# Shape-and-user-guided segmentation

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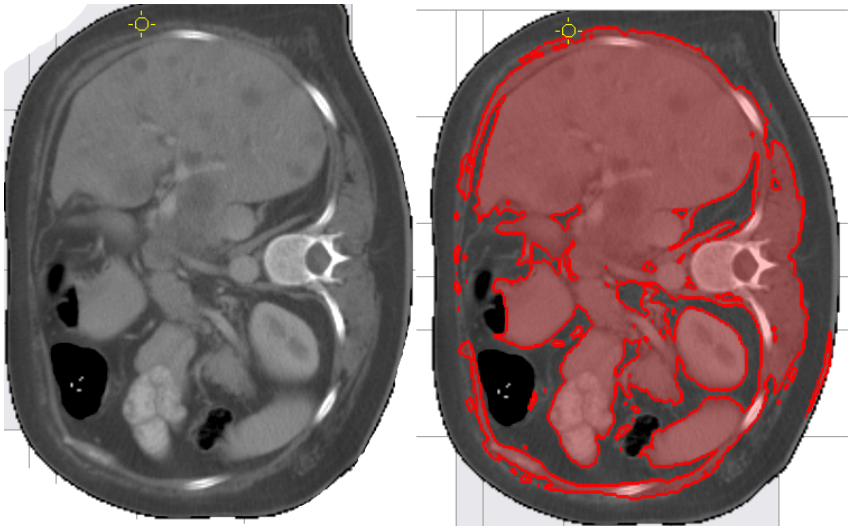
# Motivation

- Segmentation with strong intensity prior and shape prior
  - known range of intensities for liver
  - shape similar between livers
- May need user-interaction during segmentation

# Chan-Vese functional

$$F(\phi) = \int_\Omega \underbrace{-\log P_{in} H(\phi)}_{data\ \ inside} \underbrace{-\log P_{out}(1 - H(\phi))}_{data\ \ outside} + \underbrace{\delta(\phi)|\nabla\phi|}_{curve\ \ length}\, dA$$

- Shape prior: regularized with curve length



# Fixed Shape Energy

$$F(\bar{p}) = \int_{\Omega} -\underbrace{\log P_{in}\hat{H}(\bar{x})}_{data\ \ inside} - \underbrace{\log P_{out}(1-\hat{H}(\bar{x}))}_{data\ \ outside} + \underbrace{\delta(\phi)|\nabla\phi|}_{curve\ \ length}\, dA$$

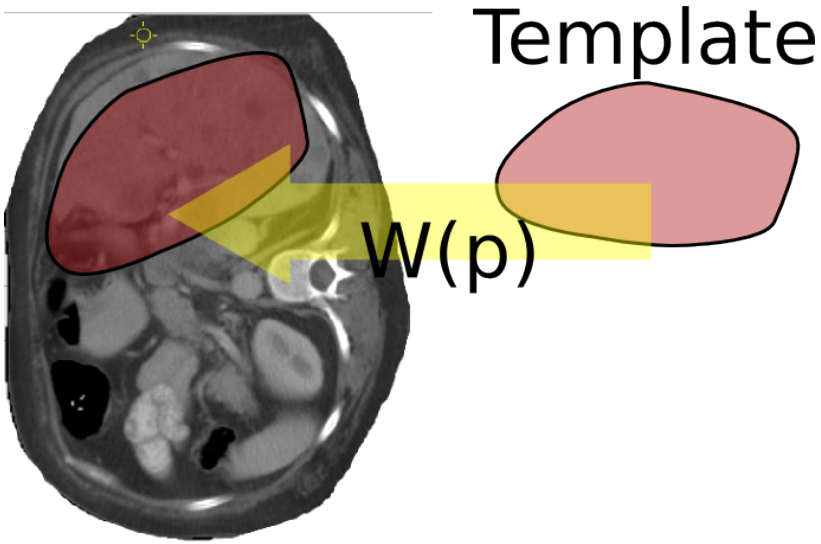
$$\hat{H} = H(\hat{\phi}(W(\bar{p},\bar{x})))$$

- single fixed prior shape (a levelset $\hat{\phi}$)
- transformation, parameterized by $\bar{p}$.
- curve length needed (e.g., when parameterization non-rigid)

# Example transforms

Transforms

- rigid $\bar{p} = [\theta, t_x, t_y]$
- affine
- FFD
- ...



