Improving Image Analysis Algorithms using Automatic Programming

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- Image analysis
- Edge detection and image segmentation
- Improving state-of-the-art algorithms with automatic programming.

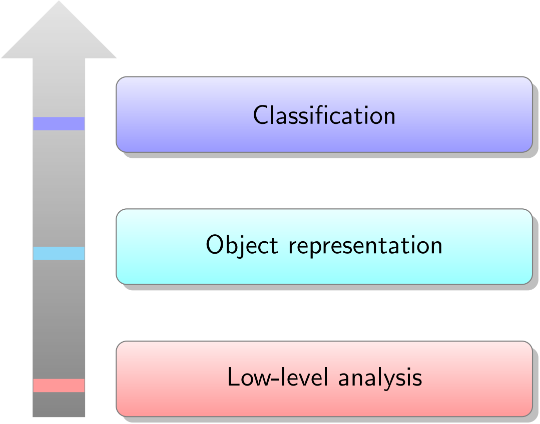
Image Analysis

Image analysis is a term used to cover a wide range of tasks that are related to computer vision i.e. we are attempting to make computers be able to see.

- Facial recognition
- Car safety systems
- Robotics
- Medical diagnosis
- Geological surveys
- ...

Image analysis is related to aritificial intelligence.

Despite the wide range of applications, most image analysis uses a variation of the pipeline below.



Edge Detection

Edge detection is the process of finding discontinuities, or abrupt changes in intensity, in digital images.

Algorithms are typically based on simple mathematic principles

- Difference
- Derivatives

Standard edge detectors.

- Sobel, Prewitt, Laplacian of Gaussian (LoG) (filter based)
- Canny [3] (filter based, but with significant additions)
- Portability boundary (Pb) [1]

Image Segmentation

Image segmentation is used to describe either the process of dividing an image into its constituent parts or separating an image into foreground and background.

Image segmentation is closely related to edge detection.

- Closed edges can be turned into regions

Standard image segmentation algorithms.

- Normalized Cut [9]
- Mean Shift [4]
- Felzenszwalb & Huttenlocher [5]

My Research

My PhD has been focused on using Automatic Programming to improve low-level image analysis algorithms.

- Image segmentation
  - Graph-Based Image Segmentation (one paper published [7] plus experimental foundation for a new one)
  - Pulse Coupled Neural Networks (PCNN) (work based on [2] in progress)
- Edge detection
  - Canny (two papers accepted [8], one in for review, several more planned)
  - gPb (experimental foundation under development)
  - Filter-based (one paper published on a logic filter [6] and one more planned)

The Approach

All attempts at improving an algorithm with automatic programming follow the same high-level recipe.

- Port the algorithm to SML
- Select target program and translate it to ADATE ML
- Define a fitness function
- Start evolution
- Evaluate the improved program

Improving Graph-based Image Segmentation

As a first example, let us look at the work we did to improve graph-based image segmentation [7].

The original algorithm [5] is modification of a standard *minimum spanning tree* algorithm.

- Build a graph based on the differences between the pixels in the image.
- Sort the edges in non-decreasing order.
- Iterate through the sorted list and merge nodes if a custom requirement is met.

The algorithm was ported to SML and tested to make sure it produces the same results as the original.

The third step of the algorithm was chosen as the target function.

Evaluating the Synthesized Programs

Segmentation quality is a matter of perception, so we need a metric that accounts for the ambiguous nature of the problem.

There are many different metrics for image segmentation.

- F-measure (fast and effective, but unclear what to do with multiple segments)
- Variation of Information (somewhat effective, but no clear way to incorporate multiple ground truths)
- Segmentation Covering (slow but effective)
- ...

Typically the type of benchmark is dependent on the type of images (ground truths) used.

Finding a Suitable Image Database

There are several image databases available on the Internet, but not all of them are suitable for our purpose.

In order to create a general improvement we need..

