



Week 2

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UCF REU

K-Means Clustering

- An algorithm to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean.

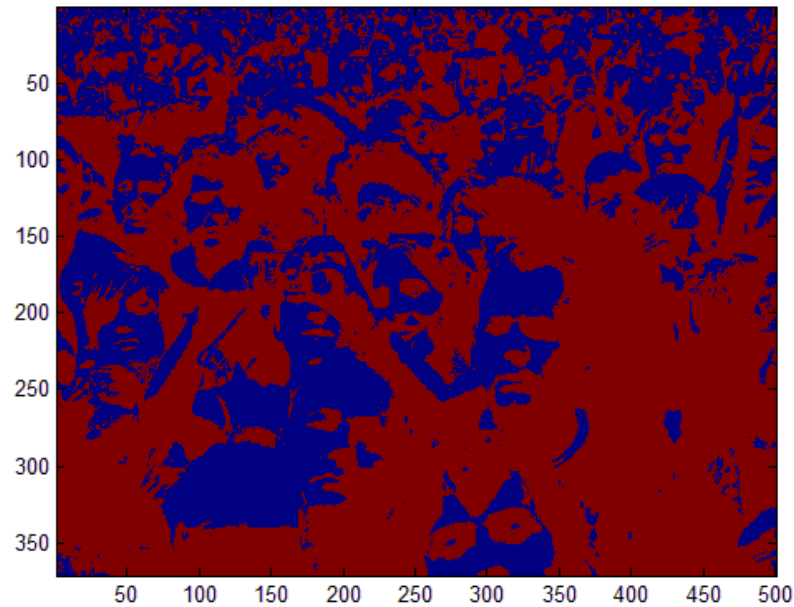
The Experiment

- Original Image:



Results

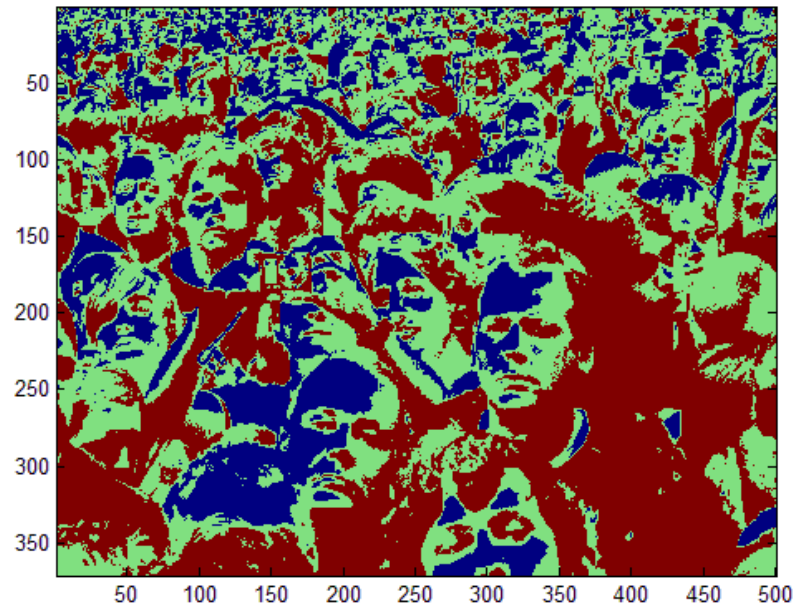
- $K = 2$:



20 100 120 500 520 300 320 100 120 200

Results

- $K = 3$:

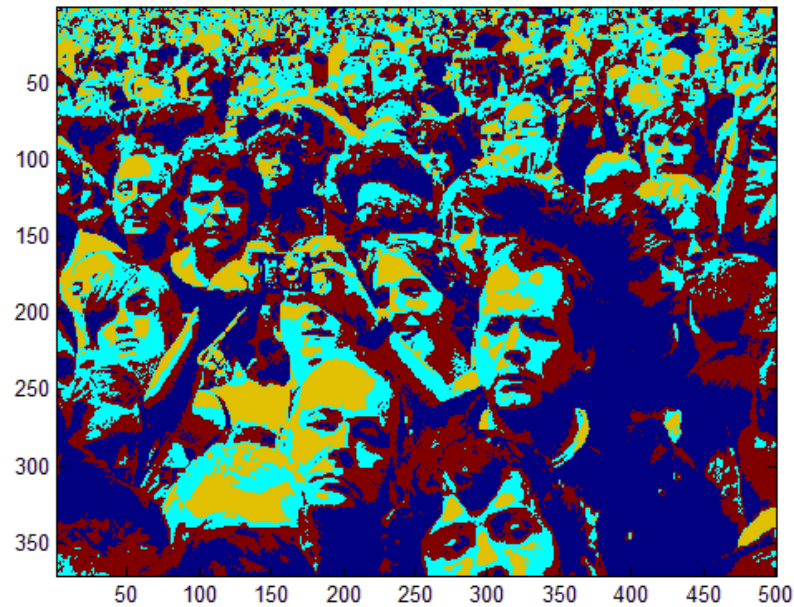


20 100 120 500 520 300 320 100 120 200

320

Results

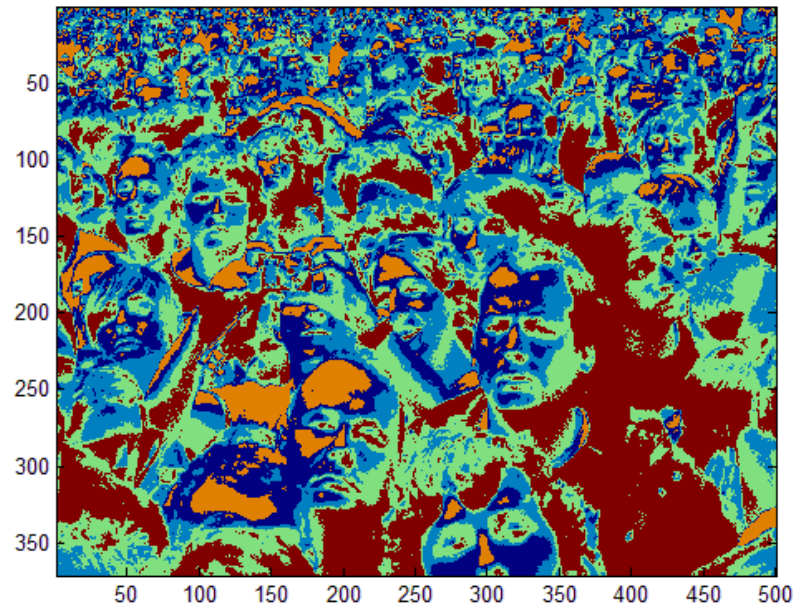
- $K = 4$:



20 100 120 500 520 300 320 100 120 200

Results

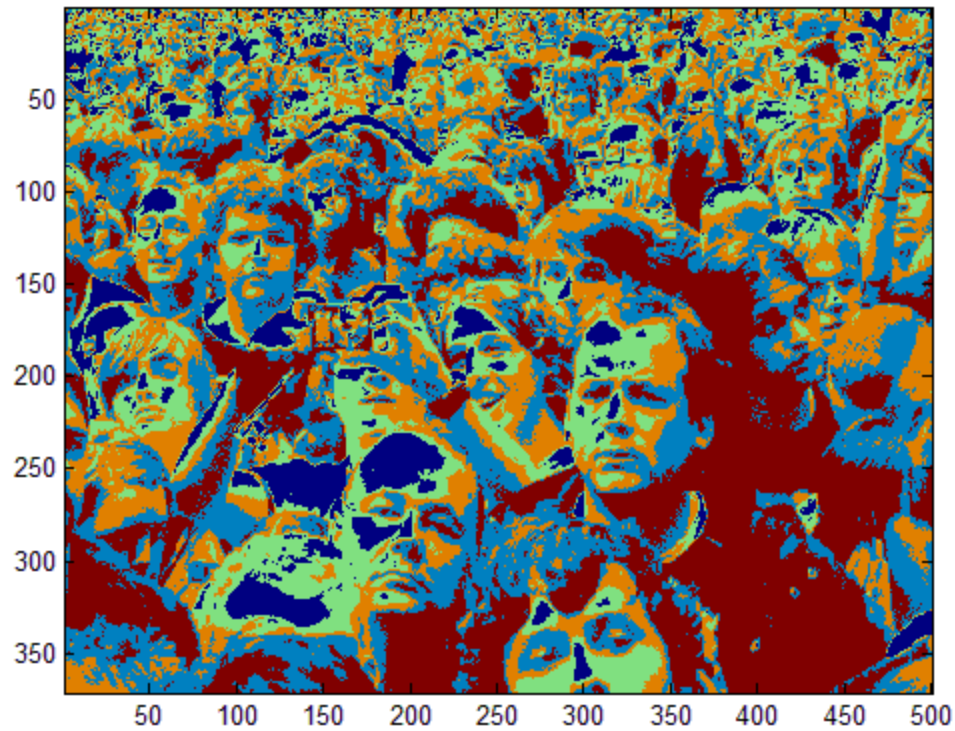
- $K = 5$:



