Object Segmentation in a Sequence of Images using Probabilistic Graphical Models

GJJ Korf (21726167) | Supervisor: Dr CE van Daalen

Department of Electrical and Electronic Engineering, Stellenbosch University, South Africa, 2021

1. Background

- **Autonomous systems** need to understand the environment around them.
- **Distinguishing between different objects** in sensor observations plays a part in this understanding and this is the problem of object segmentation.
- In this project we focus specifically on **observations obtained from moving camera.**

2. Problem

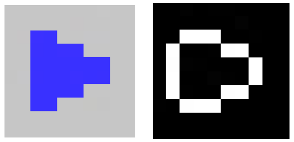
- Develop a solution that **segments objects in a sequence of images** that can be obtained from a video.
- Use **information about the contents of images** in order to determine where pixels are that are related to the boundaries of objects.
- Reason about the information using a **probabilistic graphical model** to ultimately draw the boundaries of objects on the input images.

3. Approach

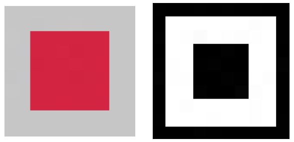
- Investigate various image processing algorithms in the **feature detection subset** to determine what value they can add to a solution of object segmentation.
- Design a PGM that incorporates the results of image processing algorithms to **reason about where the boundaries of objects are.**

4. Image Processing Algorithms

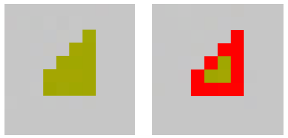
- **Canny edge detector.** Identifies edges in an image using a gradient and threshold approach. Use Otsu's method to dynamically choose thresholds for input image.



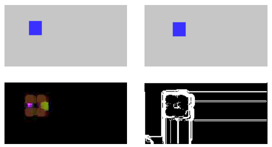
- **Image intensity gradient.** Isolate gradient process from Canny edge detector. Determine the best general using different empirical approach.



- **Contour detection.** Identifies the contours of objects within binary images. Use adaptive thresholding to dynamically convert input images to binary images.

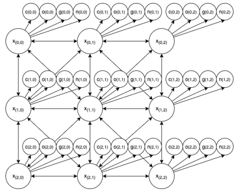


- **Optical flow.** Calculates vectors for how pixels move over two sequential images. Iterate through vectors to determine where the boundaries of object are.

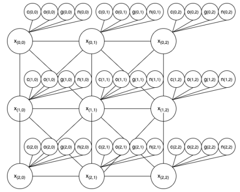


5. Probabilistic Graphical Model

- Create **variables** for every pixel in an image.
- Create **variables** for all the image processing algorithm observations.
- Create a **graph** of all the variables and link them together. Links show the influence variables have over the each other and distributions are defined for them according to the continuity of boundaries and how often image processing algorithms are wrong. Graph types can be converted to others.

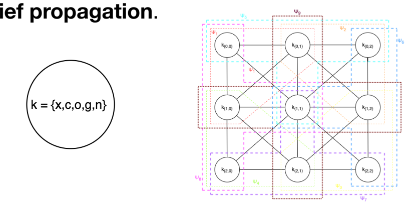


Bayesian network



Markov random field

- Group together variables to form clusters and create a **cluster graph**. Clusters can share their beliefs about common RVs through a message passing algorithm known as **loopy belief propagation**.

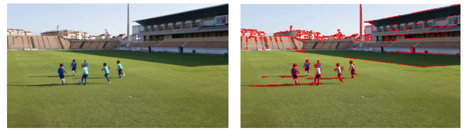


- After the beliefs clusters have converge, we can extract the probability of a pixel being a boundary of an object given the observations from the image processing algorithms. Applying a threshold to this probability and drawing boundary pixels on the original images leads to the results.

$$p(x_{(i,j)} = 1|E) \geq 0.5 \quad : \quad \text{boundary}$$
$$p(x_{(i,j)} = 1|E) < 0.5 \quad : \quad \text{not a boundary}$$

6. Results

Input *Output*



Input *Output*

Input *Output*

7. Conclusions

- Solution is **marginally successful**.
- Results improve when there is a **clear distinction between the fore- and background** in the input images.
- Objects within others are **treated separately from the main object**, such as the wheels on a car.
- There is no discrimination between 2-D and 3-D objects. Ideally we would like 3-D objects to be the focus of the segmentation as autonomous systems can interact with them.
- Future work should focus on **improving the continuity of boundaries** as the methods in this study fail under unaccounted for circumstances.
- Future work should also focus on objects we care about more, such as **3-D objects**.