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Achieving super-resolution X-ray imaging with mobile C-arm devices

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Abstract

Background The term super-resolution refers to the process of combining a set of low-resolution images into a high-resolution image using image-processing methods. This work is concerned with the reconstruction of high-resolution X-ray images. Specifically, we address the problem of acquiring X-ray images from multiple, very close view points.

Methods We propose to use a novel experimental robotic C-arm device to create high-resolution X-ray images. For this purpose, we suggest different strategies for acquiring multiple low-resolution images, and we provide the steps to achieve acquisition-error compensation. Compared to visible light images, X-ray images have the particularity that parallax effects render super-resolution very difficult. Using the acquired multi-frame data, we evaluate recent well-known super-resolution reconstruction algorithms. The same algorithms are evaluated based on synthetic 3D phantom data and real X-ray images.

Results In experiments with both synthetic and real projection data, we successfully reconstruct up to four times higher-resolution images. These images reveal structures and details which are not perceivable in the low-resolution images.

Conclusions The advantage of super-resolution techniques for X-ray is the potential reduction of radiation dose for patients and medical personnel. Potential medical applications include the diagnosis of early-stage osteoporosis and the detection of very small calcifications. Copyright © 2009 John Wiley & Sons, Ltd.

Keywords super-resolution; X-ray imaging; image processing; resolution enhancement; robotic C-arm

Introduction

The term ‘super-resolution’ (SR) refers to the process of combining a set of low-resolution (LR) images, also named multi-frame input data, into a high-resolution (HR) image using image-processing methods. In order to succeed, the LR input images must contain different information about the scene. This is the case if the images are acquired from slightly different positions, e.g. they are shifted or scaled versions of the scene.

The super-resolution task is an ill-posed inverse problem (1,2), which usually does not have a unique solution given a set of LR images, also named multi-frame input data. Two tightly coupled problems must...
be solved to reconstruct super-resolution images. First, the transformations relating the multi-frame data must be known. If the transformation parameters between the LR image frames are unknown, they must be accurately estimated using image registration techniques (3–5).

Second, the imaging process must be modelled to allow for combining multiple LR images in order to solve the reconstruction problem.

Super-resolution imaging has been a very active research field for almost 30 years, and it has many military and astronomical applications. Super-resolution algorithms can be roughly divided into frequency- and spatial-domain methods. Early works focused on frequency–space methods (6,7). Despite drawbacks of frequency–space methods, e.g. they can model only global rigid motion, they are still in use due to their low computational complexity. More recent approaches focus mainly on image–space methods to allow for complex motion models, and the joint estimation of motion and reconstruction parameters (3). Comprehensive reviews of standard super-resolution algorithms can be found, for example, in (8) and (1).

Recently, super-resolution techniques have found their way into the field of medical imaging (9,10). However, super-resolution approaches have been rarely used for medical X-ray imaging. Aoki et al. (11) describe an X-ray system with four slightly displaced CdTe-detector arrays to obtain image resolutions larger than the pixel width of the system. Bernhardt et al. (12) propose to use super-resolution techniques in paediatric radiology. However, the latter study neither provides details about the techniques employed and the image acquisition process, nor does it show detailed results. To fill this gap, we describe an X-ray multi-frame data acquisition set-up with acquisition-error compensation in detail. For this purpose we use a mobile, motorized C-arm device. We used five different super-resolution algorithms for this set-up, and provide the results of running over 500 experiments with different image-acquisition processes.

The structure of this paper is as follows. We first describe motion-based LR image acquisition processes and acquisition-error compensation methods with a novel robotic C-arm. We then give a condensed overview of standard super-resolution methods, and point out the ones used for this paper. These methods are evaluated with simulated and real X-ray projection data. Finally, we present a practical implementation of SR X-ray imaging using the new robotic C-arm device.

Acquisition of projection images

To achieve super-resolution with mobile X-ray imaging devices, we must model the image-acquisition process. We concentrate on motion-based image-acquisition, which requires no special hardware set-up [such as sub-pixel displaced detectors (11)]. One of our goals is to avoid image acquisitions with redundant information in order to minimize the radiation dose. In general, we aim for the best trade-off between image quality and a minimum number of input LR images.

X-ray images from mobile devices often exhibit inconsistencies, due to image noise, mechanical flex, geometric distortions and errors in positioning the C-arm. Because of these image-acquisition errors, we cannot expect quality high-resolution reconstruction unless we compensate for them.

Possible motion-based image-acquisition models using mobile C-arm devices are presented in the following. The projective transformations to relate the LR image frames into a common coordinate system, which is a pre-requisite step for SR reconstruction, are also discussed.