20 100 120 500 520 300 320 100 120 200

320

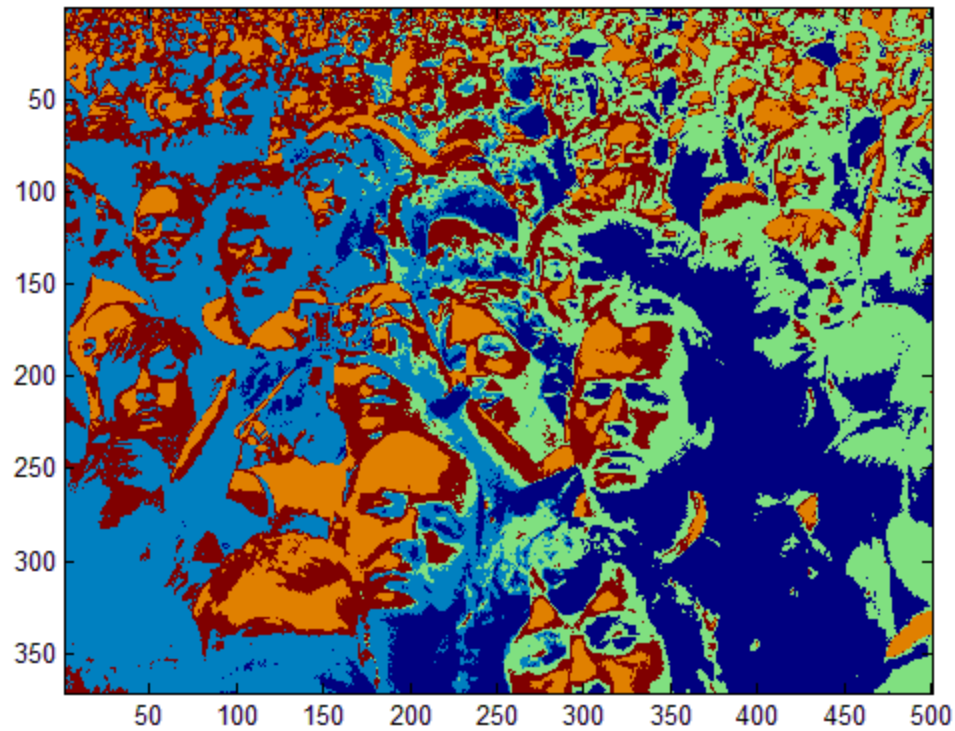
Results



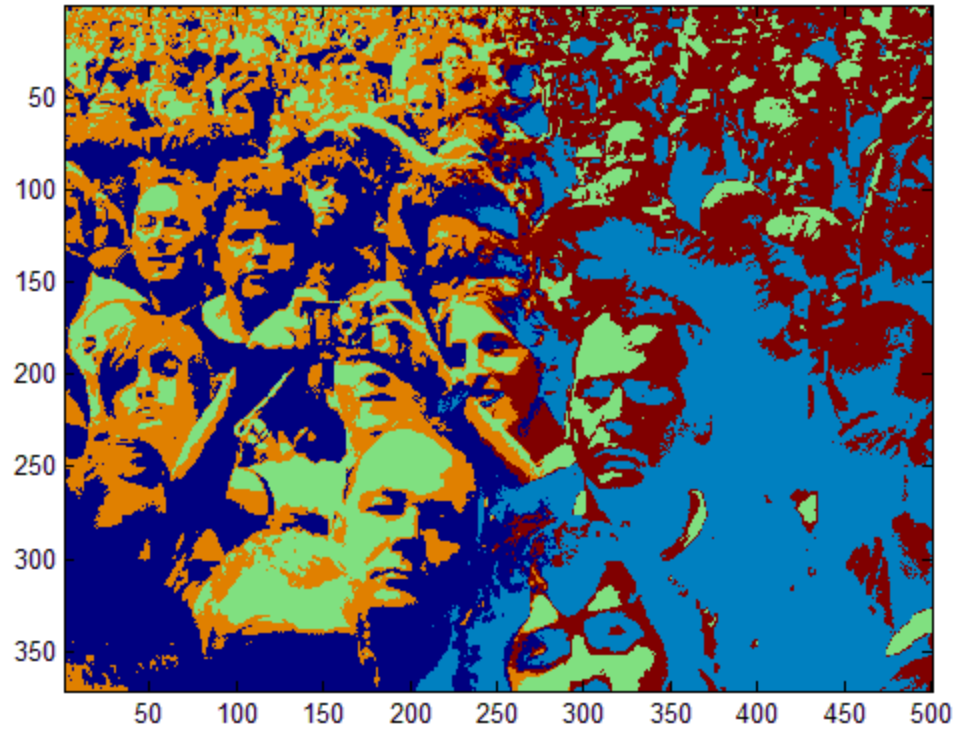
20 100 120 500 520 300 320 400 420 200

320

Results



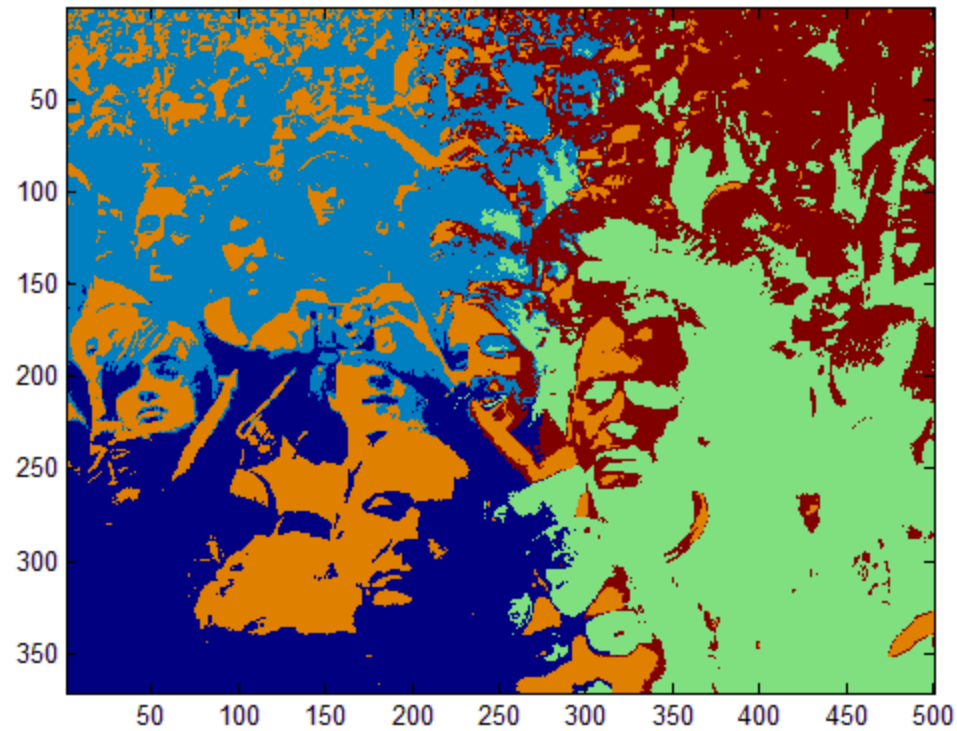
Results



20 100 120 500 520 300 320 400 420 200

320

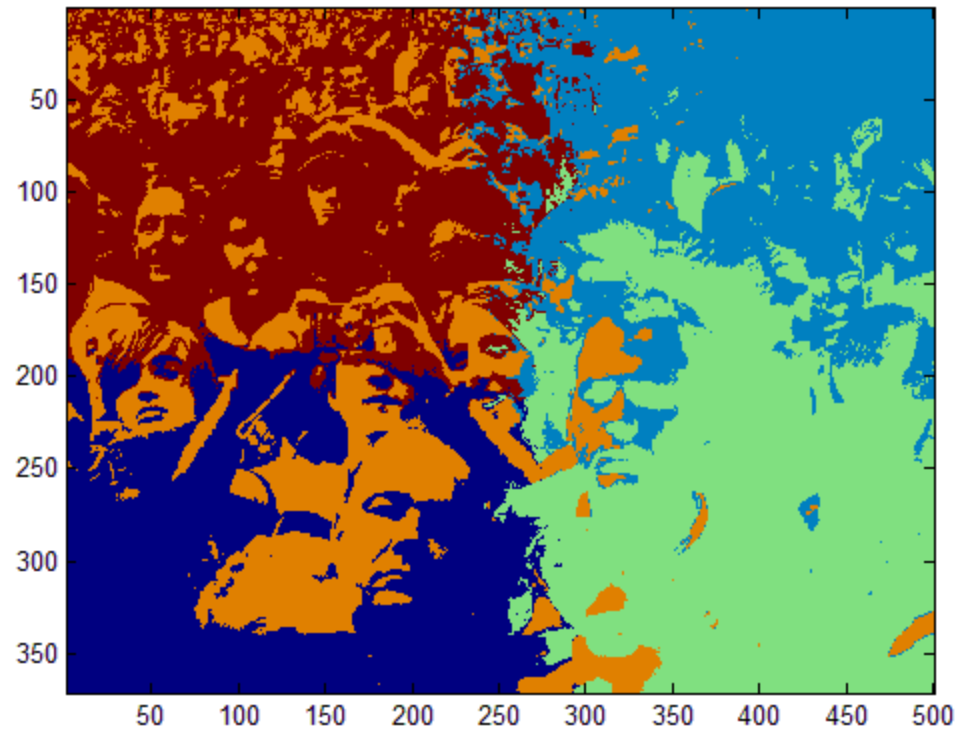
