Data Augmentation for Deep Learning

Summary:

1. SimpleITK supports a variety of spatial transformations (global or local) that can be used to augment your dataset via resampling directly from the original images (which vary in size).
2. Resampling to a uniform size can be done either by specifying the desired sizes resulting in non-isotropic pixel spacings (most often) or by specifying an isotropic pixel spacing and one of the image sizes (width,height,depth).
3. SimpleITK supports a variety of intensity transformations (blurring, adding noise etc.) that can be used to augment your dataset after it has been resampled to the size expected by your network.

This notebook illustrates the use of SimpleITK to perform data augmentation for deep learning. Note that the code is written so that the relevant functions work for both 2D and 3D images without modification.

Data augmentation is a model based approach for enlarging your training set. The problem being addressed is that the original dataset is not sufficiently representative of the general population of images. As a consequence, if we only train on the original dataset the resulting network will not generalize well to the population (overfitting).

Using a model of the variations found in the general population and the existing dataset we generate additional images in the hope of capturing the population variability. Note that if the model you use is incorrect you can cause harm, you are generating observations that do not occur in the general population and are optimizing a function to fit them.

In [1]:
```
import SimpleITK as sitk
import numpy as np
import os

import gui
%matplotlib notebook

from downloaddata import fetch_data as fdata
from utilities import parameter_space_regular_grid_sampling, similarity3D_paramet
er_space_regular_sampling, eul2quat

OUTPUT_DIR = 'output'
```

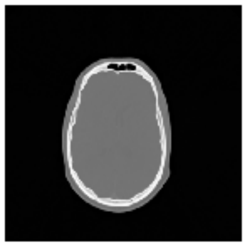
Load data

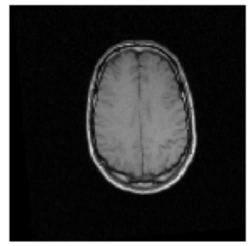
Load the images. You can work through the notebook using either the original 3D images or 2D slices from the original volumes.

In [2]:
```
data = [sitk.ReadImage(fdata("training_001_ct.mha")),
        sitk.ReadImage(fdata("training_001_mr_T1.mha"))]
# Comment out the following line if you want to work in 3D. Note that in 3D some
of the notebook visualizations are
# disabled.
data = [data[0][:,:,data[0].GetDepth()//2], data[1][:,:,data[1].GetDepth()//2]]
```

```
Fetching training_001_ct.mha
Fetching training_001_mr_T1.mha
```

In [3]:
```
def disp_images(images, fig_size, wl_list=None):
    if images[0].GetDimension()==2:
      gui.multi_image_display2D(image_list=images, figure_size=fig_size, window_l
evel_list=wl_list)
    else:
      gui.MultiImageDisplay(image_list=images, figure_size=fig_size, window_level
_list=wl_list)

disp_images(data, fig_size=(6,2))
```





The original data often needs to be modified. In this example we would like to crop the images so that we only keep the informative regions. We can readily separate the foreground and background using an appropriate threshold, in our case we use Otsu's threshold selection method.

In [4]:
```
def threshold_based_crop(image):
    '''
    '''
    # Set pixels that are in [min_intensity,otsu_threshold] to inside_value, valu
es above otsu_threshold are
    # set to outside_value. The anatomy has higher intensity values than the back
ground, so it is outside.
    inside_value = 0
    outside_value = 255
    label_shape_filter = sitk.LabelShapeStatisticsImageFilter()
    label_shape_filter.Execute( sitk.OtsuThreshold(image, inside_value, outside_v
alue) )
    bounding_box = label_shape_filter.GetBoundingBox(outside_value)
    # The bounding box's first "dim" entries are the starting index and last "dim
" entries the size
    return sitk.RegionOfInterest(image, bounding_box[int(len(bounding_box)/2):],
bounding_box[0:int(len(bounding_box)/2)])


modified_data = [threshold_based_crop(img) for img in data]

disp_images(modified_data, fig_size=(6,2))
```

At this point we select the images we want to work with, skip the following cell if you want to work with the original data.

