Motivation
In clinical medicine, high-resolution (HR) medical images are visual and effective tools for physicians to make accurate diagnoses. However, acquisition of HR medical images is complicated by many factors. Low-resolution (LR) medical images will badly influence physicians’ diagnoses; thus, super-resolution (SR) techniques for medical images have gradually become extremely crucial.

Contribution
- A new medical image SR network, namely deep multi-scale network (DMSN), in the uniform discrete curvelet transform (UDCT) domain is proposed.
- DMSN is made up of a set of cascaded multi-scale fusion (MSF) blocks. In each MSF block, we use convolution kernels of different sizes to adaptively detect the local multiscale feature, and then local residual learning (LRL) is used to learn effective feature from preceding MSF block and current multi-scale features.
- We use global feature fusion (GFF) to jointly and adaptively learn global hierarchical features in a holistic manner.
- Compared with other prediction methods in spatial domain, we applied DMSN in UDCT domain, which enables a better representation of global topological structure and local texture detail of HR images.

UDCT

The left side is the original image. The right side is the red zone of the LR image (8×), the SR image, and the original image from top to bottom

Network structure

(a) Network structure consists of three parts, the shallow feature extraction module, the multiscale feature extraction module, and the up-sample module.

(b) MSF block is constructed by a three-bypass network and different bypass uses different convolutional kernel.

(c) UDCT is used in the Network structure.

Results

Qualitative results

Original images
Bicubic images
SR images

Comparison results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>scale</th>
<th>Bicubic</th>
<th>VDSR</th>
<th>DRNN</th>
<th>MemNet</th>
<th>IDN</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breast</td>
<td>4</td>
<td>30.514/0.879</td>
<td>32.053/0.899</td>
<td>34.732/0.915</td>
<td>33.510/0.898</td>
<td>32.482/0.906</td>
<td>32.745/0.911</td>
</tr>
<tr>
<td>8</td>
<td>26.736/0.801</td>
<td>28.134/0.821</td>
<td>29.513/0.837</td>
<td>28.456/0.836</td>
<td>28.310/0.833</td>
<td>28.745/0.844</td>
<td></td>
</tr>
<tr>
<td>Brain</td>
<td>4</td>
<td>32.766/0.907</td>
<td>34.362/0.922</td>
<td>34.795/0.931</td>
<td>34.952/0.935</td>
<td>35.041/0.937</td>
<td>35.246/0.944</td>
</tr>
<tr>
<td>8</td>
<td>28.249/0.822</td>
<td>30.211/0.840</td>
<td>29.469/0.849</td>
<td>29.528/0.850</td>
<td>29.540/0.851</td>
<td>29.513/0.857</td>
<td></td>
</tr>
<tr>
<td>Lung</td>
<td>4</td>
<td>25.033/0.825</td>
<td>27.753/0.868</td>
<td>30.139/0.878</td>
<td>30.102/0.885</td>
<td>30.156/0.881</td>
<td>30.454/0.889</td>
</tr>
<tr>
<td>8</td>
<td>22.432/0.737</td>
<td>24.960/0.784</td>
<td>24.560/0.792</td>
<td>24.560/0.801</td>
<td>24.511/0.797</td>
<td>24.625/0.804</td>
<td></td>
</tr>
<tr>
<td>Kidney</td>
<td>4</td>
<td>28.369/0.848</td>
<td>31.754/0.899</td>
<td>32.166/0.906</td>
<td>32.313/0.914</td>
<td>32.210/0.911</td>
<td>32.185/0.921</td>
</tr>
<tr>
<td>8</td>
<td>24.940/0.751</td>
<td>26.257/0.777</td>
<td>26.455/0.796</td>
<td>26.513/0.805</td>
<td>26.412/0.799</td>
<td>26.891/0.811</td>
<td></td>
</tr>
</tbody>
</table>

Effectiveness of UDCT prediction

Input
UDCT
Low frequency
High frequency
Fusion
Output

Low-frequency describes global topological structure of an image
High-frequency describes the local texture details of an image, such as image edges and contours
The high-frequency coefficients of UDCT represent the details accurately