- Images of suitable size (too big $\Longrightarrow$ slow run times, too small $\Longrightarrow$ low level of detail)
- Ground truth images with identified regions from multiple subjects.
- The images to contain a wide range of different motives and objects.

Based on this we can come up with suitable candidates.

- BSDS500 (popular, large, natural images, multiple objects)
- Weizmann (smaller, natural images, single object)

The Original Algorithm

The original algorithm operates as follows.

- Build a graph where each pixel is a node connected to its 8 immediate neigbors with an edge where the weight correspond to the difference in intensity.
- Place each pixel in its own component (union find) with a threshold set to a constant C
- Sort all the edges in non-decreasing order
- Iterate the sorted edges and join the connected components if the weight is smaller than both thresholds
- The threshold of the joined component is set to be the weight plus the constant C divided by the size of the new component

The Part of the Algorithm Selected for Improvement

```
fun f( Universe, SortedEdges, Constant ) =
  case SortedEdges of
    enil => Universe
  | econs( CurrentEdge as edge( A, B, W, X ), RestEdges ) =>
  let
    val ( ComponentA, ThresholdA ) = find( A, Universe )
    val ( ComponentB, ThresholdB ) = find( B, Universe )
  in
    if differentComp( ComponentA, ComponentB ) then
      if W < ThresholdA andalso W < ThresholdB then
      let
        val NewUniverse = union( Universe, ComponentA, ComponentB )
        val ( Component, CurrentThreshold ) = find( A, NewUniverse )
          updateThresholdValue( Component, W+Constant/getComponentSize Comp )
      in
        f( updateThresholdValue( Component,
                                 W+Constant/getComponentSize Comp,
                                 NewUniverse ),
           RestEdges,
           Constant )
      end
      else
        f( Universe, RestEdges, Constant )
    else
      f( Universe, RestEdges, Constant )
  end
```

The Benchmarks

The table below contains the Precision, Recall and F-measure for both the algorithms on both the training and test data.

	Train			**Test**			**Total**		
Algorithm	**P**	**R**	**F**	**P**	**R**	**F**	**P**	**R**	**F**
New	0.79	0.86	0.79	0.81	0.82	0.78	0.80	0.84	0.79
Original	0.75	0.82	0.71	0.76	0.76	0.69	0.75	0.79	0.70

We also did a pairwise comparison of the two algorithms using student-t distribution on the differences, and we can say with 99 percent confidence that the new algorithm is between 1 and 17 percentage points better than the original on the test images.

The Improved Algorithm

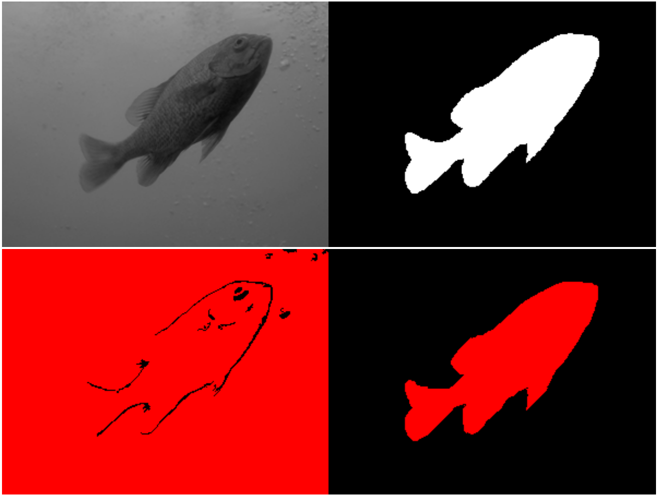
```
fun f( Universe, SortedEdges, Constant ) =
  case SortedEdges of
    enil => Universe
  | econs( CurrentEdge as edge( A, B, W, X ), RestEdges ) =>
  let
    val ( ComponentA, ThresholdA ) = find( A, Universe )
    val ( ComponentB, ThresholdB ) = find( B, Universe )
  in
    if differentComp( ComponentA, ComponentB ) then
      if W < ThresholdA andalso W < ThresholdB then
      let
        val NewUniverse =
          updateThresholdValue(
            ComponentB,
           W+Constant/
              getComponentSize(
                if Constant < ThresholdA then
                  ComponentB
                else
                  ComponentA ),
            union( Universe, ComponentA, ComponentB ) )
      in
        f( NewUniverse, RestEdges, Constant )
      end
      else if W > ThresholdA andalso W > ThresholdB then
        f( Universe, RestEdges, getComponentSize( ComponentB ) )
      else
        f( Universe, RestEdges, Constant )
    else
      f( Universe, RestEdges, Constant )
  end
```