In [5]:
```
data = modified_data
```

Augmentation using spatial transformations

We next illustrate the generation of images by specifying a list of transformation parameter values representing a sampling of the transformation's parameter space.

The code below is agnostic to the specific transformation and it is up to the user to specify a valid list of transformation parameters (correct number of parameters and correct order).

In most cases we can easily specify a regular grid in parameter space by specifying ranges of values for each of the parameters. In some cases specifying parameter values may be less intuitive (i.e. versor representation of rotation).

Create reference domain

All input images will be resampled onto the reference domain.

This domain is defined by two constraints: the number of pixels per dimension and the physical size we want the reference domain to occupy. The former is associated with the computational constraints of deep learning where using a small number of pixels is desired. The later is associated with the SimpleITK concept of an image, it occupies a region in physical space which should be large enough to encompass the object of interest.

In [6]:
```
dimension = data[0].GetDimension()

# Physical image size corresponds to the largest physical size in the training se
t, or any other arbitrary size.
reference_physical_size = np.zeros(dimension)
for img in data:
    reference_physical_size[:] = [(sz-1)*spc if sz*spc>mx  else mx for sz,spc,mx
in zip(img.GetSize(), img.GetSpacing(), reference_physical_size)]

# Create the reference image with a zero origin, identity direction cosine matrix
and dimension
reference_origin = np.zeros(dimension)
reference_direction = np.identity(dimension).flatten()

# Select arbitrary number of pixels per dimension, smallest size that yields desi
red results (non-isotropic pixels)
reference_size = [128]*dimension
reference_spacing = [ phys_sz/(sz-1) for sz,phys_sz in zip(reference_size, refere
nce_physical_size) ]

# Another possibility is that you want isotropic pixels, uncomment the following
lines.
#reference_size_x = 128
#reference_spacing = [reference_physical_size[0]/(reference_size_x-1)]*dimension
#reference_size = [int(phys_sz/(spc) + 1) for phys_sz,spc in zip(reference_physic
al_size, reference_spacing)]

reference_image = sitk.Image(reference_size, data[0].GetPixelIDValue())
reference_image.SetOrigin(reference_origin)
reference_image.SetSpacing(reference_spacing)
reference_image.SetDirection(reference_direction)

# Always use the TransformContinuousIndexToPhysicalPoint to compute an indexed po
int's physical coordinates as
# this takes into account size, spacing and direction cosines. For the vast major
ity of images the direction
# cosines are the identity matrix, but when this isn't the case simply multiplyin
g the central index by the
# spacing will not yield the correct coordinates resulting in a long debugging se
ssion.
reference_center = np.array(reference_image.TransformContinuousIndexToPhysicalPoi
nt(np.array(reference_image.GetSize())/2.0))
```

Data generation

Once we have a reference domain we can augment the data using any of the SimpleITK global domain transformations. In this notebook we use a similarity transformation (the generate_images function is agnostic to this specific choice).

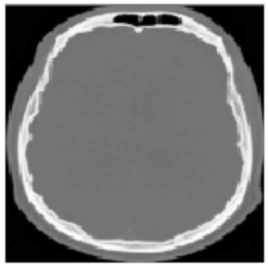
Note that you also need to create the labels for your augmented images. If these are just classes then your processing is minimal. If you are dealing with segmentation you will also need to transform the segmentation labels so that they match the transformed image. The following function easily accommodates for this, just provide the labeled image as input and use the sitk.sitkNearestNeighbor interpolator so that you do not introduce labels that were not in the original segmentation.

