**SUBJECT:** MI102 - I. Išgum and B. Landman; Image Processing

**1. TITLE:** Super-Resolution and Deblurring Enhancement for Narrow Band Imaging Bronchoscopy

**2. AUTHORS:**


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**3. PRESENTATION PREFERENCE:** poster presentation

**4. PRINCIPAL AUTHOR'S BIOGRAPHY:**

William E. Higgins received the B.S. degree in electrical engineering from the Massachusetts Institute of Technology, Cambridge, MA, and the M.S. and Ph.D. degrees in electrical engineering from the University of Illinois, Urbana-Champaign. He held positions previously at the Honeywell Systems and Research Center, Minneapolis, MN, and the Mayo Clinic, Rochester, MN. He is currently a distinguished professor in the School of Electrical Engineering and Computer Science and Biomedical Engineering at Penn State University. His research interests are in multidimensional medical image processing and image-guided intervention (IGI) systems.


**5. ABSTRACT:** Narrow band imaging (NBI) is a relatively new endoscopic imaging modality that provides enhanced views of the blood vessels situated near the surface of the airway walls. Certain vessel patterns have been shown to be potential indications of cancerous lesions developing in the airways. Some recent efforts have strived to use NBI bronchoscopy to locate such vessel patterns. To find these patterns, the physician is forced to navigate the bronchoscope through the airways and manually observe potential mucosal (airway wall) vascular patterns. Unfortunately, the bronchoscopic video is often degraded by motion blur and artifacts, thereby making an already tedious search more impractical. In addition, the degraded video can decrease the potential performance of automated vascular analysis methods. We propose to exploit the richness of the video sequence by exploring methods for super-resolution video reconstruction and image deblurring—methods which have seen spectacular success in other domains for obtaining high-resolution (HR) images from a sequence of low-resolution (LR) images. Through examples derived from NBI videos of lung-cancer patients, we demonstrate that such methods can: (1) substantially improve the image quality of images depicting NBI-based vascular patterns; and (2) quantitatively enable more effective automatic segmentation of vascular patterns.



**6. KEYWORDS:** bronchoscopy, narrow band imaging (NBI), lung cancer, super-resolution, deblurring, image enhancement, video processing.

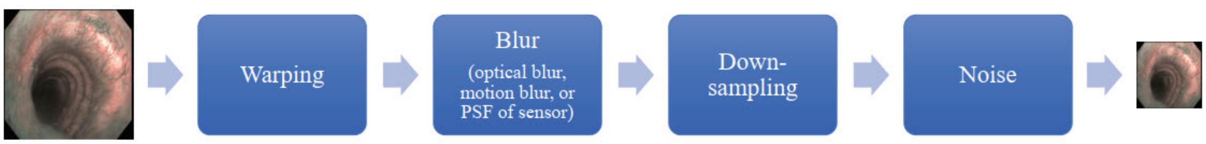
Topic areas for MI102 review: image restoration and enhancement, computer vision, quantitative imaging analysis


**7. SUMMARY:**

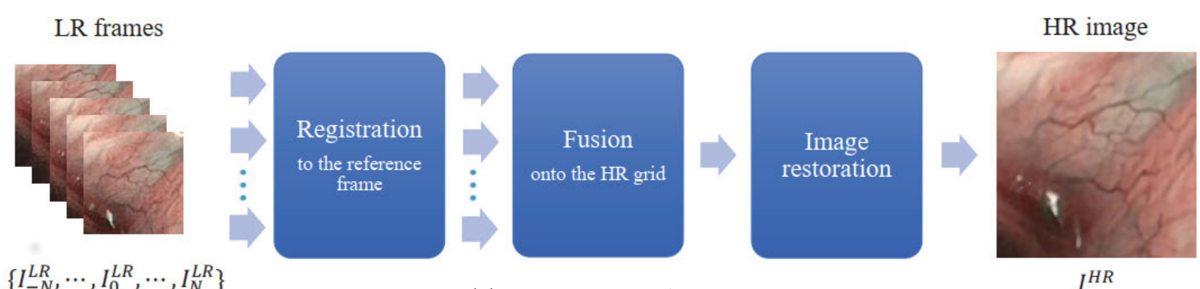
*7.1. Description Of Purpose:* With lung cancer still being the world's leading cause of cancer death, recent research has begun to consider the early detection of cancer lesions that develop in the bronchial epithelium of the lung mucosa (airway walls). For detecting such lesions, physicians look to bronchoscopy. One of the most promising bronchoscopic imaging modalities emerging for the detection of mucosal lesions is narrow-band Imaging (NBI), which illuminates the mucosa with narrow-band filtered white light [1]. In this way, the NBI bronchoscope's video stream gives a sequence of images depicting far more detailed information on the airway wall's vessel structure than standard white-light bronchoscopy. Thus, the physician can use NBI bronchoscopy to search for suspect lesions along the airway walls. Unfortunately, the resulting video stream — a very large, redundant data source — forces the physician to conduct a highly tedious visual search to manually locate lesions. Complicating this problem, the video stream is generally, degraded by blurring artifacts and other imperfections caused by device motion, patient cough, and other phenomenon, thereby making a highly tedious search process even more difficult. To date, limited research has been conducted to consider applying automatic image-processing methods to this endoscopic video problem [2]. Fortunately, the video stream represents a highly information-rich redundant data source for imaging the airway walls, albeit with degraded quality. As such, regions of interest (ROIs) generally get multiple looks during a bronchoscopic airway exam.