# Basic transforms limitations

- single transform not expressive enough
- potential solutions:
  - train FFD deformations to samples; use PCA on deformation parameters
  - do PCA on signed distance function on training data directly
  - allow arbitrary shape deformation (in levelset) but constrain it to be close to training data

# Allowing deviation from a mean shape

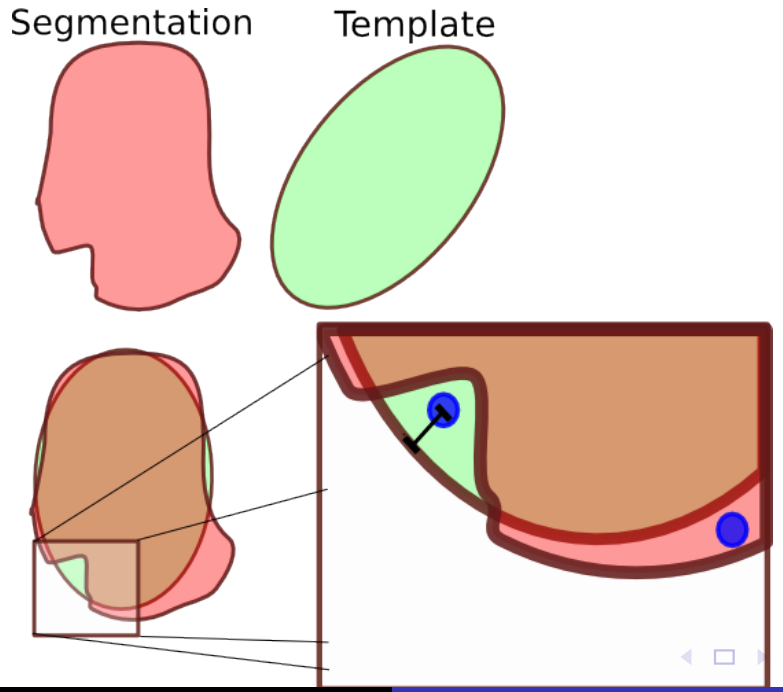
Augmented cost functional

$$F(\phi, \bar{p}) = \int_{\Omega} \underbrace{-\log P_{in} H(\phi) - \ldots}_{data+curve\ \ length} + \lambda_{prior} F_{prior}(\phi, \bar{\phi}, \bar{p})$$