Results



20 100 120 500 520 300 320 400 420 200

320

Results



20 100 120 500 520 300 320 400 420 200

320

Results

- Including a proximity term can subtly increase performance.
- Choosing a large weight for proximity in the “similarity” function can significantly decrease the quality of the output because the clusters begin to form “blobs.”

Optical Flow with Lucas-Kanade

- The **Lucas-Kanade method** is a way to estimate optical flow from two successive frames. **Optical flow** is the apparent motion of objects between an observer and the scene.

The Experiment

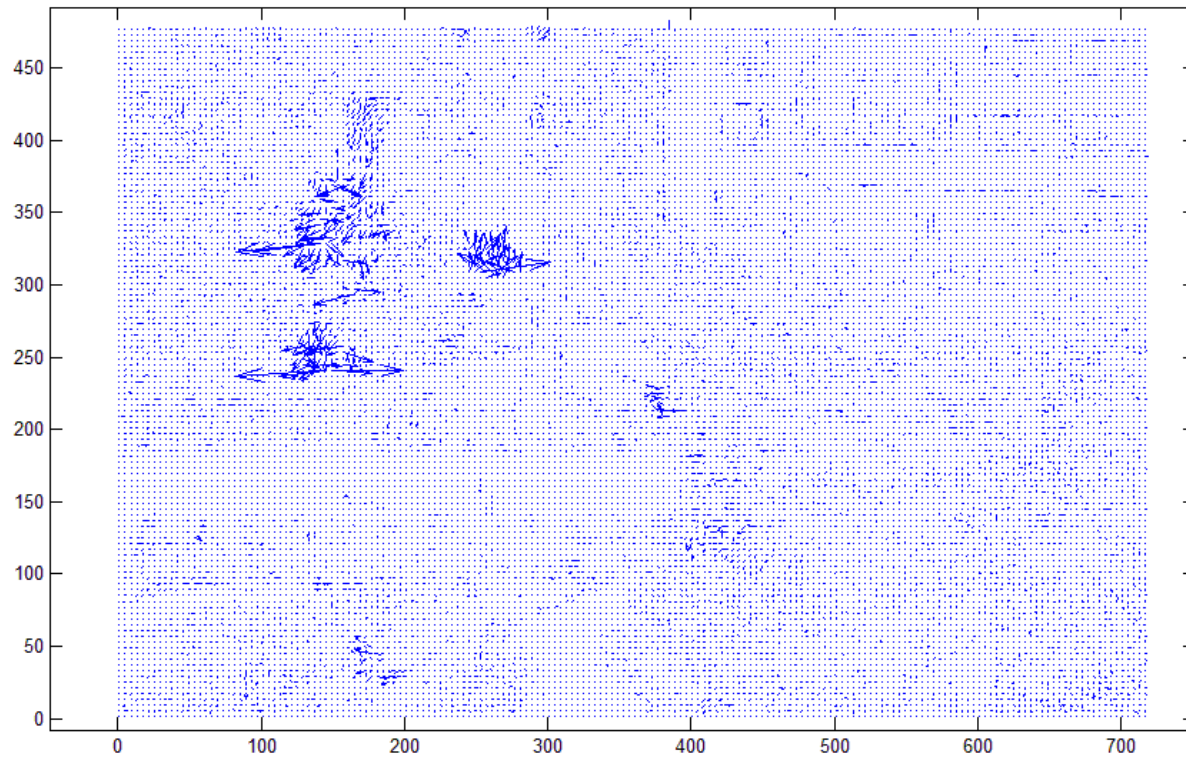
● First Image:



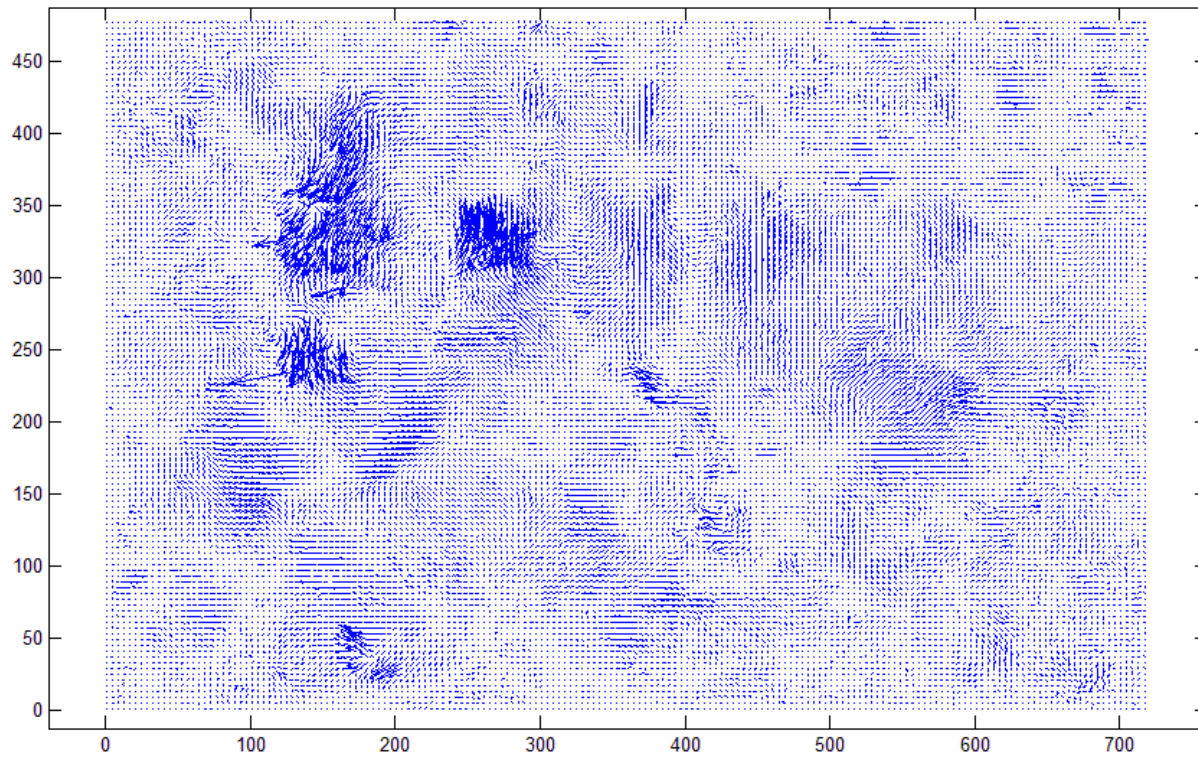
Second Image:



Results



Results



The Experiment

● First Image:

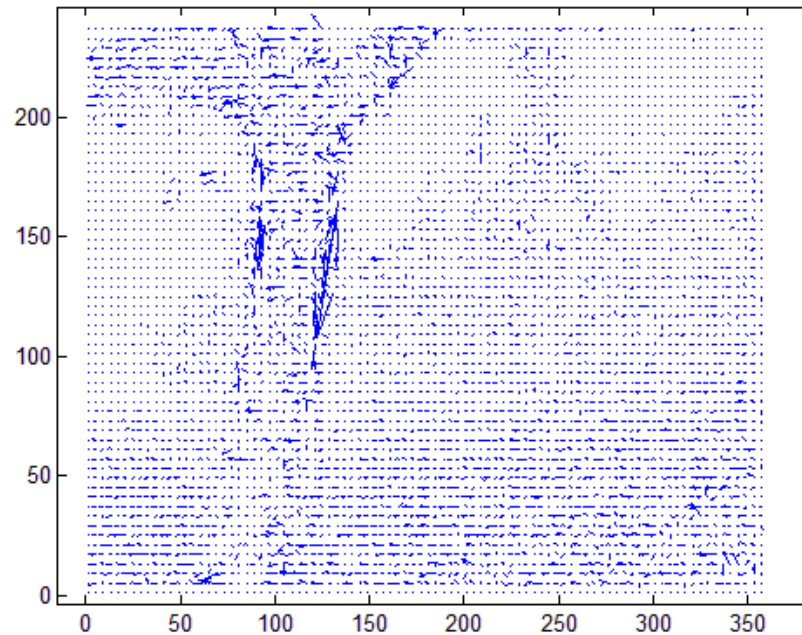


Second Image:



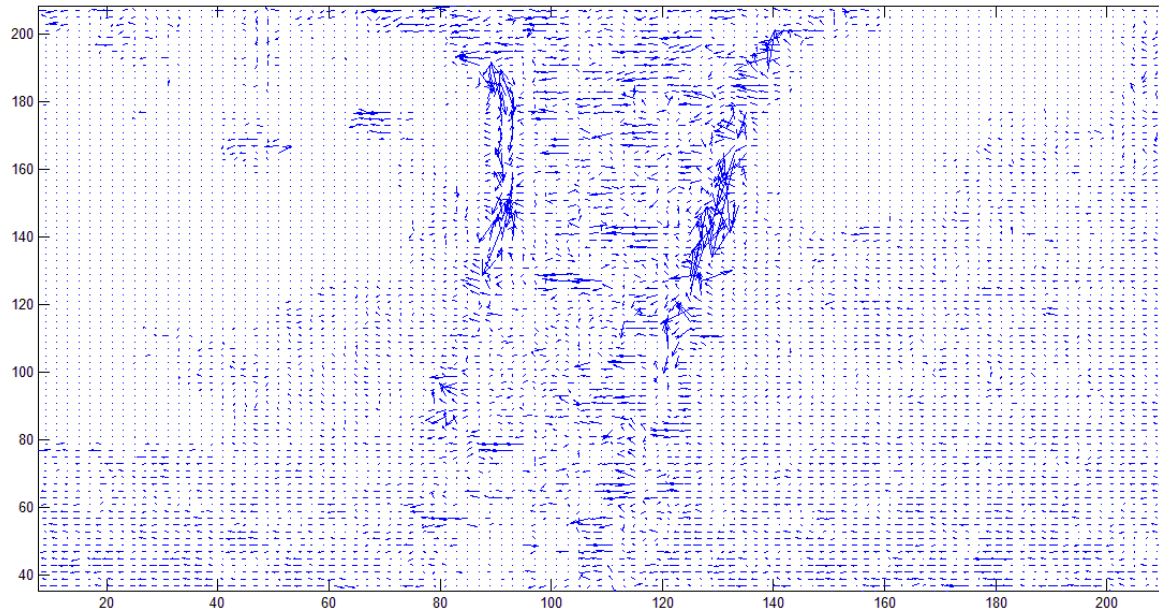
Results

- Without pyramidal refinement:



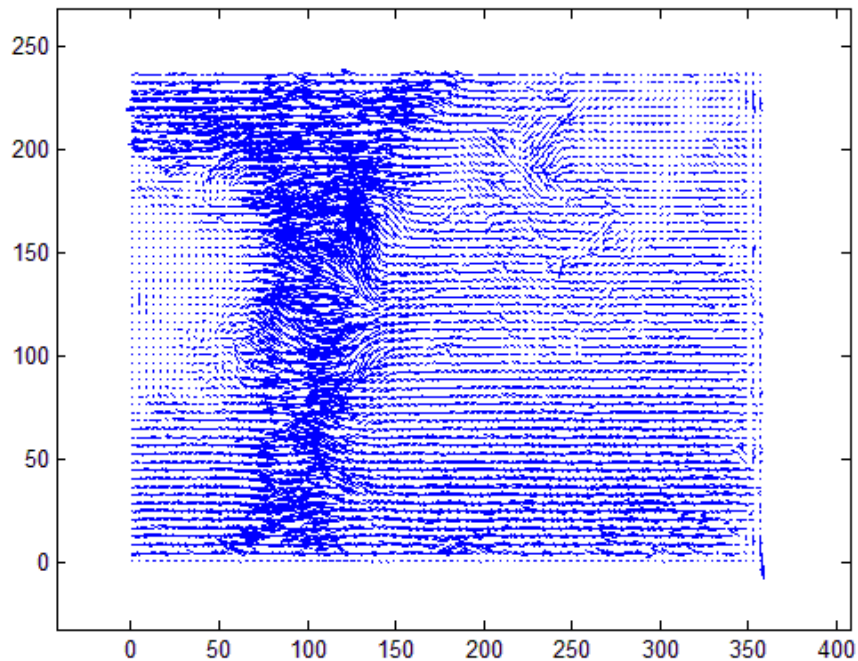
Results

- Without pyramidal refinement:



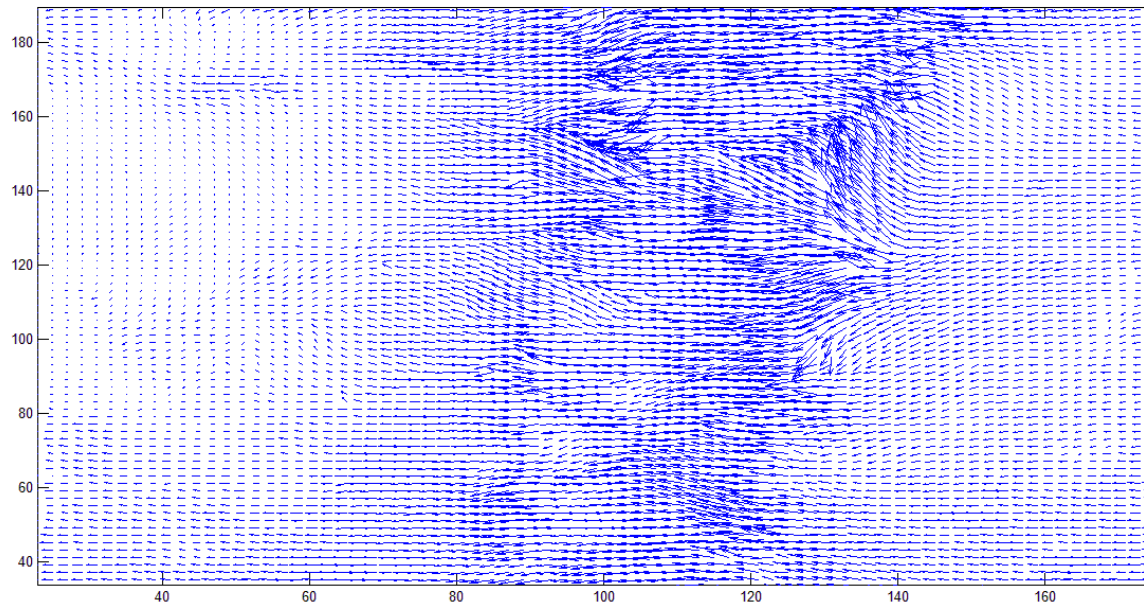
Results

- With pyramidal refinement:



Results

- With pyramidal refinement:



Results

- When a scene contains movement of more than a few pixels, pyramidal refinement dramatically increases accuracy.
- Pyramidal refinement took about 1.5 times longer due to generating the mipmaps of the pyramid and calculating the optical flow of each.

Background Subtraction

- Two methods were used:
 1. Computing the background as the median of the intensities of each pixel and rejecting the pixels which were 0.05 away (where intensity ranges from 0 to 1).
 2. Modeling the intensity of each pixel as a Gaussian distribution and rejecting the pixels which were not within 2.5 standard deviations of the mean.

Results for Method 1

Original Video



Result of Background Subtraction



Results for Method 2

Original Video



Result of Background Subtraction



Results

- Method 1 (background as median) worked better because the median ignores statistical outliers (i.e. moving foreground objects).
- Method 2 would have likely worked better if a mixture of Gaussians was allowed, rather than a single Gaussian to fit a possibly irregular distribution.
- Both methods used arbitrary thresholds, one in terms of brightness and one in terms of standard deviations. The thresholds were chosen to yield optimal results for both methods.

Research Ideas

- Augmented reality on Android phones.
- Medical image processing to detect tumors, fractures, etc.
- Image and video vectorization, interpolation, and compression.
- Detecting aggressive driving behavior with surveillance cameras.
- Optical character recognition, including mathematical typography.
- Texture recognition (bricks, wood, etc.).
- Aesthetic image scaling.
- High resolution photography from multiple low-resolution cameras.
- Shape/depth from shading and texture (i.e. not stereography).
- Estimating high dynamic range from LDR imagery.
- Remote sensing of river/stream/lake/ocean advection through optical flow methods.