On another front, the computer vision community has devised a collection of multi-frame algorithms based on super-resolution (SR) analysis, which generates high-resolution (HR) images from low-resolution (LR) imaging systems [3]. In addition, other related methods have considered the notion of multi-frame image deblurring for producing enhanced resolution images [4]. In fact, in several medical imaging areas, researchers have shown that higher-resolution images will likely improve the prospects for abnormality visualization, region segmentation, and 3D reconstruction. Unfortunately, minimal research has studied the potential of these methods for endoscopy, and none have considered NBI bronchoscopy. *We explore the use of super-resolution and image deblurring methods for NBI bronchoscopy video. We then demonstrate that such methods can greatly enhance the visual quality of the given raw video data, thereby enabling better ROI visualization and automatic vessel segmentation.*

*7.2. Methods:* We consider multi-frame super-resolution and image deblurring approaches that aim to reconstruct a high-resolution (HR) image from multiple low-resolution (LR) images. Bronchoscopic video is well-suited to this problem, as it gives many wide field of view (FOV) views of each airway mucosal site of interest. Fig. 1a outlines a common observation model assumed in super-resolution algorithms, which motivates our method [5]. The input is the uncorrupted HR video sequence, while the output is the available observed degraded LR sequence. To begin, each input image is subject to a warping arising from camera movements or local scene motion (e.g., patient breathing). Next, each image is degraded by blur occurring from motion blur or the optical blur inherent to the bronchoscopic camera's sensor elements. Continuing, the camera's point spread function (PSF) degrades each frame, where the PSF models the imaging system's response to a point source. Finally, each frame is downsampled into a discrete image, and, depending on the sensor, incurs added noise. This gives the final sequence of LR images.




(a) Observation Model




(b) Reconstruction Approach

**Figure 1:** Observation model and reconstruction approach used in reconstruction-based multi-frame SR algorithms.

Given this sequence, the multi-frame SR algorithm is usually based on the reconstruction model shown in Fig. 1b. The SR reconstruction method consists of three steps: registration, fusion, and image restoration. During registration, the relative motion of each LR frame with respect to the reference frame is estimated. Then, based on the estimated motion calculations, all LR frames are fused onto a HR grid. Thus, all input LR images are combined into an intermediate HR image. Finally, image restoration is applied to this HR image to counteract the degradations caused by noise, blur, etc.

Based on the observation model (Fig. 1a), we formulate the problem in matrix form as follows. Given LR image sequence $\{I_{-N}^{LR}, \cdots, I_{(0)}^{LR}, \cdots, I_N^{LR}\}$, the multi-frame SR method aims to estimate HR image $I^{HR}$ corresponding to reference LR image $I_{(0)}^{LR}$. Per [5], we use the following model linking the LR and HR images:

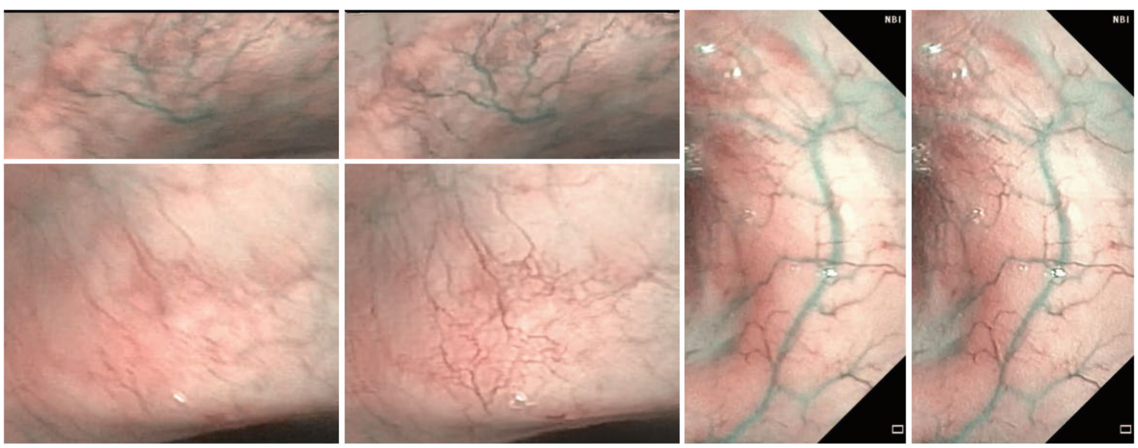
$$I_i^{LR} = DB_iF_{0\to i}I^{HR} + n, \qquad i = -N, \cdots, N, \tag{1}$$

where $D$ corresponds to the down-sampling operator, $B_i$ is the blur matrix corresponding to the PSF, motion blur, and all other types of blur, $F_{0\to i}$ corresponds to the motion from $I^{HR}$ to the $i^{\text{th}}$ frame and $n$ denotes the additive noise. Considering that the motion in NBI bronchoscopic videos is quite complex (i.e., a combination of a non-uniform shift, zoom, and rotation) we decide to use SR algorithms that utilize optical flow to estimate the motion field between two frames.

Most of the regions in an NBI video frame seem relatively uninformative; i.e., parts of a frame are either too dark, too blurry, or indistinguishable due to a build-up of mucus, blood, or water within airways. Thus, in our work, we focus on mucosal sites consisting of ROIs depicting significant vascular patterns. Hence, our input consists of a subsequence of LR images containing the ROI. Therefore, instead of processing large $1280 \times 1024$ whole-frame arrays, we reduce the computational demand of the SR algorithm by extracting smaller rectangular patches from the NBI video sequence. In particular, we choose an ROI from reference frame $I_{(0)}^{LR}$ and track the ROI for $N$ frames in both directions (forward and backward) using the KLT tracking method [6] . Next, a rectangular box is cropped from each of the $2N + 1$ frames so that the vascular area of interest always appears inscribed in a given ROI. At last, we use the cropped frames as input for the SR algorithms. The final output is an HR image, which is reconstructed from the input sequence of LR frames.

Regarding multi-frame image deblurring, which is also referred to as video deblurring, it uses observation and reconstruction models similar to those used by multi-frame SR methods [4]. A major difference is that the spatial resolution of LR and HR images are usually considered to be the same; i.e., in the fusion step of the reconstruction model the HR grid has same size as the LR grids.

*7.3. Results:* Since we have no ground-truth HR image for NBI bronchoscopy video, we assess the performance of the multi-frame SR and image deblurring methods based on improvement in (a) image perceptual quality and (b) quantitative vessel segmentation. Our NBI video database is drawn from the bronchoscopies of four lung cancer patients. For our experiments, we did evaluations based on subsequences of small ROI patches extracted from the raw large video frames, as discussed earlier. We apply the SR algorithms only to the intensity component of the images, while the color components are simply up-scaled using bicubic interpolation.




original ROI deblurred ROI original ROI deblurred ROI

**Figure 2:** Video deblurring results for three different LR image sequences. Each sequence consists of 7 LR images. Figure compares the visual quality of a reference ROI extracted from a whole video frame before (left) and after (right) deblurring. Top left image pair = video frame 4537 from case 20349_3_94; bottom left = frame 29, case 21405_157; right = frame 1367, case 21405_168.

Fig. 2 illustrates video deblurring results, where we adapted the algorithm of Kim and Lee [4]. Each input sequence consists of 7 consecutive LR images. Even though the output HR (deblurred) image has the same spatial resolution as the input LR images, the vascular structures clearly become more distinguishable from the mucosa. Also, the deblurred image reveals more vessels that previously were not visible due to significant blur.