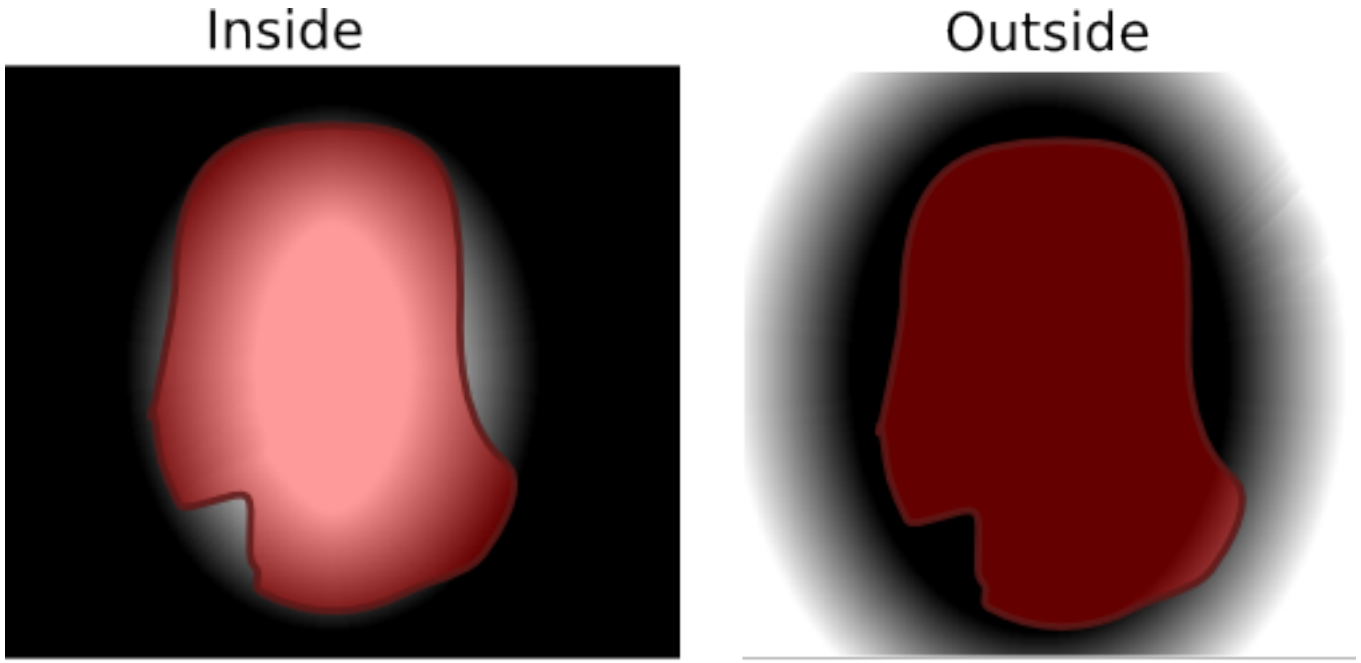
- prior penalizes devations from transformed mean (or training shapes)
- $\lambda_{prior}$ tunes between no deviation to no prior.