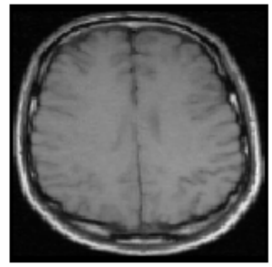
In [7]:
```
def augment_images_spatial(original_image, reference_image, T0, T_aug, transforma
tion_parameters,
                    output_prefix, output_suffix,
                    interpolator = sitk.sitkLinear, default_intensity_value = 0.0
):
    '''
    Generate the resampled images based on the given transformations.
    Args:
        original_image (SimpleITK image): The image which we will resample and tr
ansform.
        reference_image (SimpleITK image): The image onto which we will resample.
        T0 (SimpleITK transform): Transformation which maps points from the refer
ence image coordinate system
            to the original_image coordinate system.
        T_aug (SimpleITK transform): Map points from the reference_image coordina
te system back onto itself using the
               given transformation_parameters. The reason we use this transforma
tion as a parameter
               is to allow the user to set its center of rotation to something ot
her than zero.
        transformation_parameters (List of lists): parameter values which we use
T_aug.SetParameters().
        output_prefix (string): output file name prefix (file name: output_prefix
_p1_p2_..pn_.output_suffix).
        output_suffix (string): output file name suffix (file name: output_prefix
_p1_p2_..pn_.output_suffix).
        interpolator: One of the SimpleITK interpolators.
        default_intensity_value: The value to return if a point is mapped outside
the original_image domain.
    '''
    all_images = [] # Used only for display purposes in this notebook.
    for current_parameters in transformation_parameters:
        T_aug.SetParameters(current_parameters)
        # Augmentation is done in the reference image space, so we first map the
points from the reference image space
        # back onto itself T_aug (e.g. rotate the reference image) and then we ma
p to the original image space T0.
        T_all = sitk.Transform(T0)
        T_all.AddTransform(T_aug)
        aug_image = sitk.Resample(original_image, reference_image, T_all,
                                  interpolator, default_intensity_value)
        sitk.WriteImage(aug_image, output_prefix + '_' +
                        '_'.join(str(param) for param in current_parameters) +'_.
' + output_suffix)

        all_images.append(aug_image) # Used only for display purposes in this not
ebook.
    return all_images # Used only for display purposes in this notebook.
```

Before we can use the generate_images function we need to compute the transformation which will map points between the reference image and the current image as shown in the code cell below.

Note that it is very easy to generate large amounts of data, the calls to np.linspace with m parameters each having n values results in n^m images, so don't forget that these images are also saved to disk. **If you run the code below for 3D data you will generate 6561 volumes (3^7 parameter combinations times 3 volumes).**

In [8]:
```
aug_transform = sitk.Similarity2DTransform() if dimension==2 else sitk.Similarity
3DTransform()

all_images = []

for index,img in enumerate(data):
    # Transform which maps from the reference_image to the current img with the t
ranslation mapping the image
    # origins to each other.
    transform = sitk.AffineTransform(dimension)
    transform.SetMatrix(img.GetDirection())
    transform.SetTranslation(np.array(img.GetOrigin()) - reference_origin)
    # Modify the transformation to align the centers of the original and referenc
e image instead of their origins.
    centering_transform = sitk.TranslationTransform(dimension)
    img_center = np.array(img.TransformContinuousIndexToPhysicalPoint(np.array(im
g.GetSize())/2.0))
    centering_transform.SetOffset(np.array(transform.GetInverse().TransformPoint(
img_center) - reference_center))
    centered_transform = sitk.Transform(transform)
    centered_transform.AddTransform(centering_transform)

    # Set the augmenting transform's center so that rotation is around the image
center.
    aug_transform.SetCenter(reference_center)

    if dimension == 2:
        # The parameters are scale (+-10%), rotation angle (+-10 degrees), x tran
slation, y translation
        transformation_parameters_list = parameter_space_regular_grid_sampling(np
.linspace(0.9,1.1,3),
                                                                                np
.linspace(-np.pi/18.0,np.pi/18.0,3),
                                                                                np
.linspace(-10,10,3),
                                                                                np
.linspace(-10,10,3))
    else:
        transformation_parameters_list = similarity3D_parameter_space_regular_sam
pling(np.linspace(-np.pi/18.0,np.pi/18.0,3),

np.linspace(-np.pi/18.0,np.pi/18.0,3),

np.linspace(-np.pi/18.0,np.pi/18.0,3),

np.linspace(-10,10,3),

np.linspace(-10,10,3),

np.linspace(-10,10,3),

np.linspace(0.9,1.1,3))
    generated_images = augment_images_spatial(img, reference_image, centered_tran
sform,
                                              aug_transform, transformation_parameters_l
ist,
                                              os.path.join(OUTPUT_DIR, 'spatial_aug'+str
(index)), 'mha')

    if dimension==2: # in 2D we join all of the images into a 3D volume which we
use for display.
        all_images.append(sitk.JoinSeries(generated_images))
# If working in 2D, display the resulting set of images.
if dimension==2:
```





