-based methods search for similarimage patches from training LR image data, and use theircorresponding HR versions to produce the final SR output.Learning-based approaches, on the other hand, focus on modelingthe relationship between the images with different resolutionsby observing priors of specific images [8, 9, 10, 11].For example, Ma et al. [9] applied sparse coding techniques[12] and proposed to learn sparse image representation forSR; Yang et al. [11] further extended this idea byintroducinggroup sparsity constraints when learning sparse image representationfor SR. Recently, Irani et al. [13] advanced animage pyramid structure which downsamples an input imageinto several lower-resolution versions, and they integratesboth classical and example-based approaches for SR. Thismethod overcomes the limitation of example/learning-basedapproaches which require the collection of training imagedata in advance. Although promising SR results were reportedin [13], the assumption of image patch self-similaritywithin or across image scales might not be practical.Motivated by [13], Min-Chun Yang Chang-Heng Wang proposeda novel self-learning SRframework which does not require the reoccurrence of imagepatches, nor the collection of training LR/HR image datais needed in advance. They applied the image pyramid in [13]and learn context-aware sparse representation for SR. The organization of this article is as follows. In Section II we study Super-Resolution as an inverse problem and address related regularization issues. In Section III we describe three recent trends in super-resolutionFinally,we conclude with a list of challenges to be addressed in futurework on Super-Resolution.Journal of Engineering, Computing and

II. SUPER-RESOLUTION AS AN INVERSE PROBLEMSuper-resolution algorithms attempt to extract the high-resolution image corrupted by the limitations of the optical imaging system. This type of problem is an example of an inverse problem, wherein the source of information (high-resolution image) is estimated fromthe observed data (low-resolution image or images). Solving an inverse problem in general requires first constructing a forward model. By far, the most common forward model for the problem of Super-Resolution is linear in form:$Y(t)=M(t)X(t)+V(t)$(1)where Y is the measured data (single or collection of images), M represents the imaging system, X is the unknown high-resolutionimage or images, V is the random noise inherent to any imagingsystem, and t represents the time of image acquisition. An inherent difficulty with inverse problems is the challenge of inverting the forward model without amplifying the effect of noise in the measured data. In the linear model, this results from the very high, possibly infinite, condition number for the model matrix M.Solving the inverse problem, as the name suggests, requires inverting the effects of the system matrix M. At best, this system matrix is ill conditioned, presenting the challenge of inverting the matrix in a numerically stable fashion (Golub and Loan, 1994. In many real scenarios, the problem is worsened by the factthat the system matrix M is singular. For a singular model matrix M, there is an infinite space of solutions.Thus, for the problem of Super-Resolution, some form of regularization must be included in the cost function tostabilize the problem or constrain the space of solutions. Tikhonov regularization, is a widely employed form of regularization, where T is a matrix capturing some aspect of the image such as its general smoothness. This form ofregularization has been motivated from an analytic standpoint tojustify certain mathematical properties of the estimated solution. Forinstance, a minimal energy regularizationeasily leads to aprovably unique and stable solution. Often, however, little attentionis given to the effects of such simple regularization on the superresolutionresults. For instance, the regularization often penalizesenergy in the higher frequencies of the solution, opting for a smoothand hence blurry solution. From a statistical perspective, regularizationis incorporated as a priori knowledge about the solution. Thus,using the maximum a-posteriori (MAP) estimator, a much richerclass of regularization functions emerges, enabling us to capture thespecifics of the particular application [e.g., Schultz and Stevenson(1996) captured the piecewise-constant property of natural imagesby modeling them as Huber-Markov random field data].Unlike the traditional Tikhonov penalty terms, robust methodsare capable of performing adaptive smoothing based on the localstructure of theimage. In recent years there has also been a growing number of learning-based MAP methods, where the regularization-like penaltyterms are derived from collections of training samples (Atkins et al.,1999; Baker and Kanade, 2002; Haber and Tenorio, 2003; Zhu andMuford, 1997). For example, in Baker and Kanade (2003) an explicitrelationship between low-resolution images of faces and theirknown high-resolution image is learned from a face database.