The X-ray camera is modeled as a pinhole camera, which is a common approximation of the X-ray imaging process (13). A pinhole camera is specified by the intrinsic camera parameters: focal length \( f \), horizontal and vertical pixel scales \( s_h \) and \( s_v \), the principal point \( (u_0, v_0) \) and the angle \( \phi \) between the image plane axes. The X-ray projection process can be described using a matrix notation. The camera projection matrix \( K \) maps a point \( p \in \mathbb{R}^3 \) to a projected point \( p_0 \in \mathbb{R}^2 \) expressed in homogeneous coordinates:

\[
p_0 = Kp
\]

with the camera projection matrix \( K \):

\[
K = \begin{bmatrix}
-f_{sh} & f_{sh} \tan \phi & u_0 \\
0 & -f_{sv} \sin \phi & v_0 \\
0 & 0 & 1
\end{bmatrix}
\]

To solve the SR reconstruction problem, one needs to know the projective transformations that relate the LR images in a common coordinate system. Without loss of generality, the world coordinate system is aligned to the coordinate system of the first camera. The projection images \( I_i(x,y), i \in 1, \ldots, m \) are acquired from slightly different camera positions, using transformation \( T_i \). The transformations can be decomposed in a \( 3 \times 3 \) rotational part \( R_i \) and a translational part \( t_i \). The relation between a point \( p \) and its two-dimensional (2D) projection \( p_i \) in image \( I_i \), expressed in homogeneous coordinates, is:

\[
p_i = K(R_ip + t_i)
\]

By using the projective depth \( z \) of the point \( p = (x, y, z)^T \), the projection operation can be written according to the equation:

\[
p = zK^{-1}p_0, \quad R_ip + t = z'K^{-1}p_i
\]

We consider three LR image acquisition models which are illustrated in Figure 1 and will be described in the following.
Figure 1. Cone beam X-ray imaging measures the attenuation of diverging X-ray beams (a). The goal of SR X-ray imaging is the reconstruction of these X-ray measurements on a high-resolution grid (b). Visualization of parallax effects for an X-ray camera which underwent a translation (c). Parallax-free projections with a pure camera rotation around the camera centre (d).

**Model I: Rotation around the ray source**

By rotating around the ray source (camera centre) the translational part becomes zero and the projective transformation \( H_i \) relating points in the projection images becomes:

\[
\begin{align*}
z'K^{-1} p_i &= zR_iK^{-1} p_0 \\
p_i &= \left( \frac{z}{z'} \right) K_i K^{-1} p_0
\end{align*}
\]

(5)

The homography \( H_i = KR_iK^{-1} \) (the scalar \( z/z' \) can be dropped) is independent of the imaged 3D scene and holds for all points. This homography is known as a conjugate rotation, and has a rich mathematical structure. For details, we refer to (14).

**Model II: Pure planar translation**

In case of translational motion, only coplanar points can be related by a homography. This means that the homography \( H \) holds only for points lying on a plane \( \pi = (n, d) \), defined by the plane normal \( n \) and a distance \( d \) to the origin.

\[
\begin{align*}
n^T p - d &= 0 \\
(n^T (zk^{-1} p_0) - d &= 0 \\
p_i &= \left( \frac{z}{z'} \right) K_i K^{-1} p_0 + \left( \frac{z}{z'} \right) d K_i n^T K^{-1} p_0
\end{align*}
\]

(6)

This equation leads to a well-known homography, \( H_i = KR_iK^{-1} + 1/dK_i n^T K^{-1} \), used for image mosaicing and panoramic image stitching (13,15). Using this type of motion, we cannot expect good SR results if the imaged object is large in the direction of the plane normal \( n \).

**Change of intrinsic camera parameters**

Changing the X-ray source [detector distance, as described in (12)], allows the acquisition of scaled LR input images suitable for SR imaging. The operation is equivalent to changing the focal distance \( f \) by a factor \( l_i \). Assuming an orthogonal detector set-up \((\phi = \pi/2)\), the projection matrix \( K_i \) becomes:

\[
K_i = \begin{bmatrix}
-l_{i} s_{h} & 0 & t_{0} \\
0 & -f_{i} & 0 \\
0 & 0 & 1
\end{bmatrix} K_i^{-1}
\]

Then the homography \( H = K_i K^{-1} \) simplifies to a simple scaling matrix with magnification factor \( l_i \):

\[
H = \begin{bmatrix} l_{i} s_{h} & 0 & (1 - l_{i}) t_{0} \\
0 & l_{i} s_{v} & (1 - l_{i}) v_{0} \\
0 & 0 & 1
\end{bmatrix}
\]

(9)

This acquisition type requires non-standard C-arm hardware that allows a changeable detector distance. Therefore, we could not implement it in our test environment. However, an advantage of this approach might be the simple motion model from a hardware point of view.