What about flipping

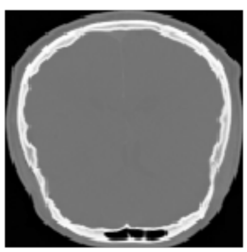
Reflection using SimpleITK can be done in one of several ways:

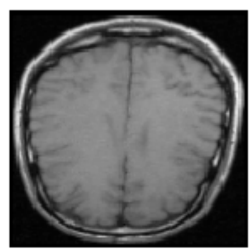
1. Use an affine transform with the matrix component set to a reflection matrix. The columns of the matrix correspond to the $\mathbf{x}, \mathbf{y}$ and $\mathbf{z}$ axes. The reflection matrix is constructed using the plane, 3D, or axis, 2D, which we want to reflect through with the standard basis vectors, $\mathbf{e}_i, \mathbf{e}_j$, and the remaining basis vector set to $-\mathbf{e}_k$.
   - Reflection about xy plane: $[\mathbf{e}_1, \mathbf{e}_2, -\mathbf{e}_3]$.
   - Reflection about xz plane: $[\mathbf{e}_1, -\mathbf{e}_2, \mathbf{e}_3]$.
   - Reflection about yz plane: $[-\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3]$.
2. Use the native slicing operator(e.g. img[:,::-1,:]), or the FlipImageFilter after the image is resampled onto the reference image grid.

We prefer option 1 as it is computationally more efficient. It combines all transformation prior to resampling, while the other approach performs resampling onto the reference image grid followed by the reflection operation. An additional difference is that using slicing or the FlipImageFilter will also modify the image origin while the resampling approach keeps the spatial location of the reference image origin intact. This minor difference is of no concern in deep learning as the content of the images is the same, but in SimpleITK two images are considered equivalent iff their content and spatial extent are the same.

The following cell corresponds to the preferred option, using an affine transformation:

In [9]:
```
flipped_images = []
for index,img in enumerate(data):
    # Compute the transformation which maps between the reference and current ima
ge (same as done above).
    transform = sitk.AffineTransform(dimension)
    transform.SetMatrix(img.GetDirection())
    transform.SetTranslation(np.array(img.GetOrigin()) - reference_origin)
    centering_transform = sitk.TranslationTransform(dimension)
    img_center = np.array(img.TransformContinuousIndexToPhysicalPoint(np.array(im
g.GetSize())/2.0))
    centering_transform.SetOffset(np.array(transform.GetInverse().TransformPoint(
img_center) - reference_center))
    centered_transform = sitk.Transform(transform)
    centered_transform.AddTransform(centering_transform)

    flipped_transform = sitk.AffineTransform(dimension)
    flipped_transform.SetCenter(reference_image.TransformContinuousIndexToPhysica
lPoint(np.array(reference_image.GetSize())/2.0))
    if dimension==2: # matrices in SimpleITK specified in row major order
        flipped_transform.SetMatrix([1,0,0,-1])
    else:
        flipped_transform.SetMatrix([1,0,0,0,-1,0,0,0,1])
    centered_transform.AddTransform(flipped_transform)

    # Resample onto the reference image
    flipped_images.append(sitk.Resample(img, reference_image, centered_transform,
sitk.sitkLinear, 0.0))
disp_images(flipped_images, fig_size=(6,2))
```





