# Tracking Through Clutter Using Graph Cuts

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## *Overview*

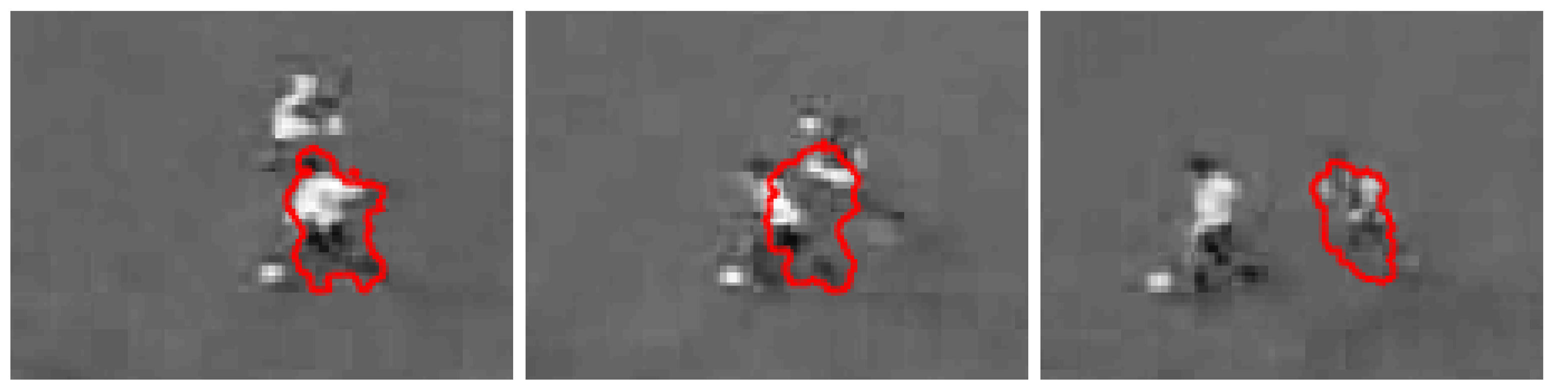
The standard graph cut technique is a robust method for globally optimal image segmentation. However, because of its global nature, it is prone to capture outlying areas similar to the object of interest. This paper proposes a method to adaptively constrain the standard graph cut technique for tracking objects in a region of interest at real-time rates. By introducing an additional penalty on pixels based upon their distance from a region of interest, segmentation is biased to remain in this area.

## *Distance Penalty*

The standard graph cut technique is capable of finding regions matching the object intensity located anywhere in the image. By penalizing pixels based on their distance from the expected location, a potential well is formed biasing segmentation to a region of interest. Below you see the effect of the standard unconstrained graph cut segmentation *(left)* and segmentation constrained with the distance penalty $\phi$ centered around a player *(right)*.

## *Location Prediction*

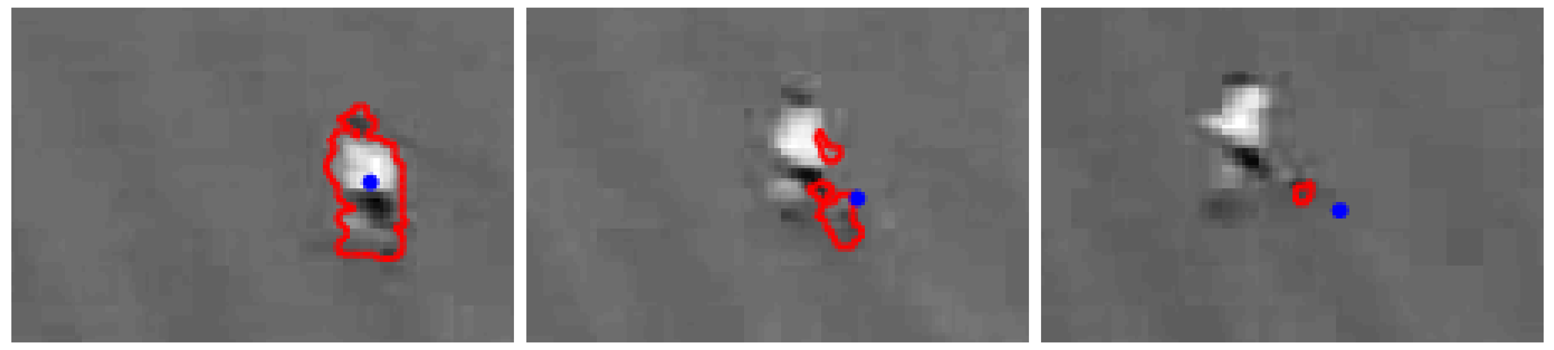
Often the object makes a large movement, large enough at times to place it in an area of high distance penalty. Below, assuming the object did not move causes the tracker to lag behind and incorrectly grab another player when the target moves suddenly *(left to right)*.



