An implementation of the minimization of region-scalable fitting energy levelsets

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Abstract

Intensity inhomogeneities often occur in medical images, especially when using magnetic resonance imaging. In these images, the standard Chan-and-Vese levelset segmentation method may not work properly, as it assumes constant intensity distributions for foreground and background. Recently, a novel method was published that models the intensities as piece-wise smooth, and thus is more suitable to segment images with intensity homogeneities. However, this method was not yet implemented in ITK. This submission introduces our implementation of the region-scalable-fitting levelset segmentation method within the ITKv4 levelset framework.

Contents

1 Introduction of the region-scalable fitting levelset method

The level set method is a numerical technique for evolving interfaces and shapes [4]. It is non parametric and allows changes of topology. Levelset evolution can be steered by two types of image information: boundary information (Geodesic Active Contour [1]) and regional information (Chan-and-Vese model [2]). A typical levelset method steered by boundary information consists of two terms: a curvature term and an advection term. A typical levelset method using regional information has been presented by Chan-and-Vese [2]. assuming piecewise constant regions, their levelset equation consists of three terms: an internal regional term, an external term as well as a curvature term to minimize the length/area of a curve/surface. Additionally, some levelset methods also include a propagation term to speed up the evolution.

The regional levelset method of Chan-and-Vese assumes that the intensity inside and outside the segmentation is constant. In the presence of intensity inhomogeneities, which often occur in MR images, a bias correction method [5] is usually performed to guarantee this assumption. Li et al. [3] presented a levelset segmentation method that does not require any preprocessing of images with intensity inhomogeneity; instead, they model the intensity inhomogeneities as part of the segmentation problem. This method is called region-scalable-fitting (RSF). The theoretical description of this method can be found in the paper by Li et al. [3]. We implemented the two phase segmentation in ITKv4, i.e., there is only one foreground and one background.

2 Implementation

In ITKv4, each of the levelset terms can be implemented separately such that the users can easily combine different levelset terms. These terms are derived from the class `itk::LevelSetTermBase`.

We implement the RSF method using the ITKv4 scheme such that combination of this method with other levelset terms remains feasible. The RSF levelset uses an piecewise smooth regional term for the internal area (foreground), an piecewise smooth regional term for the background area as well as a curvature term. Since the curvature term already exists in ITKv4, we only implemented both piecewise smooth regional terms. Equations of the paper by Li et al. [3] show that the internal and external RSF term computation depend on each other. Therefore we combined the two RSF terms into one RSF term. In order to implement this, we first derive a piecewise constant regional term `itk::LevelSetEquationChanAndVeseGlobalTerm` which is actually a combination of the existing internal piecewise constant regional term `itk::LevelSetEquationChanAndVeseInternalTerm` and external piecewise constant term `itk::LevelSetEquationChanAndVeseExternalTerm`. Then the `itk::LevelSetEquationSparseRSFTerm` is derived from the `itk::LevelSetEquationChanAndVeseGlobalTerm`.

2.1 Algorithmic Overview

The Chan-and-Vese piecewise constant regional term models the foreground/background mean intensity after the i_{th} iteration to be a constant c_i, which is the mean over the current foreground and background after each iteration. The RSF models the foreground/background mean intensity to be a function of physical location $\boldsymbol{x}$, i.e $f_i(\boldsymbol{x})$. We name $f_i(\boldsymbol{x})$ the mean image. We calculate $f_i(\boldsymbol{x})$ according to the Eq. 1 (Eq. 14 from Li et al. [3]): $K_\sigma(\boldsymbol{x})$ is the Gaussian function at scale σ, $H_i(\phi(\boldsymbol{x}))$ is the Heaviside function, $\phi(\boldsymbol{x})$ is the levelset function, $*$ denotes the convolution operation.

$$f_i(\boldsymbol{x}) = \frac{K_\sigma(\boldsymbol{x}) * [H_i(\phi(\boldsymbol{x}))I(\boldsymbol{x})]}{K_\sigma(\boldsymbol{x}) * H_i(\phi(\boldsymbol{x}))}, \quad i = 1,2 \tag{1}$$