The Improved Algorithm Explained

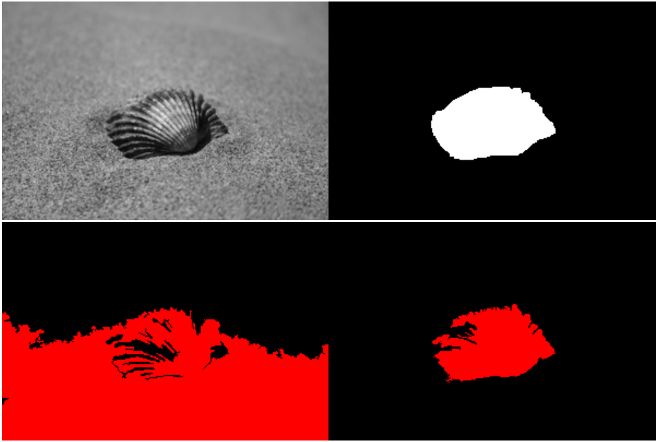
The improved algorithm is quite similar to the original algorithm. There are three minor changes.

- Updates to the threshold are always made to *ComponentB*
- It does not use the size of the new component to calculate the new threshold.
- It has introduced a mechanism that changes the constant if the weight of the current edge is larger than both the connected components thresholds.

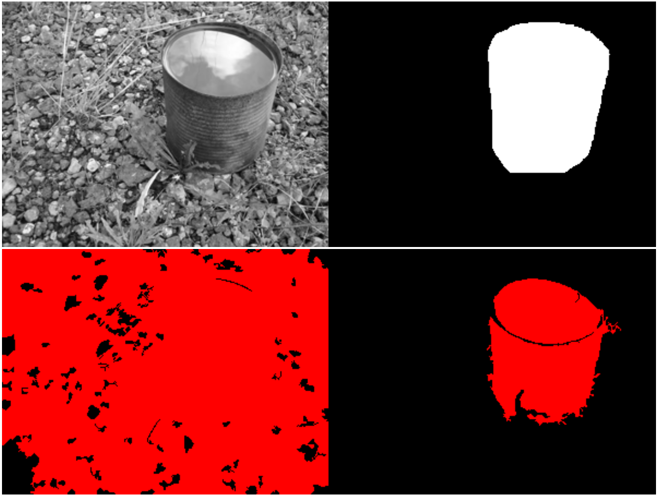
Segmentation Comparison



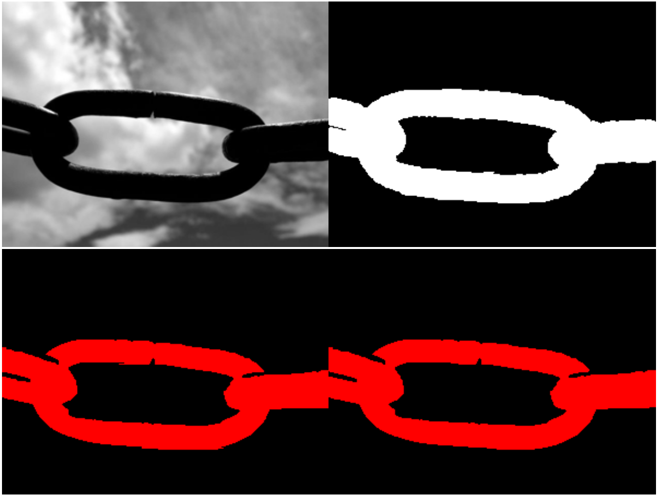
Segmentation Comparison



Segmentation Comparison



Segmentation Comparison



Improving the Canny Edge Detector

The Canny edge detector [3] is a popular algorithm that can be found in most image analysis platforms.