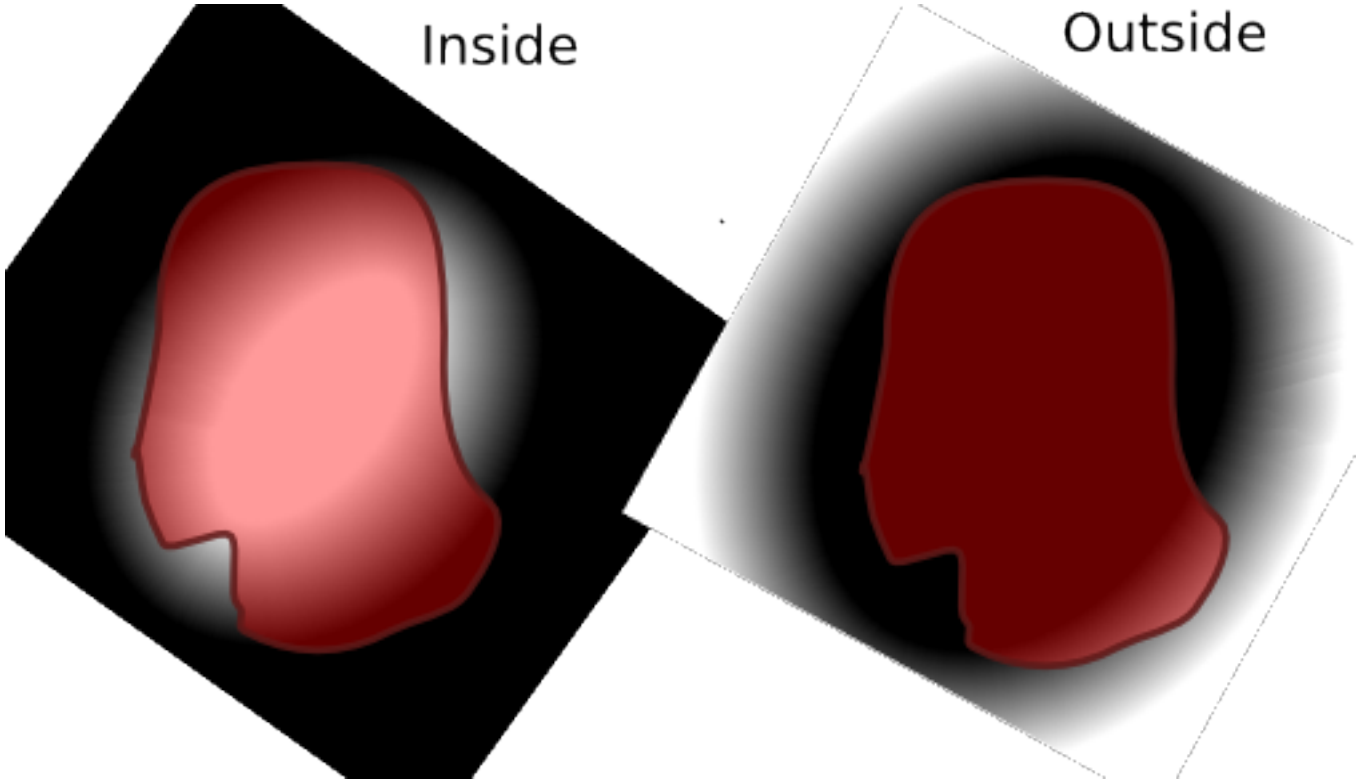
# Prior

$$F_{prior} = \begin{cases} 0 & \text{if } H(\phi(\mathbf{x})) = H(\bar{\phi}(W(\bar{p}, \mathbf{x}))) \\ |\bar{\phi}(W(\bar{p}, \mathbf{x}))| & \text{if } |\bar{\phi}(W(\bar{p}, \mathbf{x}))| < \sigma \\ \infty & \text{otherwise} \end{cases}$$



# Prior




Inside
Outside

# Optimization

Joint optimization of segmentation and transformation parameters

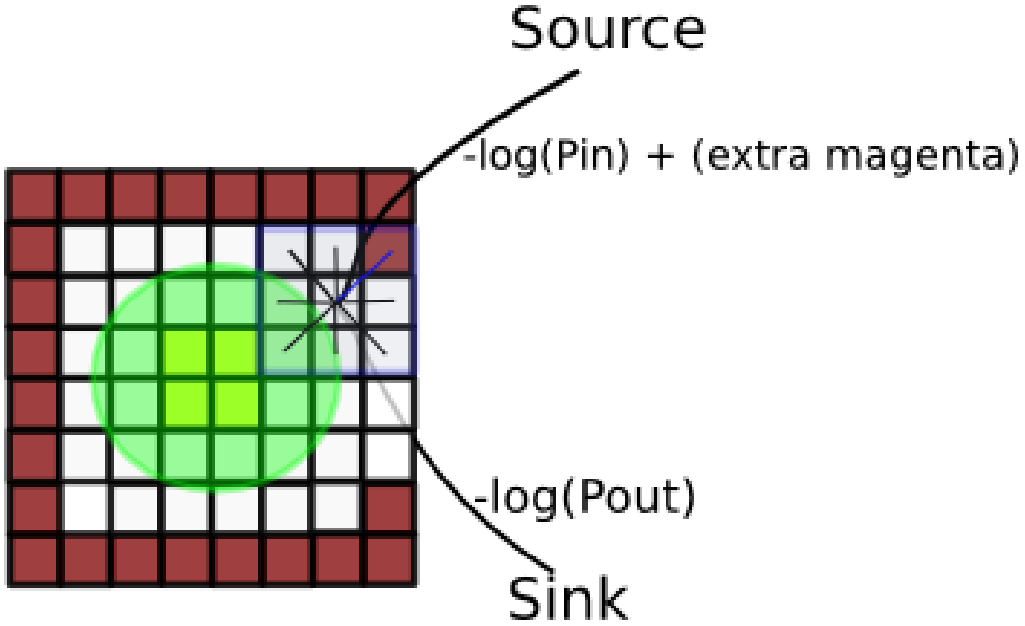
$$F(\bar{p}) = \min_{\theta} \int_{\Omega} \underbrace{-\log P_{in} H(\phi) - \ldots}_{data+curve\ \ length} + \lambda_{prior} F_{prior}(\phi, \bar{\phi}, \bar{p})$$

- Use conjugate gradient over parameters $\bar{p}$, where cost functional is then evaluated optimally using graph-cuts
- Bandwidth sigma means problem only needs to be solved within band
  - Everything that maps to $|\bar{\phi}(W(\bar{p}, \mathbf{x}))| >= \sigma$ is fixed, just need to adjust border weights appropriately.