To overcome this problem, we use a first order track-point filter to predict the location of the object in each frame $\tilde{c}$ and center the distance penalty $\phi$ at this predicted location.

## *Error Feedback*

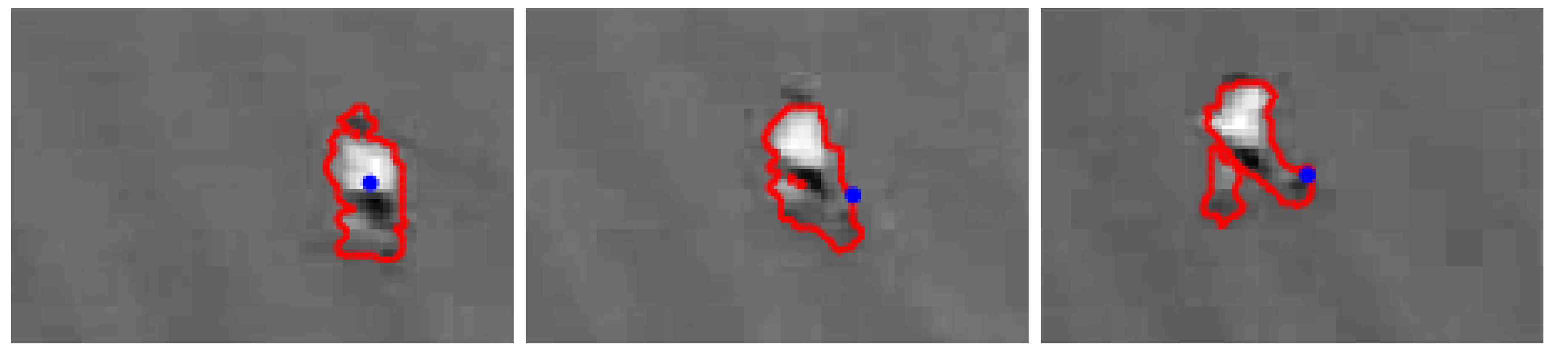
We now have the distance penalty constraining segmentation and the filter predicting where to center this distance penalty, but what if the filter is wrong? Below, the system loses track as the centroid *(blue)* begins to lag behind the moving target.



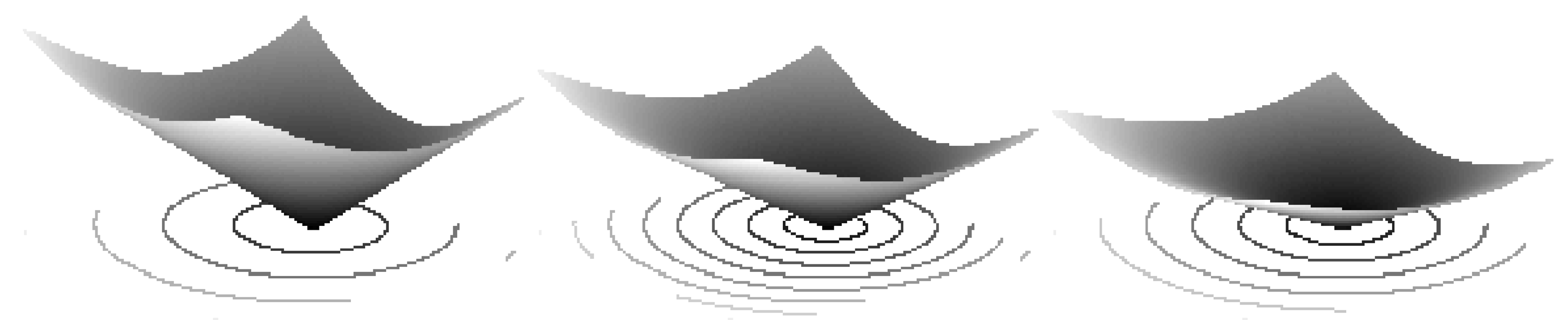
As the predicted centroid $\tilde{c}$ begins to be off from the centroid obtained from segmentation $c$, we use this error to scale the distance penalty according to an exponential distribution:

$$\alpha(\|\tilde{c} - c\|) = \exp\left(-\|\tilde{c} - c\|^2/\rho^2\right)$$

Below we see that, as the centroid lags behind, the distance penalty is lowered to still capture the object. After locking back onto the object, the prediction error decreases, and the $\alpha$ automatically raises the distance penalty back up to tighten around the object.



Below, the corresponding distance is scaled by $\alpha$ for the increasing prediction error. Notice the basin of attraction widening.