Radial Distortion

Some 2D medical imaging modalities, such as endoscopic video and X-ray images acquired with C-arms using image intensifiers, exhibit radial distortion. The common model for such distortion was described by Brown ["Close-range camera calibration", Photogrammetric Engineering, 37(8):855–866, 1971]:

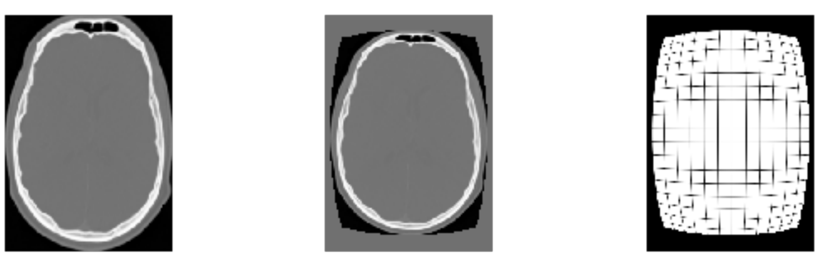
$$\mathbf{p}_u = \mathbf{p}_d + (\mathbf{p}_d - \mathbf{p}_c)(k_1 r^2 + k_2 r^4 + k_3 r^6 + \dots)$$

where:

- $\mathbf{p}_u$ is a point in the undistorted image
- $\mathbf{p}_d$ is a point in the distorted image
- $\mathbf{p}_c$ is the center of distortion
- $r = \|\mathbf{p}_d - \mathbf{p}_c\|$
- k_i are coefficients of the radial distortion

Using SimpleITK operators we represent this transformation using a deformation field as follows:

In [10]:
```
def radial_distort(image, k1, k2, k3, distortion_center=None):
    c = distortion_center
    if not c: # The default distortion center coincides with the image center
        c = np.array(image.TransformContinuousIndexToPhysicalPoint(np.array(image
.GetSize())/2.0))

    # Compute the vector image (p_d - p_c)
    delta_image = sitk.Image(image.GetSize(), sitk.sitkVectorFloat64)
    delta_image.CopyInformation(image)
    index_ranges = [np.arange(0,i) for i in image.GetSize()]
    for indexes in np.nditer(np.meshgrid(*index_ranges)):
        index = tuple(map(np.asscalar, indexes))
        delta_image[index] = np.array(image.TransformContinuousIndexToPhysicalPoi
nt(index)) - c
    delta_image_components = [sitk.VectorIndexSelectionCast(delta_image,index) fo
r index in range(image.GetDimension())]

    # Compute the radial distortion expression
    r2_image = sitk.Image(image.GetSize(), sitk.sitkFloat64)
    r2_image.CopyInformation(image)
    for img in delta_image_components:
        r2_image+=img**2
    r4_image = r2_image**2
    r6_image = r2_image*r4_image
    disp_image = k1*r2_image + k2*r4_image + k3*r6_image
    displacement_image = sitk.Compose([disp_image*img for img in delta_image_comp
onents])

    displacement_field_transform = sitk.DisplacementFieldTransform(displacement_i
mage)
    return sitk.Resample(image, image, displacement_field_transform)

# We only run the distortion on 2D images (the code will work for 3D but it is sl
ow)
if dimension==2:
    k1 = 0.00001
    k2 = 0.0000000000001
    k3 = 0.0000000000001
    original_image = data[0]
    distorted_image = radial_distort(original_image, k1, k2, k3)
    # Use a grid image to highlight the distortion.
    grid_image = sitk.GridSource(outputPixelType=sitk.sitkUInt16, size=original_i
mage.GetSize(),
                                 sigma=(0.1,0.1), gridSpacing=(20.0,20.0))
    grid_image.CopyInformation(original_image)
    distorted_grid = radial_distort(grid_image, k1, k2, k3)
    disp_images([original_image, distorted_image, distorted_grid], fig_size=(6,2)
)
```



Transferring deformations - exercise for the interested reader

Using SimpleITK we can readily transfer deformations from a spatio-temporal data set to another spatial data set to simulate temporal behavior. Case in point, using a 4D (3D+time) CT of the thorax we can estimate the respiratory motion using non-rigid registration and Free Form Deformation or displacement field transformations. We can then register a new spatial data set to the original spatial CT (non-rigidly) followed by application of the temporal deformations.