# Graph example

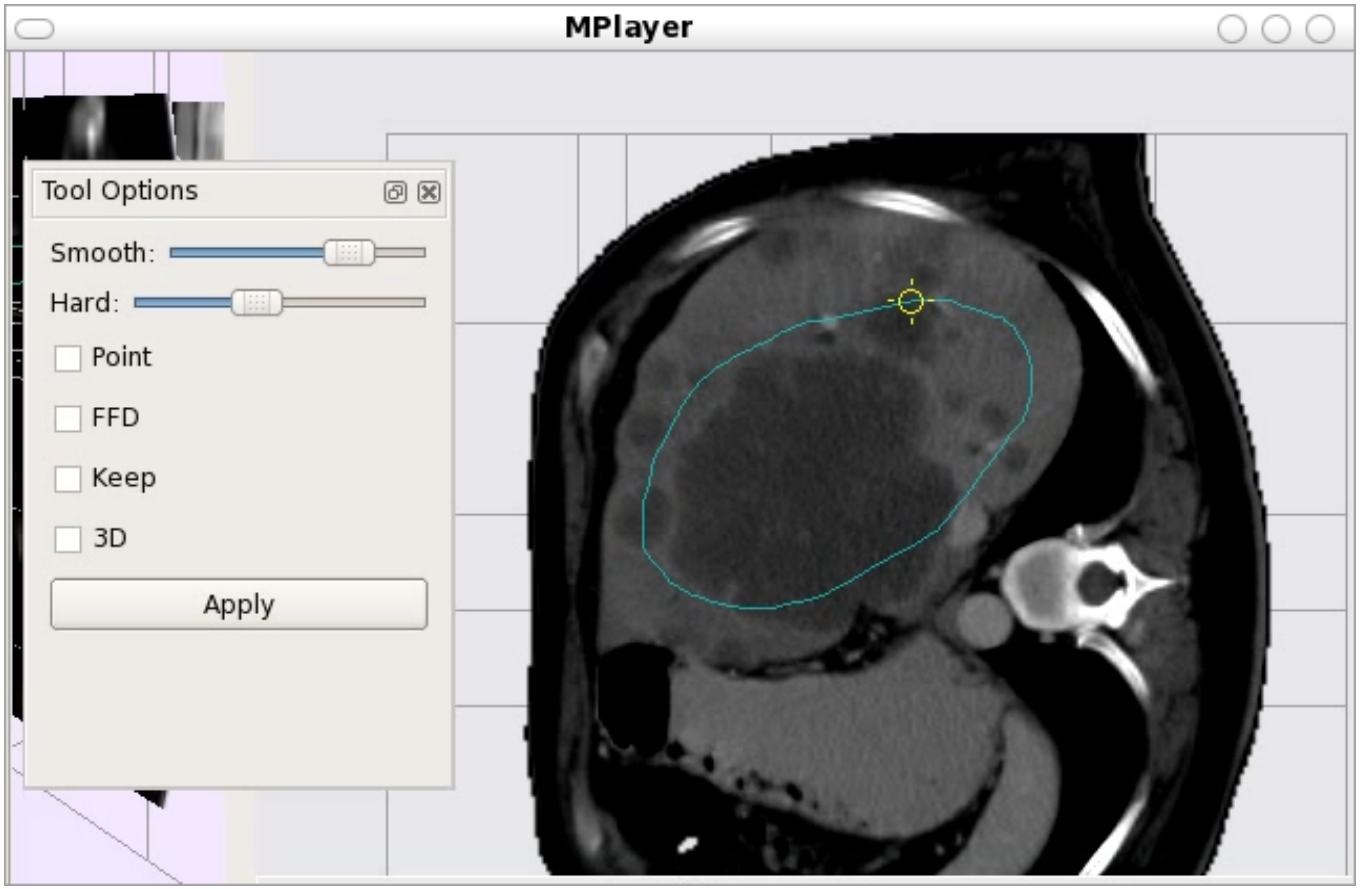
Assume bandwidth is 1.

- Green circle denotes transformed mean/template
- Magenta squares are always outside
- Green squares are inside.