Thislearned information is later used in reconstructingface images fromlow-resolution images. Because of the need to gather a vast amountof examples, often these methods are effective when applied to veryspecific scenarios, such as faces or text.Needless to say, the choice of regularization plays a vital role inthe performance of any Super-Resolution algorithmIII. RESCENT TRENDS IN SUPERRESOLUTIONVarious techniques used for super resolution in use are discussed in this section.A.Hallucination Algorithm:A variety of super-resolution algorithms have been described tillthe date. Most of theseare based on the same source of information however;that the super-resolution image should generate the lower resolutioninput images when appropriately warped and down-sampled tomodel image formation. (This information is usually incorporated intosuper-resolution algorithms in the form of reconstruction constraintswhich are frequently combined with Journal of Engineering, Computing and smoothnessprior to regularizetheir solution.) There is need to find how much extrainformation is actually added by having more than one image forsuper-resolution. .It is derived froma sequence of analytical resultsby Simon Baker and Takeo Kanadethat the reconstruction constraints provide far lessuseful information as the decimation ratio increasesthey proposeda superresolutionalgorithm which uses a completely different source of information,in addition to the reconstruction constraints. The algorithmrecognizes local “features” in the low resolution images and then enhancestheir resolution in an appropriate manner, based on a collectionof high and low-resolutiontraining samples. such an algorithm is a hallucination algorithm.B.Polygon Based InterpolationIn [14]a polygon intersection scheme is presented as a linear interpolator.formulating polygon intersection as a linear operator proves to be fundamental in its application to super-resolution reconstruction. A low-resolution output image can be expressed as:b=Ax(2)The motivation for the polygon interpolation operator is as follows: A camera sensor is a grid of photo-sensitive cells (think of them as photonbuckets, each representing a pixel). Due to micro-lenses, the gaps between the cells are negligible. During imaging, the sensor irradiance is integrated over each cell for the duration of exposure, after which the values are read out as a matrix. Now, imagine two sensors, one with large cells (low-resolution) and the other with small cells (high-resolution), rotated relative to one another. Howare the cell values for the different sensors related? StefanJohann van der.

Walt proposed solution tomeasure the overlap between the larger and smaller cells, The value of a (large) low-resolution cell is set to a weighted sum of all (small)high-resolution cells; the weights depend on their overlap. A linear interpolation operator that models the individual pixels of the camera sensor using polygons, a new model matrix is constructed at low cost; unlike other approaches, no parameters need to be specified. Using one of several least-squares techniques, the over-determined system is solved using regularization. C.Context Aware Sparse RepresentationforSingle Image Super Resolution:Given an input low-resolutionimage and its image pyramid, Min-Chun Yang, Chang-Heng Wang, Ting-Yao Hu, and Yu-Chiang Frank Wang proposedto perform context constrained image segmentation and construct an image segmentdataset with different context categories. By learning context-specific image sparse representation, their method aims to model the relationship between the interpolated image patches and their ground truth pixel values from different context categories via support vector regression (SVR). To synthesize the final SR output, we upsample the input image by bicubic interpolation, followed by the refinement of eachimage patch using the SVR model learned from the associated context category. Unlike prior learning-based SR methods, their approach does not require the reoccurrence of similar image patches (withinor across image scales), and they do not need to collect training low and high-resolution image data in advance either. Empirical results show that their proposedmethod is quantitatively and qualitatively more effective thanexisting interpolation or learning-based SR approaches. IV.