**Positioning error compensation**

It is well known that super-resolution techniques are limited by the exact determination of the motion parameters between the multiple LR-images (1). In theory, a motorized C-arm should supply the exact camera positioning. However, in practice, only a motorized C-arm guarantees the exact camera positioning.
positions. In practice, inaccuracies in C-arm positioning occur due to noise, mechanical flex, geometric distortions and errors in positioning the C-arm. Because of these image-acquisition errors, we can not expect quality HR reconstruction unless we compensate for them. To compensate for these errors, we employ 2D rigid image registration techniques.

We have tested two methods for determining the subpixel displacements needed to approximate the rigid transformation between images: the frequency-domain approach proposed by Vanderwalle (4) and a spatial-domain approach proposed by Keren et al. (5). The frequency–space method assumes that the input images are only partially aliased. Therefore, low-frequency parts can be used to determine the phase shift, which is related to a planar shift between the LR images. The phase shift is then robustly determined using a least squares method.

Both methods succeeded well in removing small positioning errors, but the spatial-domain approach proved to be more robust with respect to noisy input data. We thus briefly give an overview of the method in (5).

Kerens et al. (5) spatial-domain method uses a Taylor expansion of the transformation with parameters $\phi$, $t_x$ and $t_y$ to relate the coordinate systems of the images $f_0(x, y)$ and $f_1(x, y)$:

$$f_0(x, y) = f_1(x \cos(\phi) - y \sin(\phi) + t_x, y \sin(\phi) + x \sin(\phi) + t_y)$$

(10)

Using a second-order Taylor expansion for $\sin(\phi)$ and $\cos(\phi)$, we get:

$$f_0(x, y) \approx f_1 \left( \frac{x - x\frac{\phi^2}{2} - y\phi + t_x}{y - y\frac{\phi^2}{2} + x\phi + t_y} \right)$$

(11)

Expanding $f_1$ itself, using a first-order Taylor expansion, yields:

$$f_0(x, y) \approx f_1(x, y) + \left( t_x - y\phi - x\frac{\phi^2}{2} \frac{\partial f_1}{\partial x} \right) + \left( t_y + x\phi - y\frac{\phi^2}{2} \frac{\partial f_1}{\partial y} \right)$$

(12)

Now the error function between the images $f_0(x, y)$ and $f_1(x, y)$, depending on the transformation parameters, is given by:

$$E(t_x, t_y, \phi) = \frac{1}{2} \sum_{x, y, f_0, f_1} \left( f_1(x, y) + \left( t_x - y\phi - x\frac{\phi^2}{2} \frac{\partial f_1}{\partial x} \right) + \left( t_y + x\phi - y\frac{\phi^2}{2} \frac{\partial f_1}{\partial y} - f_0(x, y) \right) \right)^2$$

(13)

To compute the optimal transformation parameters, the partial derivatives of the error function are set to zero. By removing the non-linear terms and using the abbreviation $R = x \frac{\partial f_1}{\partial x} - y \frac{\partial f_1}{\partial y}$, we must solve the following linear system to get the optimal transformation parameters:

$$\begin{align*}
&\sum \left( \frac{\partial f_1}{\partial x} \right)^2 \frac{x}{2} + \sum \frac{\partial f_1}{\partial x} \frac{\partial f_1}{\partial y} \frac{t_y}{2} \\
&+ \sum R \frac{\partial f_1}{\partial x} \phi = \sum \left( \frac{\partial f_1}{\partial x} \right)^2 \frac{x}{2} \\
&+ \sum \frac{\partial f_1}{\partial y} \phi = \sum \left( \frac{\partial f_1}{\partial y} \right)^2 \frac{x}{2} \\
&+ \sum \frac{\partial f_1}{\partial x} \frac{\partial f_1}{\partial y} \frac{t_y}{2} \\
&+ \sum R \frac{\partial f_1}{\partial x} \frac{t_y}{2} \\
\end{align*}$$

(14)

Due to these approximations, the convergence range of this method is rather limited, i.e. it allows only very small rotational movements ($\leq 3^\circ$). However, we only need very small motions for our application scenario, where the method showed excellent results. In experiments with known ground truth data, where exact transformation parameters are known, we measured an average error of 0.023 pixel for shift estimation, and an average rotational error of 0.0038°. For the purpose of SR reconstruction, the compensation of positioning errors must be very accurate, while requiring only a very small convergence range, which makes this algorithm our method of choice for positioning-error correction.