The algorithm works as follows.

- Smooth the image and find the gradient image.
- Perform *non-max suppression*.
- Find the final edge image by *hysteresis thresholding*.

We ported the entire algorithm into SML, and we decided to investigate the possibility of improving the three stages separately.

Let us first consider improving the second stage, non-max suppression.

Improving Non-Max Suppression

Non-max suppression was designed to reduce multiple responses to a single edge.

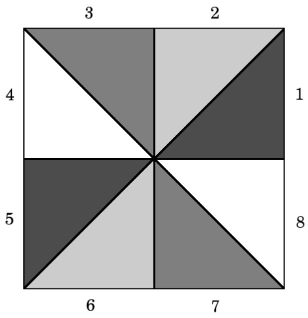
The idea is to suppress gradient magnitudes that are less than either of the magnitudes along the gradient angle.

The Matlab implementation generates two gradient images, one for each axis.

Consider d_x and d_y as the x- and y-gradient for a given position.

If d_y is positive and d_x larger than d_y, or if d_y is negative and d_x is less than d_y, the gradient angle is in sector 1 or 5 respectively.

In this case the positions magnitude is suppressed if it is smaller than either of its neigbors along the gradient angle (found using linear interpolation).



Experimental Setup

We used the BSDS500 [1] in our experiments.

- Specifically designed for training contour detectors
- High quality annotations by multiple subjects
- Widely adopted by the industry

We used the *average* **F-measure** for evaluating the programs.

We reduced the time needed to evaluate by using only the *best* ground truth in each set.

- The ground truth with the highest F-measure when evaluated against the other ground truths in the set.

The Original Program

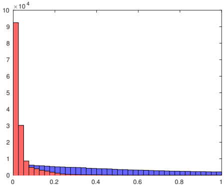
```
fun f( d1, d2, m, m1, m2, m3, m4 ) =
  let
    fun lerp( x, y, t ) =
      x*( 1.0-t )+y*t
  in
    case abs( d1/d2 ) of t =>
    case lerp( m1, m2, t ) of tm1 =>
    case lerp( m3, m4, t ) of tm2 =>
    case m < tm1 of
      false => (
        case m < tm2 of
          false => m
        | true => 0.0 )
    | true => 0.0
  end
```

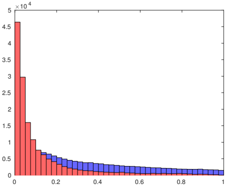
The Improved Program

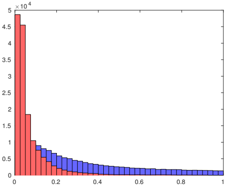
```
fun f( d1, d2, m, m1, m2, m3, m4 ) =
let
  fun lerp( x, y ) = x*( 1.0-m3 ) + y*m3
in
  case m < lerp( m1, m2 ) of
    false => (
      case m < lerp( m3, m4 ) of
        false =>
          abs( m/tanh( m/d2 ) )
      | true => 0.0 )
  | true => 0.0
end
```

- smaller than the original.
- the interpolation parameter t has been removed.
- *lerp* has changed to use m_3 instead of t.
- now returns $m/(\tanh(m/d2))$ instead of m on unsuppressed values.

The Semantics of the Improved Program





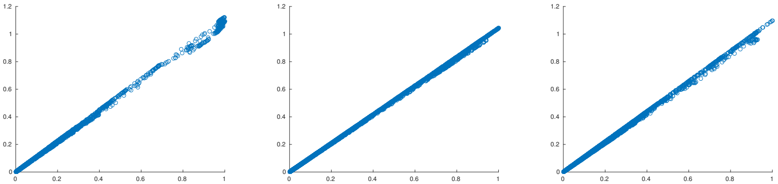


The histograms show the distributions of $m3$ in red and t in blue.