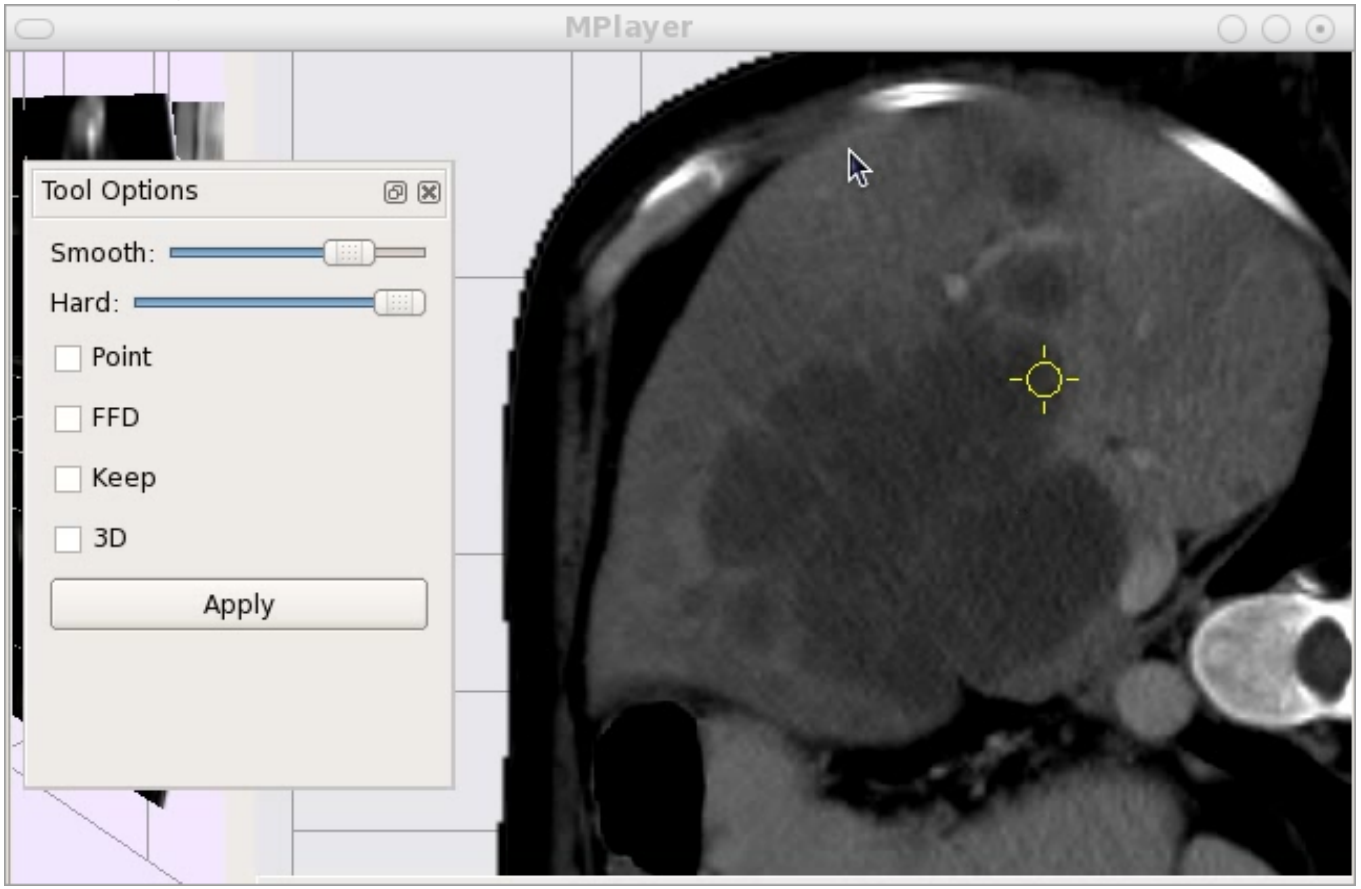
# Example 1

Selection indicates *mean shape* optimization uses this shape.



# Example 1

Varying the hardness parameter.