SUMMARY AND FURTHER CHALLENGESIn Section III we presented only a few methods and insights for specific scenarios of single image super-resolution. Many questions still persist in developing a generic Super-Resolution algorithm capable of producing high-quality results on general image sequences. In this section, we outline a few areas of research in Super-Resolution that remain open. The types of questions to be addressed fall into mainlytwo categories. The first concerns analysis of the performance limits associated with Super-Resolution. The second is that of Super-Resolution system level design and understanding. A thorough study of Super-Resolution performance limits will have a great effect on the practical and theoretical activities of the image reconstruction community. In deriving such performancelimits, one gains insight into the difficulties inherent to super resolution. One example of recent work addressing the limitations Journal of Engineering, Computing and Architecture of optical systems is given by Sharam and Milanfar (2004), where the objective is to study how far beyond the classical Rayleigh resolution limit one can reach at a given signal to noise ratio. Another recent study (Baker and Kanade, 2002), shows that, for a large enoughresolution enhancement factor, any smoothness prior will result in reconstructions with very little high-frequency content. Lin and Shum (2004), for the case of translational motion, studied limits based on a numerical perturbation model of reconstruction-basedalgorithms. However, the question of an optimal resolution factor (r) for an arbitrary set of images is still wide open. Also, the role of regularization has never been studied as part of the analysis is proposed.

Given that it is the regularizationthat enables the reconstruction in practice, any future contribution of worth on this matter must take it into effect. Systematic study of the performance limits of Super-Resolution would reveal the true information bottlenecks, hopefully motivating focused research to address these issues. Furthermore, analysis of this sort could possibly provide understanding of the fundamental limits to the Super-Resolution imaging, thereby helping practitioners to find the correct balance between expensive optical imaging system and image reconstruction algorithms. Such analysis may also be phrased as general guidelines when developing practical super resolution systems. In building a practical Super-Resolution system, many important challenges lay ahead. For instance, in many of the optimization routines used in this and other articles, the task of tuning the necessary parameters is often left up to the user. Parameters such as regularization weighting can play an important role in the performanceof the Super-Resolution algorithms. Although the cross validation method can be used to determine the parameter values forthe nonrobust Super-Resolution method (Nguyen et al., 2001a), acomputationally efficient way of implementing such method for therobust Super-Resolution case has not yet been addressed.Although some work has addressed the joint task of motionestimation and Super-Resolution (Hardie et al., 1997; Schultz et al.,1998; Tom and Katsaggelos, 2001), the problems related to this stillremain largely open. Another open challenge is that of blind superresolutionwherein the unknown parameters of the imaging system'sPSF must be estimated from the measured data. Many single-frameblind deconvolution algorithms have been suggested in the last 30 years (Kondur and Hatzinakos, 1996), and recently (Nguyen et al.,2001a) incorporated a single parameter blur identification algorithm in their Super-Resolution method, but there remains a need for more research to provide a Super-Resolution method along with a more general blur estimation algorithm from aliased images. Also, recently the challenge of simultaneous resolution enhancement in time as well as space has received growing attention (Robertson and Stevenson 2001; Shechtman et al., 2002). Finally, it is the case that the low-resolution images are often, if not always, available in compressed format. Although a few articles have addressed resolution enhancement of DCT-based compressed video sequences (Segall et al., 2001; Altunbasak et al., 2002), the more recent advent and utilization of wavelet-based compressionmethods requires novel adaptive Super-Resolution methods. Adding features such as robustness, memory and computation efficiency, color consideration, and automatic selection of parameters in super resolution methods will be the ultimate goal for the Super-Resolution researchers and practitioners in the future.V.

REFERENCES:-

[1] R. C. Hardie et al., "Joint map registration and high-resolution image estimation using a sequence of undersampled images,"IEEETrans. Image Processing, 1997.

[2] S. Farsiu et al., "Fast and robust multi-frame super-resolution,"IEEE Trans. Image Processing,2003.

[3] M.E.Tipping and C. M. Bishop, "Bayesian image superresolution,"in NIPS, 2002

.[4] S. Baker and T. Kanade, "Limits on super-resolution and how to break them," IEEE PAMI, 2002.

[5] H. Y. Shum and Z. C. Lin, "Fundamental limits ofreconstruction-based superresolution algorithms under local translation," IEEE PAMI, 2006

.[6] W. T. Freeman, T. Jones, and E. Pasztor, "Example-based superresolution," IEEE Computer Graphics and Applications, 2002.

[7] H. Chang, D.-Y. Yeung, and Y. Xiong, "Super-resolution through neighbor embedding," IEEE CVPR, 2004.

[8] K. S. Ni and T. Q. Nguyen, "Image superresolution using support vector regression," IEEE Trans. Image Processing, 2007