C-arm positioning for LR image acquisition

To avoid redundant image acquisitions, we use a grid-like sampling pattern, illustrated in Figure 2. We proceed by acquiring the first, reference LR image. If we wish to obtain a HR image with a resolution $n$ times larger than that of the LR image, the pixel around the principal point is divided into $n^2$ uniform sub-patches. The camera is then transformed to target the centre of such a sub-patch in order to acquire a new LR image.

The position of the C-arm is encoded by a point $p$ and a beam direction vector $z$ of the principal ray. The camera transformation is then determined as the position where the principal ray intersects the centre of such a sub-patch, assuming that the camera undergoes the motion models described above.

To reposition the C-arm to the newly computed position, the configuration of the C-arm joints is determined via an inverse kinematic solution (16). To correct acquisition errors, the newly acquired projection image is registered to the reference image.
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Figure 2. (Left) Super-resolution software environment. The user defines the region of interest and the target resolution. The system automatically acquires the required number of LR projection images based on the upscale factor. (Right) Near-optimal sample pattern shown as plot of subpixel displacements of corrected camera projection images using 2D registration. Every mark represents a different LR image for a \( \times 3 \) resolution enhancement problem.

using the methods described above. We check the target position and continue the acquisition process until we have at least one sample of each sub-patch.

SR image reconstruction

Many different types of methods can be identified in the field of super-resolution. We briefly describe here four different approaches and point out important references. We compare five algorithms selected from these types, viz. the robust-SR method after Zomet et al. (17), projection on convex sets (18,19) (POCS), the Papoulis–Gerchberg algorithm (6,20), non-uniform bicubic interpolation (21,4) and normalized convolution (NC) (22). Describing the five algorithms in detail is beyond the scope of this paper. For completeness, the main ideas of the best performing method, normalized convolution, are given.

Reconstruction-based methods

Reconstruction-based methods, such as the iterated backprojection algorithm (23), use an iterative approach to minimize the error between simulated and acquired LR images. The algorithm (23) starts with an initial estimate of the HR output image, e.g. an interpolated version. The difference between the current estimate for the simulated images and the acquired images is used as a correction term for the new HR image. Similar to CT-imaging methods, the parts of the HR image causing the error are corrected using a backprojection operator. However, a unique solution cannot be found without introducing prior constraints. The robust-SR method after Zomet et al. (17) builds on the algorithm from (23). The method uses the median of the errors with respect to all input images in the backprojection step, which results in a more stable algorithm in the presence of noise.

Set theoretical methods

The projection on convex sets (POCS) method uses a set-theoretic approach originally proposed by Oskui and Stark (18,19). Based on the assumption that convex constraint sets can be defined on the HR image, a current estimate of the HR image is iteratively projected onto these convex constraint sets. The constraint sets are defined by the LR measurements and by prior assumptions about the HR output. Assuming a non-zero intersection of the constraint sets, the method converges to a solution in this intersection. The method also presents an alternative and elegant way to incorporate prior knowledge about the desired properties of the HR image.

Frequency domain methods

A well-known member of frequency domain methods is the Papoulis–Gerchberg algorithm (6,20). By assuming that some HR grid positions are known, the method sets all remaining unknown positions to zero. The image signal is then projected onto the set of band-limited signals, by removing all parts of the frequency spectrum which are higher than a maximal frequency (\( f_{\text{max}} \)). This operation results in filling the unknown grid positions with estimated values. Subsequently, the known HR grid positions are set again and the algorithm is repeated in an iterative fashion. Papoulis (6) showed that the algorithm converges if the number of known grid positions is greater than the number of unknown Fourier coefficients.

Non-uniform interpolation methods

Non-uniform data interpolation methods (21,22) in the spatial domain are a straightforward approach for SR reconstruction. These methods reconstruct the HR image signal by locally modelling the image with interpolation functions. The functions interpolate between known samples in a small neighbourhood. Subsequently, a
uniform resampling on the high-resolution grid is carried out. The normalized convolution (NC) (22) approach belongs to this class of interpolation methods. Local image neighbourhoods are modelled by projecting the acquired images onto a set of basis functions.

This approach is similar to a Taylor series expansion when polynomial basis functions \( (1, x, y, xy, x^2, y^2, \ldots) \) are used. After calculating the coefficients of the basis functions, denoted as \( p \), the HR image is resampled on the high resolution grid. The image intensity value at position \( s \) in the vicinity of \( s_0 \) is thus given by the following expansion:

\[
\hat{I}(s, s_0) = p_0(s_0) + p_1(s_0)x + p_2(s_0)y + p_3(s_0)x^2 + p_4(s_0)xy + p_5(s_0)y^2 + \ldots
\]

To determine the coefficients \( p \) with respect to the chosen basis functions, the approximation error is minimized over the support of an applicability function \( a \), centred at \( s_0 \). This function \( a \) localizes the fit, and weights the samples with respect to their distances. Weights are often determined employing Gaussian functions. In addition NC uses a certainty function \( c(s) \) to model the individual reliability of each LR image.