The code for computing the foreground and background mean image is in the function

```
template< class TInput, class TLevelSetContainer >
void LevelSetEquationSparseRSFTerm< TInput, TLevelSetContainer >
::UpdateMeanImage()
```

whose block diagram of calculating the Eq. 1 from Li et al. is shown in Fig. 1. This function gives six outputs: the foreground and background mean image, the blurred foreground and background mean image, as well as the blurred squared foreground and background mean image. These outputs will be used to calculate the internal or external force for each voxel according to Eq. 2 (Eq. (16) from Li et al. [3]).

$$\begin{aligned} e_i(\boldsymbol{x}) &= \int K_\sigma(\boldsymbol{y}-\boldsymbol{x})(I(\boldsymbol{x}) - f_i(\boldsymbol{y}))^2 d\boldsymbol{y} \\ &= I(\boldsymbol{x})^2 1_K - 2I(\boldsymbol{x})(f_i(\boldsymbol{x}) * K_\sigma(\boldsymbol{x})) + f_i^2(\boldsymbol{x}) * K_\sigma(\boldsymbol{x}), \quad i = 1,2 \end{aligned} \tag{2}$$

1_K is $\int K_\sigma(\boldsymbol{y}-\boldsymbol{x})d\boldsymbol{y}$, which should be 1 everywhere except near the boundary of the image domain.

Code of computations of these two kinds of forces is in following function: at voxel index iP.

```
template< class TInput, class TLevelSetContainer >
typename LevelSetEquationSparseRSFTerm< TInput, TLevelSetContainer >::InputPixelRealType
LevelSetEquationSparseRSFTerm< TInput, TLevelSetContainer >
::CalculateVariance(const LevelSetInputIndexType& iP, const LevelSetOutputRealType&
 iData,  InputImagePointer bluredMeanImage, InputImagePointer bluredMeanSquareImage)
{
//Here calculate e1, we assume that 1K =1 see Eq.16 in Li's paper
 in IEEE Image Processing 2008
const InputPixelRealType intensity =
static_cast< const InputPixelRealType >( this->m_Input->GetPixel( iP ) );

const InputPixelRealType bluredMeanImageValue =
static_cast< const InputPixelRealType >( bluredMeanImage->GetPixel( iP ) );

const InputPixelRealType bluredMeanSquareImageValue =
static_cast< const InputPixelRealType >( bluredMeanSquareImage->GetPixel( iP ) );

const InputPixelRealType e =
intensity * intensity * this->m_ConvolutionOfUnitImageWithGaussian->GetPixel( iP )
 - 2. * bluredMeanImageValue * intensity + bluredMeanSquareImageValue;

return e;
```