## *Algorithm*

1. Predict object location $\tilde{c}$ in new frame
2. Determine $\alpha$ scaling based on error in previous frame
3. Build scaled distance penalty $\phi$
4. Graph cut segmentation

## *New graph cut edge weight*

Our goal is to determine the best label assignment $a$ given an image , that is to maximize $P(a|I)$. Bayes rule tells us that,

$$P(a|I) \propto P(I|a)P(a).$$

The negative log-likelihood of this is used to determine the graph cut regional edge weights. Notice that if the prior is assumed uniform, then its log-likelihood is zero, and we have the typical edge weight:

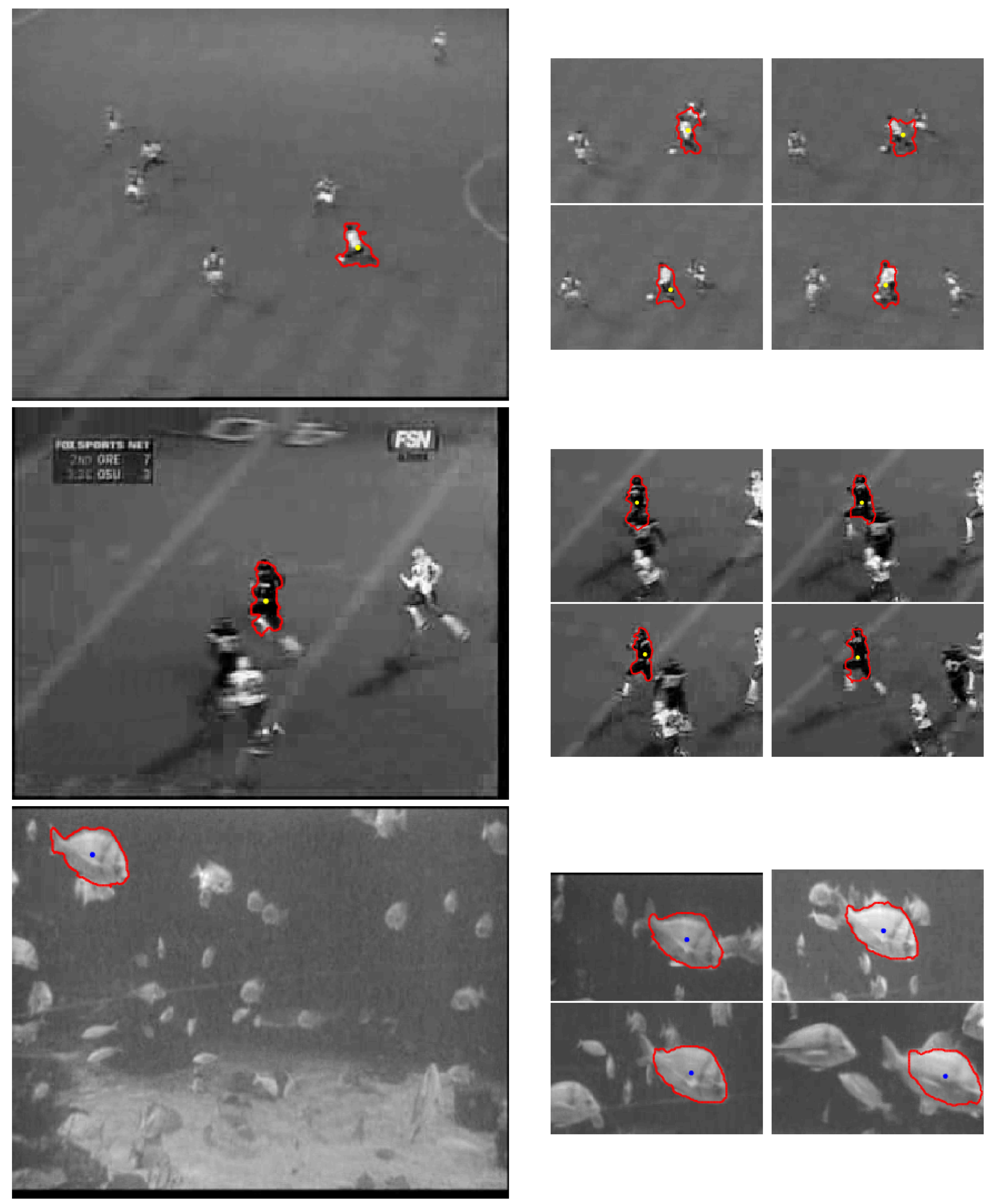
$$R(a) = -\ln P(a|I) = -\ln P(I|a) - \ln P(a) = -\ln P(I|a).$$

Now we assume non-uniform prior and claim $-\ln P(obj) = \alpha(\|\tilde{c} - c\|)\phi$ for the object region. This augments the final regional object edge weights:

$$\begin{aligned} R(obj) &= -\ln P(I|obj) - \beta \ \ln P(obj) \\ &= -\ln P(I|obj) + \beta \ \alpha(\|\tilde{c} - c\|)\phi(p) \\ R(bg) &= -\ln P(I|bg) - \beta \ \ln P(bg) \\ &= -\ln P(I|bg) \end{aligned}$$

## *Experiments*

Below are full images and selected cropped frames for sequences involving soccer players, football players, and fish. The dots indicate the predicted centroids.

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