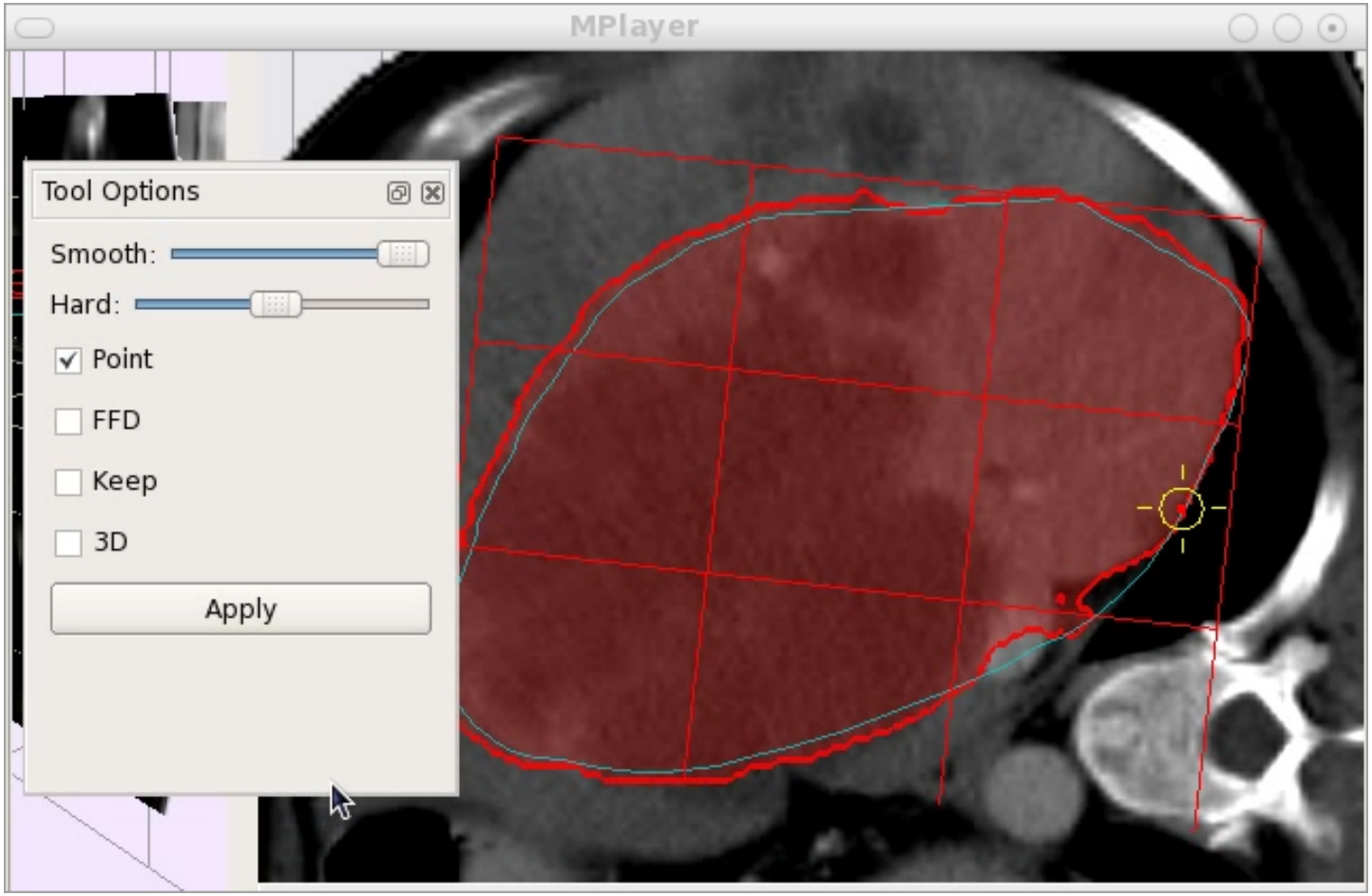


# Point Constraints

- Point constraints can easily be embedded in the cost:

$$E_{pt}(\mathbf{x}_i) = \bar{\phi}(W(\mathbf{p}, \mathbf{x}_i))$$

# Sample Point Constraints



# Demo