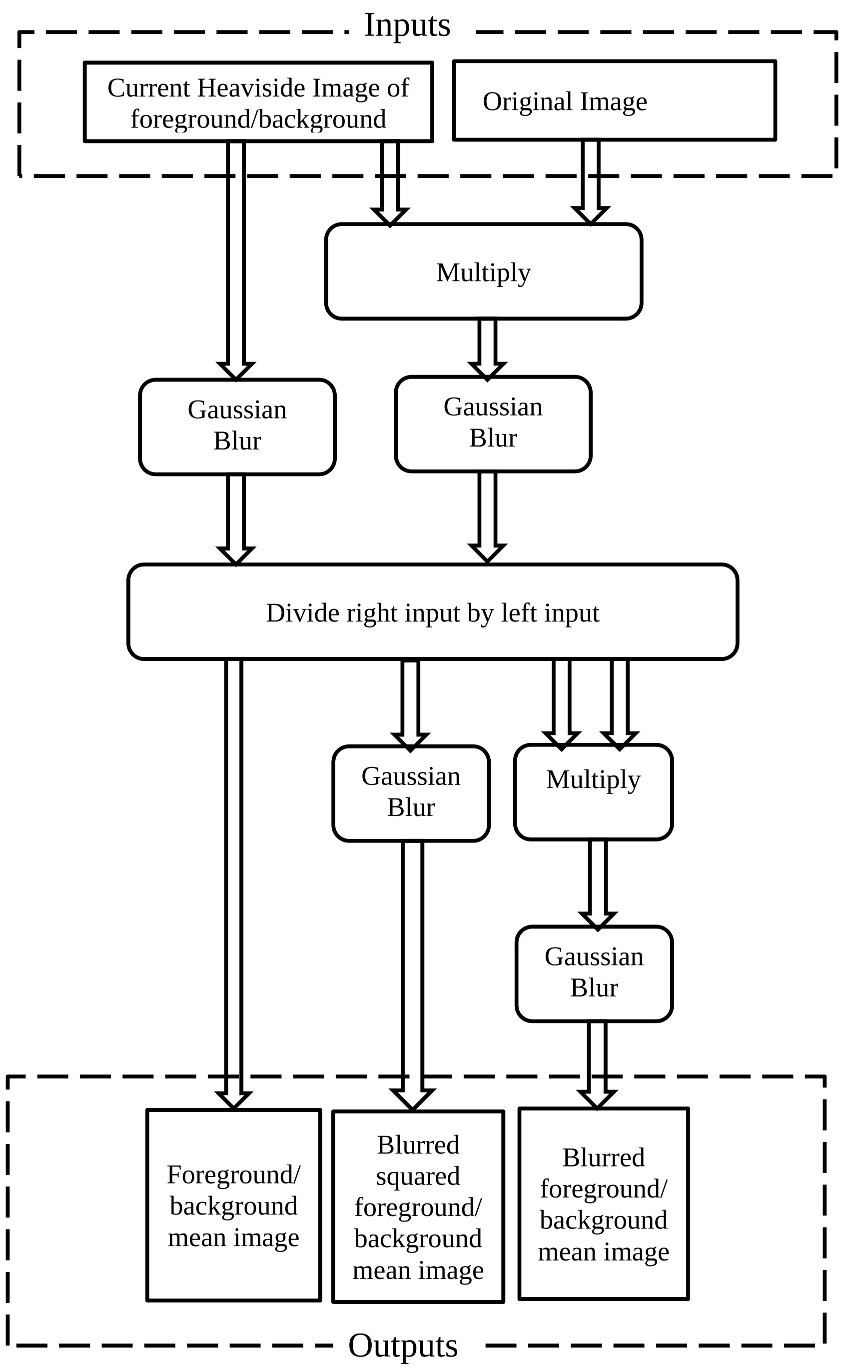

Figure 1: The block diagram the the UpdateImage() function

```
}
```

To complete the method by Li et al. in [3], users need to put the itk::LevelSetEquationSparseRSFTerm and the itk::LevelSetEquationCurvatureTerm into the same levelset container.

2.2 Parameters

We have three parameters for this RSF term.

- m_GaussianBlurScale.

  is a parameter related to the severity of intensity inhomogeneities, and should decrease with increasing inhomogeneities. (default=1)

- m_InternalCoefficient.

  The coefficient of the internal term. (default=1)

- m_ExternalCoefficient.

  The coefficient of the external term. (default=1)

2.3 Test

In the test code RSFTermTest.cxx, we added the RSF term and the curvature term. Users can directly use RSFTermTest to perform a segmentation. The program can be used as follows:

```
RSFTermTest.exe initial.mhd originalImage.mhd output.mhd internalWeight externalWeight
                              curvatureWeight gausianBlurScale iterationTime dimension
```

Users can also combine their own levelset terms with the RSF levelset. In that case the levelset image should be represented as a sparse image using itk::WhitakerSparseLevelSetImage, itk::WhitakerSparseLevelSetImage, itk::ShiSparseLevelSetImage or itk::MalcolmSparseLevelSetImage.