To study super resolution's impact on vessel segmentation, we consider the vesselness filter and vessel segmentation method proposed in [7]. The vesselness filter takes values from 0 to 255, where higher values correspond to a higher probability of being a blood vessel. We adapt the multi-frame SR algorithm of Köhler *et al* using a sequence of 7 LR images as input and an HR-image up-scaling factor equal to 2 [3]. Since the LR and HR frames have different spatial resolutions, we first upscale the LR image using bicubic interpolation and then apply the vesselness filter. As Fig. 3 shows, super resolution improves the vesselness filter response as it decreases the false alarms in the filter response and detects the blood vessels that were not identified in the LR image.

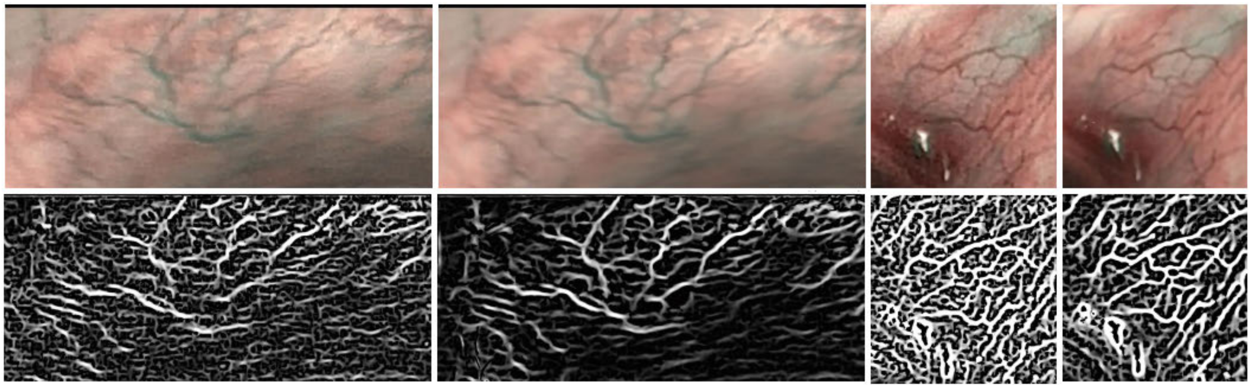


**Figure 3:** Results of the multi-frame SR algorithm applied on two different sequences of LR images. Each sequence consists of 7 LR images while we compare the visual quality (top row) and the vesselness results (bottom row) of the reference frame before (left) and after (right) employing super-resolution. [left: frame 4537, case 20349.94, right: frame 1146, case 21405.171]

After final vessel segmentation, we obtain the results of Table 1 — the metric results clearly suggest that HR processing quantitatively enable more effective vessel segmentation.

**Table 1:** Segmentation performance of super-resolution for NBI bronchoscopy video frames. Accuracy, sensitivity, and specificity statistics are determined for automatic vessel segmentation [7] relative to a reference labeling. All measures are averaged over 4 ROIs extracted from different NBI bronchoscopy video frames and presented as mean ± std. dev.

| image quality | accuracy | sensitivity | specificity |
|---|---|---|---|
| LR | $0.76 \pm 0.1$<br>$[0.66, 0.89]$ | $0.60 \pm 0.05$<br>$[0.54, 0.65]$ | $0.80 \pm 0.1$<br>$[0.67, 0.90]$ |
| HR | $\mathbf{0.81 \pm 0.09}$<br>$[0.70, 0.92]$ | $\mathbf{0.61 \pm 0.04}$<br>$[0.55, 0.67]$ | $\mathbf{0.84 \pm 0.09}$<br>$[0.71, 0.94]$ |

*7.4. New or Breakthrough Work:* This is the first work to study the prospects of image enhancement algorithms to improve NBI bronchoscopic video. Our preliminary results exhibit improvement in both visualization and segmentation of vasculature structures.

*7.5. Conclusion:* We have demonstrated that super-resolution and deblurring image-enhancement techniques can indeed improve the image quality of NBI bronchoscopy video frames and also enable more complete segmentation of vascular patterns. By improving visual quality, the physician can conceivably better visualize and identify significant vessel structures (e.g., dotted, tortuous, spiral, or screw type vessels). Finally, through better vessel segmentation, automatic quantitative detection of bronchial lesions could become a practical operation. The final paper will give fuller method description and results.

*7.6. Submission History:* This work has not been submitted for publication or presentation elsewhere, nor is it currently in the process of being submitted elsewhere.

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