Note that unlike the arbitrary spatial transformations we used for data-augmentation above this approach is more computationally expensive as it involves multiple non-rigid registrations. Also note that as the goal is to use the estimated transformations to create plausible deformations you may be able to relax the required registration accuracy.

Augmentation using intensity modifications

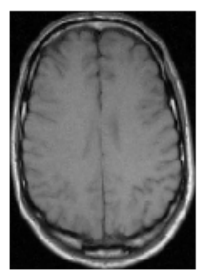
SimpleITK has many filters that are potentially relevant for data augmentation via modification of intensities. For example:

- Image smoothing, always read the documentation carefully, similar filters use use different parametrization σ vs. variance (σ^2):
  - Discrete Gaussian (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1DiscreteGaussianImageFilter.html)
  - Recursive Gaussian (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1RecursiveGaussianImageFilter.html)
  - Smoothing Recursive Gaussian (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1SmoothingRecursiveGaussianImageFilter.html)
- Edge preserving image smoothing:
  - Bilateral image filtering (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1BilateralImageFilter.html), edge preserving smoothing.
  - Median filtering (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1MedianImageFilter.html)
- Adding noise to your images:
  - Additive Gaussian (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1AdditiveGaussianNoiseImageFilter.html)
  - Salt and Pepper / Impulse (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1SaltAndPepperNoiseImageFilter.html)
  - Shot/Poisson (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1ShotNoiseImageFilter.html)
  - Speckle/multiplicative (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1SpeckleNoiseImageFilter.html)
- Adaptive Histogram Equalization (https://itk.org/SimpleITKDoxygen/html/classitk_1_1simple_1_1AdaptiveHistogramEqualizationImageFilter.html)

In [11]:
```
def augment_images_intensity(image_list, output_prefix, output_suffix):
    '''
    Generate intensity modified images from the originals.
    Args:
        image_list (iterable containing SimpleITK images): The images which we wh
ose intensities we modify.
        output_prefix (string): output file name prefix (file name: output_prefix
i_FilterName.output_suffix).
        output_suffix (string): output file name suffix (file name: output_prefix
i_FilterName.output_suffix).
    '''

    # Create a list of intensity modifying filters, which we apply to the given i
mages
    filter_list = []

    # Smoothing filters

    filter_list.append(sitk.SmoothingRecursiveGaussianImageFilter())
    filter_list[-1].SetSigma(2.0)

    filter_list.append(sitk.DiscreteGaussianImageFilter())
    filter_list[-1].SetVariance(4.0)

    filter_list.append(sitk.BilateralImageFilter())
    filter_list[-1].SetDomainSigma(4.0)
    filter_list[-1].SetRangeSigma(8.0)

    filter_list.append(sitk.MedianImageFilter())
    filter_list[-1].SetRadius(8)

    # Noise filters using default settings

    # Filter control via SetMean, SetStandardDeviation.
    filter_list.append(sitk.AdditiveGaussianNoiseImageFilter())

    # Filter control via SetProbability
    filter_list.append(sitk.SaltAndPepperNoiseImageFilter())

    # Filter control via SetScale
    filter_list.append(sitk.ShotNoiseImageFilter())

    # Filter control via SetStandardDeviation
    filter_list.append(sitk.SpeckleNoiseImageFilter())

    filter_list.append(sitk.AdaptiveHistogramEqualizationImageFilter())
    filter_list[-1].SetAlpha(1.0)
    filter_list[-1].SetBeta(0.0)

    filter_list.append(sitk.AdaptiveHistogramEqualizationImageFilter())
    filter_list[-1].SetAlpha(0.0)
    filter_list[-1].SetBeta(1.0)

    aug_image_lists = [] # Used only for display purposes in this notebook.
    for i,img in enumerate(image_list):
        aug_image_lists.append([f.Execute(img) for f in filter_list])
        for aug_image,f in zip(aug_image_lists[-1], filter_list):
            sitk.WriteImage(aug_image, output_prefix + str(i) + '_' +
                            f.GetName() + '.' + output_suffix)
    return aug_image_lists
```

