

Image Mosaicing and Super-resolution

Abstract

This book investigates the problem of how information contained in multiple, overlapping images of the same scene may be combined to produce images of superior quality. This area, generically titled *frame fusion*, offers the possibility of reducing noise, extending the field of view, removal of moving objects, removing blur, increasing spatial resolution and improving dynamic range. As such, this research has many applications in fields as diverse as forensic image restoration, computer generated special effects, video image compression, and digital video editing.

An essential enabling step prior to performing frame fusion is *image registration*, by which an accurate estimate of the point-to-point mapping between views is computed. A robust and efficient algorithm is described to automatically register multiple images using only information contained within the images themselves. The accuracy of this method, and the statistical assumptions upon which it relies, are investigated empirically.

Two forms of frame-fusion are investigated. The first is *image mosaicing*, which is the alignment of multiple images into a single composition representing part of a 3D scene. Various methods of presenting the composite image are demonstrated, and in particular, a novel algorithm is developed for automatically choosing an optimal viewing transformation for certain cases. In addition, a new and efficient method is demonstrated for the matching of point features across multiple views.

The second frame-fusion method is *super-resolution*, which aims to restore poor-quality video sequences by removing the degradations inherent in the imaging process. The framework presented here uses a generative model of the imaging process, which is discussed in detail and an efficient implementation presented. An algorithm is developed which seeks a maximum likelihood estimate under this model, and the factors affecting its performance are investigated analytically and empirically.

The use of “generic” prior image models in a Bayesian framework is described and shown to produce dramatically improved super-resolution results. Finally, super-resolution algorithms are developed which make use of image models which are tuned to specific classes of image. These algorithms are shown to produce results of comparable or better quality than those using generic priors, while having a lower computational complexity. The technique is applied to images of text and faces.

Throughout this work, the performance of the algorithms is evaluated using real image sequences. The applications demonstrated include the separation of latent marks from cluttered, non-periodic backgrounds in forensic images; the automatic creation of full 360° panoramic mosaics; and the super-resolution restoration of various scenes, including text and faces in low-quality video.

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