For the purpose of algorithm evaluation, we have implemented six different versions of this method in order to enhance the SR reconstruction performance. Versions 1–3 use a polynomial basis of the order 1, 2 and 3, exemplified in Figure 3 without certainty optimization, and versions 4 to 6 are analogous to version 1–3; however, they employ an additional certainty optimization term. This term weights samples with high variance lower, in order to reduce the influence of outliers.

Materials and methods

The five SR algorithms were tested on synthetic data with known ground truth and on real data acquired with the C-arm. For both data types, two different acquisition procedures were implemented: rotation around the ray source and planar motion. To test the robustness of algorithms to noisy input data, we have added zero mean additive Gaussian noise, \( \sigma = 3\% \), to the synthetic data.

Resolution improvement is often tested using the modulation transfer function (MTF) (24). However, two important issues occur when evaluating the MTF of SR algorithms using simulated radiographs. First, the violation of the shift invariance for the sampling MTF (24) hampers the MTF evaluation, since the position of the samples plays a major role. Second, we used the MTF in our experiments, but the outcomes of the different SR algorithms are hard to compare using the MTF values, since contrast measurements do not account for reconstruction artefacts. We choose to show results for the \( L_2 \) error metric. This is meaningful because in our experiments we do have an exact ground truth available, i.e. the digital reconstructed radiograph at the high-resolution grid, which is a standard error method that can also account for reconstruction artefacts.

The remainder of the set-up for these experiments is detailed in the following.

Synthetic projection data

In order to measure the performance of the five SR algorithms, we created a synthetic 3D phantom dataset, as shown in Figure 4. We refer to the Appendix for the exact definition of the phantom. From this 3D dataset we created simulated radiographs, at four resolutions (568², 1136², \ldots, 2272² pixels) which are multiples of the real C-arm set-up, using the motion models I and II (see above). The LR simulated radiographs (568² pixels) served as input data for the algorithms, while the HR radiographs served as ground truth. The intrinsic camera parameters were chosen analogous to the real mobile X-ray device: focal length 960 mm, and pixel size 0.40 mm/pixel. The simulated radiographs were obtained using a ray-tracing technique analogous to (25). All experiments with synthetic data were performed without

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Figure 4. Synthetic test datasets. From the synthetic 3D dataset (a), we simulated projection data in different resolutions (b, d), using the motion models I and II. Some datasets were corrupted with zero mean additive Gaussian noise (c) to test the algorithms with respect to acquisition error.

Figure 5. Circuit boards served as test objects for real data experiments. Some datasets (d, e) were acquired with various radiation settings (48–75 KV, 1.7–8.0 mA, 0.1 s pulse duration) to investigate the effect of image noise on SR reconstruction algorithms.

Real projection data

Real projection data was acquired with an experimental robotized C-arm (Ziehm imaging). The used C-arm was a modified Ziehm Vista C-arm with a 230 mm image intensifier system. The focal length of the system is 960 mm and the final image resolution is 568² pixels with a dynamic range of 12 bits. Due to the direct and inverse kinematics, the C-arm can be automatically positioned at arbitrary positions in order to acquire LR images. Details about the kinematic solution and the calibration of the robotic C-arm device are given in (26,27,16). The C-arm software (see Figure 2) is implemented in C/C++, using the libraries VTK (28), CLapack (29) and FFTW (30). The geometric distortions of the C-arm camera were determined using a calibration grid, and a distortion model based on bivariate polynomials of degree five (31). However, this error correction step becomes obsolete for the next generation of robotized C-arm devices, which will be equipped with non-distorting, digital flat panel detector technology.

We used very small circuit boards as a test object for the real data experiments because they allow for good visual judgement of the SR reconstruction result. We also used different radiation dose settings to investigate the effect of different noise levels on the SR reconstruction algorithms.

Results

First we turned our attention to simulated data, and analysed SR reconstruction results for different image-acquisition processes. The algorithms were run on both noisy and noiseless data. We then evaluated SR reconstructions with real X-ray data. Due to the lack of ground truth in this situation, the SR outcomes were compared visually.

Simulated X-ray data results

The simulated image was the ground truth in these experiments. The error between the reconstructed and the simulated ground truth image was measured using the $L_2$ norm. Table 1 shows results for a $\times 3$ resolution enhancement from noiseless input data. The POCS approach and the interpolation-based methods yield good results. The normalized convolution algorithm produces almost perfect reconstructions, as can be seen in Tables 1 and 2. This algorithm robustly reconstructs images even when given few LR inputs.