On average $m3$ is significantly smaller than t.

This has the effect that the linear interpolation will prioritize the axis-aligned neighbors over the diagonal when angles are close to the diagonal.

The Semantics of the Improved Program



The scatter plots show the difference between m and $m/(\tanh(m/d2))$.

Considerable correlation between the two, but the latter is slightly larger.

The variation is caused by the denominator $\tanh(m/d2)$.

Values will be largest when the gradient angle is axis aligned and reduced when approaching the diagonal.

Benchmarks

We did our bencmarks with the dedicated test set in BSDS500, and we evaluated using the same function as in [1] (*accumulated* F-measure).

We test each of the algorithms using two constant configurations; one optimized for the entire dataset (OD), and one optimized for each image (OI).

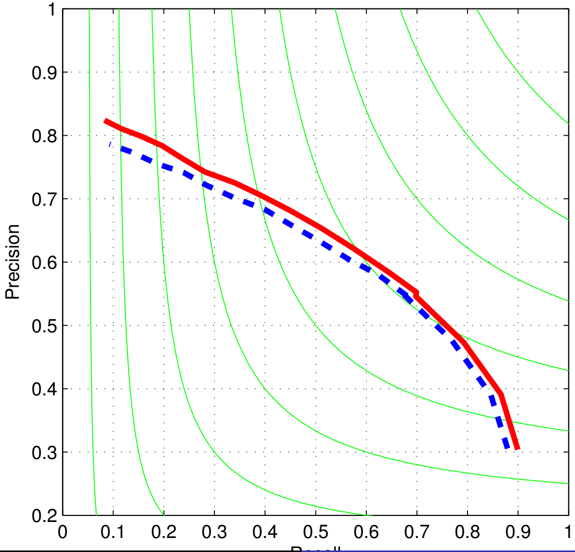
	ODF	**OIF**
SCG	0.71	0.73
ADATE-Improved	0.618	0.657
Canny	0.606	0.652

The ADATE-improved algorithm has been improved by 1.1 percentage points or 1.9% with OD constants, and by 0.5 percentage points or 0.8% with OI constants.

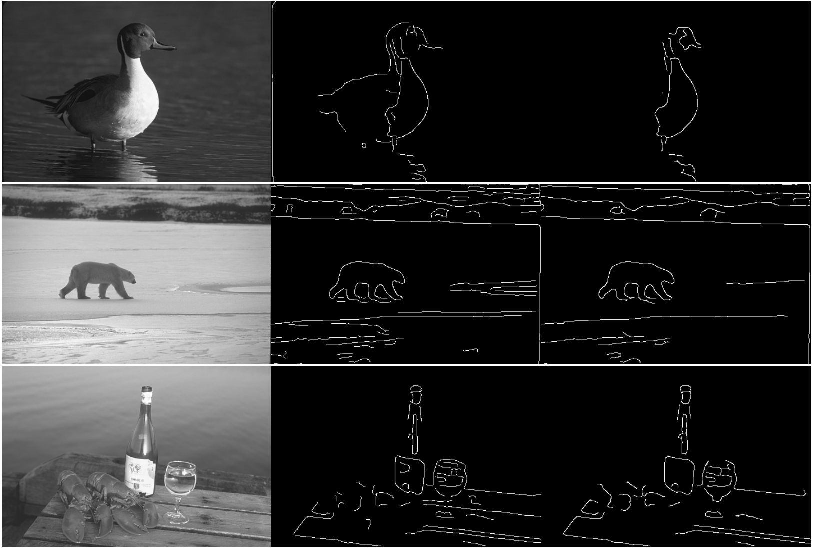
A student-t test and a Wilcoxon signed-rank testgave a p-value of 6.45×10^{-9} and 1.649×10^{-9} respectively.

ROC

The ROC curves for the improved (red) and the original (blue).



Examples



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