3 Examples

The following software is required:

- Insight Toolkit 4.2.
- CMake 2.4

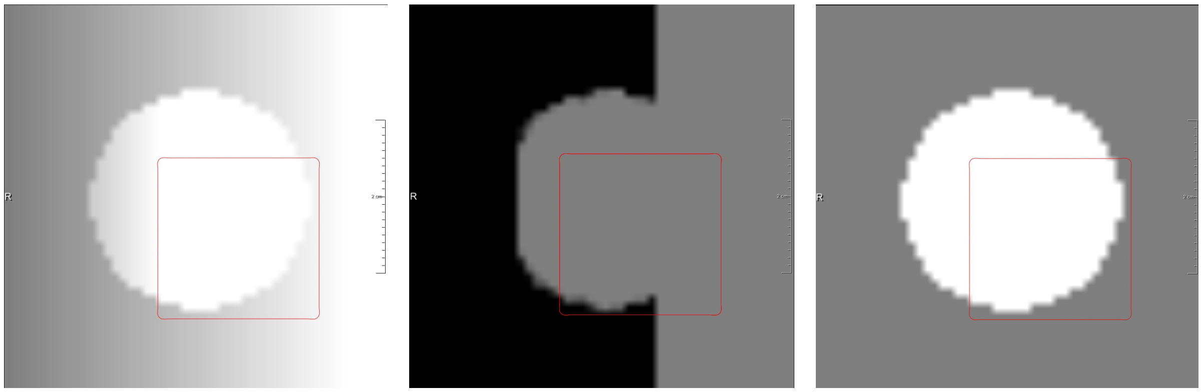

Figure 2: (a) original image in 2D (b) segmentation using Chan-Vase in 2D contour (c) segmentation using RSF in 2D. The red contour shows the initialization.

3.1 Segmentation of a 2D synthetic image with intensity inhomogeneity

```
RSFTermTest.exe initial.mhd originalImage.mhd output.mhd 1 1 1 20 1000 2
```

Fig. 2 shows the original image, initial contour in red and segmentation image.

Fig. 3 shows the original image presented by Li et al. in [3], and the segmented image.

```
RSFTermTest.exe 2ini.mhd 2.mhd 2out.mhd 1 1.1 10 1 2000 2
```

3.2 Segmentation of a 3D synthetic image with intensity inhomogeneity

```
RSFTermTest.exe initial.mhd originalImage.mhd output.mhd 1 1 1 20 2000 3
```

Fig. 4 shows the original image, initial surface in green and segmentation image.

4 Conclusion and discussion

We implemented the two-phase version of the region-scalable fitting energy levelsets method in the framework of ITKv4. This implementation only support a sparse representation of levelsets and would not work on the dense representation `itk::LevelSetDenseImage`. We showed the segmentation results by this implementation on 2D and 3D synthetic images, and compared the results to the segmentation by the piecewise smooth Chan-and-Vese levelset. In the future, we would like to improve this implementation by extending it to multiphase levelsets and make it feasible for dense levelset representation.

References

[1] V. Caselles, R. Kimmel, and G. Sapiro. Geodesic active contours. *International Journal of Computer Vision*, 22(1):61–79, 1997. 1