In general, the reconstruction quality increases with the number of input images. The HR reconstructions from
Table 1. Reconstruction results as a function of the number of LR-inputs for a \( \times 3 \) times resolution enhancement. The numbers represent the \( L_2 \) errors between the ground truth image and the reconstructed image (lower values denote better results).

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Image acquisition – pure rotation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interpolation</td>
<td>227.4 232.2 212.0 196.1 182.6 181.5 178.5 176.5 174.5</td>
</tr>
<tr>
<td>NC (v2)</td>
<td>137.9 110.1 99.0 68.6 53.3 43.8 38.6 31.1 26.9</td>
</tr>
<tr>
<td>Papoulis G.</td>
<td>13405.1 10485.7 5735.8 2044.3 2042.1 302.7 302.8 303.0 303.0</td>
</tr>
<tr>
<td>POCS</td>
<td>348.6 294.1 222.4 184.2 184.7 205.6 204.3 203.6 203.6</td>
</tr>
<tr>
<td>Zomet</td>
<td>1728.5 1580.9 1602.9 1630.6 1650.7 1471.6 1700.8 1772.5 1834.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Image acquisition – pure translation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interpolation</td>
<td>604.6 576.9 865.7 1471.0 1207.9 1266.5 1574.6 1025.0 1241.1</td>
</tr>
<tr>
<td>NC (v2)</td>
<td>168.6 138.0 105.5 99.5 99.2 98.3 101.4 101.4 96.6</td>
</tr>
<tr>
<td>Papoulis G.</td>
<td>12077.5 10091.9 6572.4 3185.9 3186.2 3186.9 3185.0 3184.8 126.9</td>
</tr>
<tr>
<td>POCS</td>
<td>349.5 241.2 141.9 114.4 114.6 114.7 123.9</td>
</tr>
<tr>
<td>Zomet</td>
<td>1930.3 1913.1 2403.3 2469.3 2699.7 2866.1 3014.5 2622.1</td>
</tr>
</tbody>
</table>

Table 2. Reconstruction results as a function of the number of noiseless LR inputs for a \( \times 4 \) resolution enhancement (\( L_2 \) errors between the ground truth image and the reconstructed image).

<table>
<thead>
<tr>
<th>Algorithm</th>
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<tr>
<td>Interpolation</td>
<td>427.1 421.9 420.7 425.1 423.6 424.4 421.9 421.6 419.8</td>
</tr>
<tr>
<td>NC (v5)</td>
<td>114.9 112.7 111.4 113.0 112.9 112.0 109.9 108.8 107.5</td>
</tr>
<tr>
<td>Papoulis G.</td>
<td>10918.3 17240.6 17237.8 13801.4 13805.7 11225.3 7225.1 4699.2 2281.7</td>
</tr>
<tr>
<td>POCS</td>
<td>370.1 369.8 369.6 301.1 301.0 271.1 233.8 219.9 214.1</td>
</tr>
<tr>
<td>Zomet</td>
<td>3507.8 3432.3 3586.7 3751.7 3804.1 3770.8 3711.9 3800.4 3872.1</td>
</tr>
</tbody>
</table>

Clinical CT data results

To show the benefits of SR techniques on real clinical CT data, we modified a clinical dataset of a distal femur bone by virtually drilling a small hole into the bone, as shown in Figure 8a. After this modification, we generated DRRs from the dataset and applied the NCv1 method with a \( \times 4 \) resolution enhancement. Compared to the magnified input image Figure 9a, the super-resolved image 9b shows a clear delineation of the artificially inserted cavity. However, the contrast of the image is rather low and the resulting HR image must be carefully inspected. Nevertheless, this example demonstrates that...
Table 3. Reconstruction results as a function of the number of noisy LR inputs for a \( \times 3 \) resolution enhancement (\( L_2 \) errors between the ground truth image and the reconstructed image)

<table>
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<th>Algorithm</th>
<th>Image acquisition – pure rotation</th>
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<tr>
<td>Interp.</td>
<td>1635.5 1434.0 1402.9 1355.3 1296.7 1341.8 1359.7 1458.4 1423.4</td>
</tr>
<tr>
<td>NC (v5)</td>
<td>872.9 849.6 819.9 805.9 780.3 770.0 784.7 779.7 762.2</td>
</tr>
<tr>
<td>Papoulis G.</td>
<td>2130.2 1741.9 1738.6 1722.5 1722.5 1354.6 1355.0 9802.3 9796.9</td>
</tr>
<tr>
<td>POCs</td>
<td>1847.2 1825.5 1833.1 1839.5 1841.5 1970.0 1970.7 2056.7 2060.5</td>
</tr>
<tr>
<td>Zomet</td>
<td>2379.0 2290.5 2566.9 2467.9 2812.1 2636.2 3036.6 2811.4 3102.3</td>
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</table>