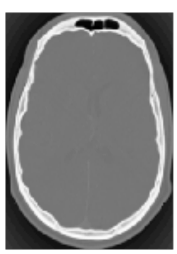
Modify the intensities of the original images using the set of SimpleITK filters described above. If we are working with 2D images the results will be displayed inline.

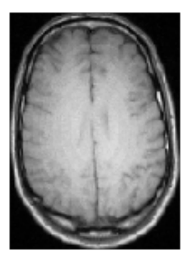
In [12]:
```
intensity_augmented_images = augment_images_intensity(data, os.path.join(OUTPUT_D
IR, 'intensity_aug'), 'mha')

          # in 2D we join all of the images into a 3D volume which we use for dis
play.
if dimension==2:
    def list2_float_volume(image_list) :
        return sitk.JoinSeries([sitk.Cast(img, sitk.sitkFloat32) for img in image
_list])

    all_images = [list2_float_volume(imgs) for imgs in intensity_augmented_images
]

    # Compute reasonable window-level values for display (just use the range of i
ntensity values
    # from the original data).
    original_window_level = []
    statistics_image_filter = sitk.StatisticsImageFilter()
    for img in data:
        statistics_image_filter.Execute(img)
        max_intensity = statistics_image_filter.GetMaximum()
        min_intensity = statistics_image_filter.GetMinimum()
        original_window_level.append((max_intensity-min_intensity, (max_intensity
+min_intensity)/2.0))
    gui.MultiImageDisplay(image_list=all_images, shared_slider=True, figure_size=
(6,2), window_level_list=original_window_level)
```



Finally, you can easily create intensity variations that are specific to your domain, such as the spatially varying multiplicative and additive transformation shown below.

In [13]:
```
def mult_and_add_intensity_fields(original_image):
    '''
    Modify the intensities using multiplicative and additive Gaussian bias fields
.
    '''
    # Gaussian image with same meta-information as original (size, spacing, direc
tion cosine)
    # Sigma is half the image's physical size and mean is the center of the image
.
    g_mult = sitk.GaussianSource(original_image.GetPixelIDValue(),
                             original_image.GetSize(),
                             [(sz-1)*spc/2.0 for sz, spc in zip(original_image.Ge
tSize(), original_image.GetSpacing())],
                             original_image.TransformContinuousIndexToPhysicalPoi
nt(np.array(original_image.GetSize())/2.0),
                             25,
                             original_image.GetOrigin(),
                             original_image.GetSpacing(),
                             original_image.GetDirection())

    # Gaussian image with same meta-information as original (size, spacing, direc
tion cosine)
    # Sigma is 1/8 the image's physical size and mean is at 1/16 of the size
    g_add = sitk.GaussianSource(original_image.GetPixelIDValue(),
                             original_image.GetSize(),
               [(sz-1)*spc/8.0 for sz, spc in zip(original_image.GetSize(), origi
nal_image.GetSpacing())],
               original_image.TransformContinuousIndexToPhysicalPoint(np.array(or
iginal_image.GetSize())/16.0),
               25,
               original_image.GetOrigin(),
               original_image.GetSpacing(),
               original_image.GetDirection())

    return g_mult*original_image+g_add

disp_images([mult_and_add_intensity_fields(img) for img in data], fig_size=(6,2))
```





(basic_registration.ipynb)

Next » (basic_registration.ipynb)