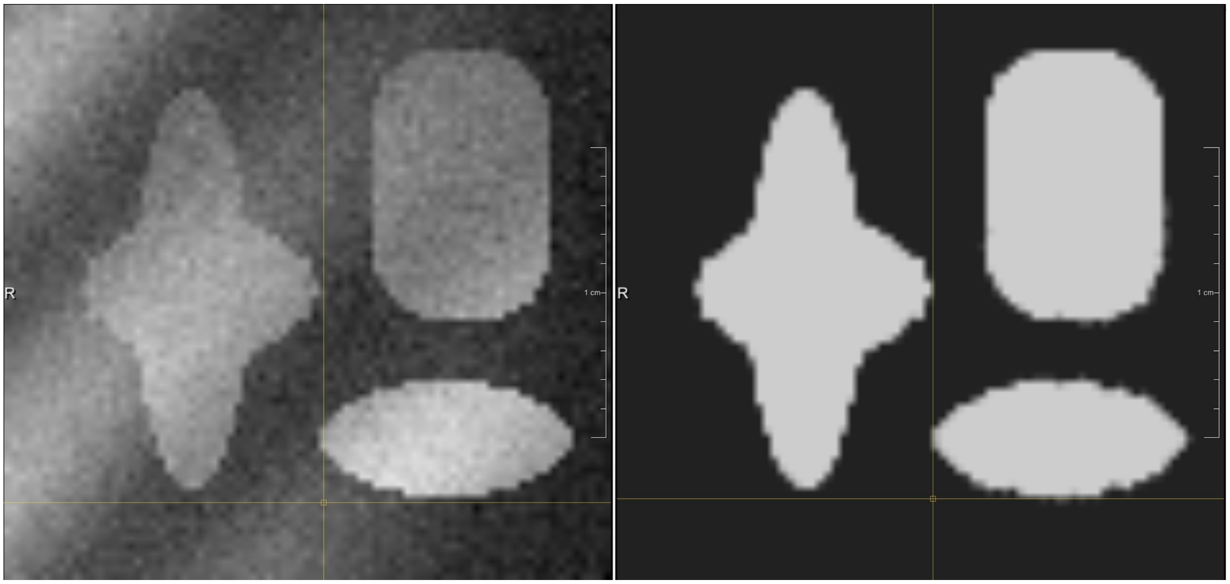

Figure 3: (a) Testing of the example in Li et al. [3]

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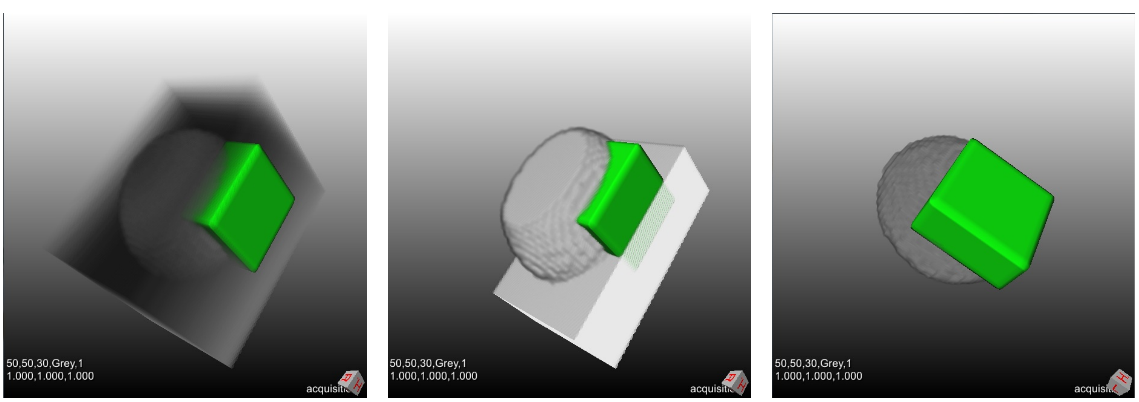

Figure 4: (a) original image in 3D (b) segmentation using Chan-Vase in 3D (c) segmentation using RSF in 3D. Initialization is shown in green

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[2] T. F. Chan and L. A. Vese. Active contours without edges. *IEEE Transactions on Image Processing*, 10(2):266–277, 2001. 1

[3] C. Li, C. Kao, J. C. Gore, and Z. Ding. Minimization of region-scalable fitting energy for image segmentation. *IEEE Transactions on Image Processing*, 17 (10):1940–1949, 2008. 1, 2, 2.1, 2.1, 2.1, 3.1, 3

[4] J. A Sethian. *Level Set Methods and Fast Marching Methods*. Cambridge University Press, 1999. 1

[5] N.J. Tustison, B.B. Avants, P.A. Cook, Yuanjie Zheng, A. Egan, P.A. Yushkevich, and J.C. Gee. N4ITK: Improved N3 bias correction. *IEEE Transactions on Medical Imaging*, 29(6):1310 – 1320, 2010. 1