<table>
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<tbody>
<tr>
<td>Interp.</td>
<td>1748.9 1499.8 1648.4 2713.2 1832.5 1826.9 1704.9 1594.1 1773.8</td>
</tr>
<tr>
<td>NC (v5)</td>
<td>1115.1 1054.8 1070.3 1068.1 1016.8 978.7 991.6 983.5 973.3</td>
</tr>
<tr>
<td>Papoulis G.</td>
<td>21302.8 17411.9 17386.6 17326.4 17225.1 13546.9 13550.9 9802.3 9796.9</td>
</tr>
<tr>
<td>POCs</td>
<td>1847.2 1835.5 1838.1 1839.5 1841.6 1970.0 1970.7 2057.6 2060.5</td>
</tr>
<tr>
<td>Zomet</td>
<td>2379.0 2290.5 2566.9 2467.9 2812.1 2636.2 3036.6 2811.4 3102.3</td>
</tr>
</tbody>
</table>

Table 4. Reconstruction results as a function of the number of noisy LR inputs for a \( \times 4 \) resolution enhancement (\( L_2 \) errors between the ground truth image and the reconstructed image)

<table>
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<tr>
<td>Interp.</td>
<td>2465.1 2592.9 2565.4 2666.1 2484.9 2521.9 2545.2 2518.7 2523.6</td>
</tr>
<tr>
<td>NC (v5)</td>
<td>1764.1 1782.0 1662.8 1701.8 1622.7 1663.0 1626.2 1645.8 1610.6</td>
</tr>
<tr>
<td>Papoulis G.</td>
<td>24203.3 29999.6 26157.1 2372.2 18585.8 18601.6 18619.9 14823.0 14840.5</td>
</tr>
<tr>
<td>POCs</td>
<td>2830.6 2904.1 2903.1 2956.9 3032.4 3037.8 3044.6 3150.4 3157.4</td>
</tr>
<tr>
<td>Zomet</td>
<td>6015.6 5770.4 5602.1 5541.3 5609.4 5542.4 5470.2 5523.9</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Image acquisition – pure translation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interp.</td>
<td>3304.1 3381.2 3325.2 3573.1 3759.0 3572.7 3574.1 3561.2 3362.4</td>
</tr>
<tr>
<td>NC (v2)</td>
<td>2397.1 2392.1 2369.2 2388.0 2393.9 2445.5 2389.7 2252.7 2264.0</td>
</tr>
<tr>
<td>Papoulis G.</td>
<td>3172.5 15886.0 15867.7 12975.0 11920.8 11889.6 11889.9 15404.2 11354.0</td>
</tr>
<tr>
<td>POCs</td>
<td>3824.5 3824.5 3824.0 3560.3 3790.3 4313.8 4313.8 3573.1 3551.0</td>
</tr>
<tr>
<td>Zomet</td>
<td>7212.8 7401.3 6902.1 7115.7 6113.5 7360.6 7152.0 6906.0 5497.2</td>
</tr>
</tbody>
</table>

Figure 6. Evaluation of the normalized convolution (NC) algorithm of orders 1–3 with noiseless input data. The plot shows the distance (\( L_2 \) norm) of the result image to the ground truth as a function of the number of input images, using the methods NCv1, NCv2 and NCv3 (a) and NCv4, NCv5 and NCv6 (b)
Figure 7. Evaluation of versions of the normalized convolution algorithm with input data corrupted with additive Gaussian noise. The plot shows the distance (L2 norm) of the result image to the ground truth as a function of the number of input images, using the methods NCv1, NCv2 and NCv3 (a) and NCv4, NCv5 and NCv6 (b).

Figure 8. Experiment with a clinical dataset of a distal femur bone (a). The red circle shows the position of a small artificial hole. Generated X-ray (DRR) projection of the modified dataset (b).

Figure 9. Comparison of the relevant image region from Figure 8. (a) The magnified input image. The super-resolved image (b) shows a clear delineation of the artificially inserted cavity.
Figure 10. SR reconstruction from real data (48 KV, 1.7 mA): (a) Exemplary LR input image. SR results: (b) Zomet; (c) bi-cubic interpolation; (d) POCS; (e) NCv2; (f) NCv5

Figure 11. SR reconstruction from real data taken with higher radiation dose (75 KV, 8.0 mA): (a) Exemplary LR input image. SR results: (b) Zomet; (c) Bi-cubic interpolation; (d) POCS; (e) NCv2; (f) NCv5

Clinical applications might benefit from SR techniques that allow for an adaptive zooming of relevant image regions.

Real X-ray data results

The SR reconstructions from real X-ray data must be evaluated by visual comparison, because a ground truth HR image is not available. In this set-up, we used very small circuit boards as test objects. By using different radiation settings, we investigated the effect of different noise levels present. In Figure 11 one may observe that the HR reconstructions using the lower radiation dose settings show very little noise. This might help to reduce the overall radiation dose by acquiring a set of very noisy low-dose X-ray images and combining them into an HR image using SR techniques. We increased the tube current and acceleration voltage to reduce the noise level in the LR images. These experiments allow the identification of small conductor pathways on the...
1. circuit board. However, the reconstruction performance is comparable to the low-dose experiments. Zomet's algorithm produces sharp edges, but it exhibits severe reconstruction artifacts around these edges, as can be seen in Figure 10b. The bi-cubic interpolation and the POCS method show good and stable results. The NC method is again slightly superior. For instance, the delineation of the processor pins is slightly better with the NC method compared to the other algorithms. Very high resolution enhancements, e.g., resolution enhancement factors $\geq 5$, are difficult to achieve, and the SR reconstructions become corrupted by artifacts. This effect is depicted in Figure 12. The $\times 5$ resolution enhancement shows small ripples, which are most likely due to reconstruction errors. However, the image is substantially enhanced compared to the original LR multi-frame images, and provides many more details, as can be seen in Figure 13. Despite the reconstruction artifacts, a practical application of such high-resolution enhancements is questionable, due to the high number (usually $>30$) of required LR images.
However, the SR reconstructions show many details which are not visible in the original images. For instance, the judgement of solder straps (pin size 0.3 mm) is only possible in the HR image, as shown in the red box in Figure 13.

Discussion and future work

Although the mathematical foundations of super-resolution imaging have been thoroughly researched (1, 8), they have had few applications in the domain of medical, mobile X-ray imaging. To the best of our knowledge, very little literature exists about super-resolution imaging using mobile X-ray devices. One reason might be the difficult acquisition of the low-resolution multi-frame images using conventional C-arms. The use of a robotized C-arm for this purpose is an elegant solution that enables super-resolution in a simple and adaptive manner.

In this paper we have described methods to achieve super-resolution X-ray imaging with a new experimental robotic C-arm device. We showed important aspects of X-ray super-resolution concerning multi-frame image acquisition, positional error compensation and HR reconstruction. We shed some light on the practical application of super-resolution X-ray imaging by providing numerical results for standard super-resolution algorithms. The synthetic data experiments showed the superiority of the normalized convolution method, especially in the case of sparse and noisy input data. The visual results with real X-ray images also support this result. Simple interpolation and the POCS method led to good results as well. However, in the case of noisy measurements, the NC method performed better.

In conclusion, the proposed system allows for the reconstruction of images with substantially increased resolution. In the reconstruction process, image noise is considerably reduced. The calculated high-resolution images reveal details that are not perceptible in the input data.

Our future work will concentrate on the improvement of SR techniques with respect to robustness to noisy input data, and on the elimination of positional inconsistencies. It would be also very interesting to compare the signal: noise ratio of a high-dose X-ray image with the signal: noise ratio of a super-resolution image reconstructed from low-resolution X-ray images acquired using an equivalent or smaller amount of radiation dose. Additionally, we will investigate the usefulness of SR techniques with respect to real medical applications, such as the early detection of osteoporosis or the detection of calcifications.

Appendix

We provide the exact definition for the used 3D phantom dataset and the DRR data generation process to allow the reproduction of the results obtained by the used SR techniques.

Circular grid phantom dataset

The phantom is composed of five spheres with radius 12 mm. They are composed of 3D grids with a line thickness of 0.3 mm. The spacing between the grid elements, as shown in Figure 4 a, is 0.3 mm for the centre sphere and 0.6, 0.9, 1.2 and 1.5 mm for the respective surrounding spheres. The centres of the spheres are located at (0.0, 0.0, 0.0), (18, 18, 18), (−18, −18, −18), (18, −18, −18) and (−18, 18, 18) with respect to a coordinate frame. The centre of the volume (3D phantom) corresponds to (0, 0, 0) and all coordinates are expressed in mm. The volume data structure consists of 512 voxels with an isotropic voxel size of 0.3 mm. The camera coordinate system was aligned with the coordinate axes of the 3D dataset. The focus-to-object distance was 750 mm, the object-to-detector distance was 150 mm. The extent of the object in the z-direction (principal axis of the camera) was therefore 2 × (18 + 12) = 60 mm.
References


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