# Generalizing Foreground Estimation Algorithms in Dynamic Background Conditions

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# Introduction

- Every scene consists of foreground and background.
- Foreground and background depends on the context of a scene. The context could be better understood when the scene is a frame of a video.
- Estimating what part of the frame is foreground is useful for all computer vision applications (e.g: Surveillance, object detection etc:)
- Foreground estimation is trivial in static background - dynamic foreground conditions.
- Foreground estimation is challenging in dynamic backgrounds.

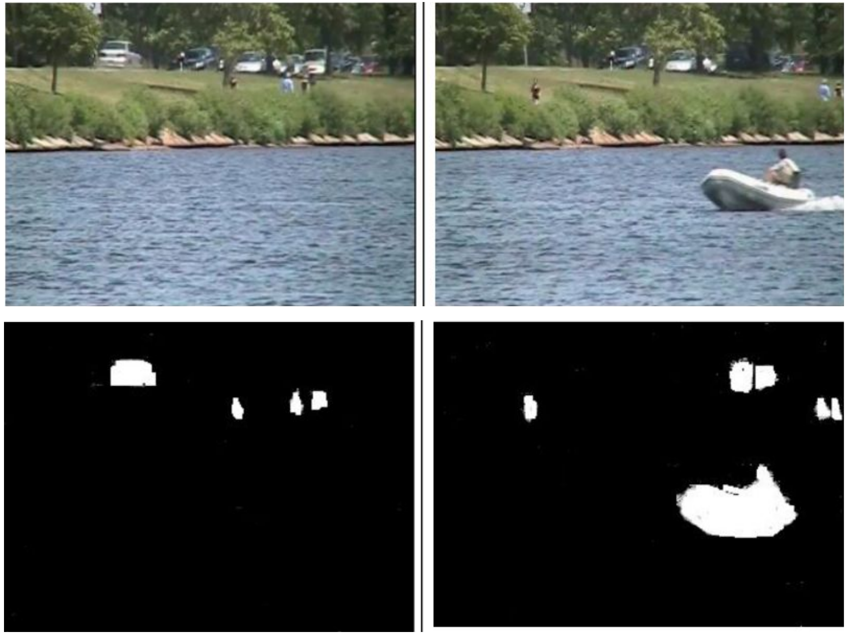
# Problem Definition

A. Analyze the efficiency of foreground estimation algorithms over a range of situations.
B. Explore the contribution of hyper-parameters for the performance of these algorithms.
C. Explore the possibility of aggregating algorithms to improve the performance.

Note: this study focuses on the classical algorithms (pre deep learning)

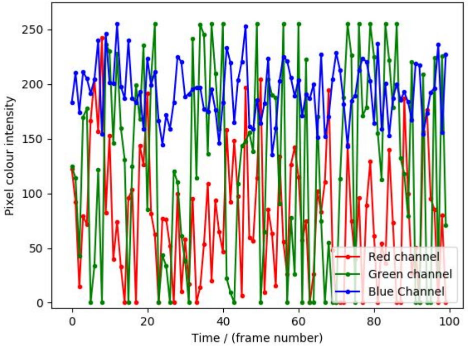
# Defining a test bench (and groundtruth)

- Background
  - Static background
  - Dynamic background
    - Shaking trees
    - Rippling water
- Foreground
  - People
  - Vehicles
  - Boat

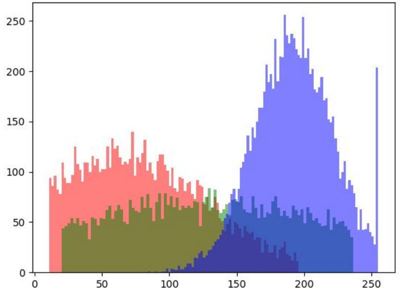


Row 1: Input frames
Row 2: Ground truth
(*white* = foreground, *black*=background)

# Overview of all the algorithms




Time series analysis




Histogram analysis

All algorithms explored in this work try to model the background by it's time series or histogram (or a combination of both) and use that model as an discriminator to identify whether a particular pixel at a particular time belongs to the background or foreground.

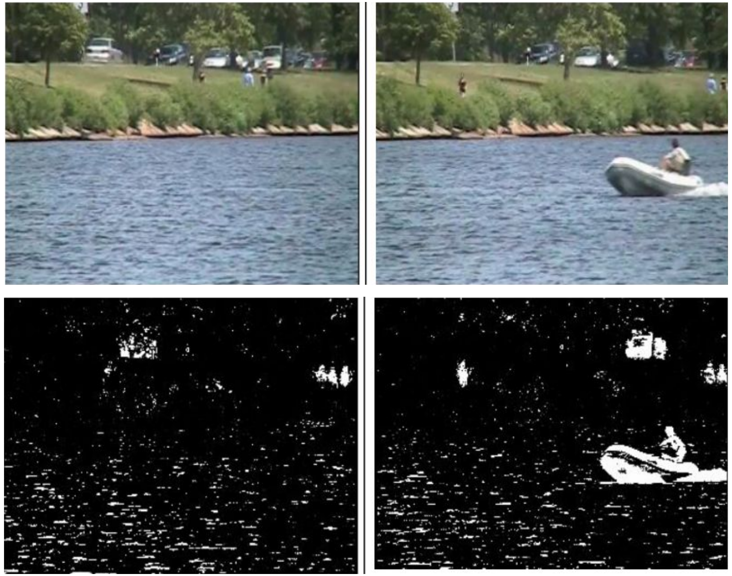
# Algorithms

1. Mixture models
    a. Non adaptive mixture models
        i. Gaussian mixture model
        ii. Cylindrical mixture model
    b. Adaptive mixture models
        i. Adaptive gaussian mixture model
        ii. Adaptive cylindrical mixture model
2. Pixel Based Adaptive Segmentation
3. Graph segmentation

# Non Adaptive Mixture Models

- These models assume the time series of individual pixels come from mixtures (shaped like ellipsoids (Gaussian) or cylinders).
- Expectation maximization algorithm is used for clustering (the number of clusters = 6 is taken as a heuristic prior and they are randomly initialized)

# Non Adaptive Mixture Models : Results



Row 1: Input frames
Row 2: GMM results

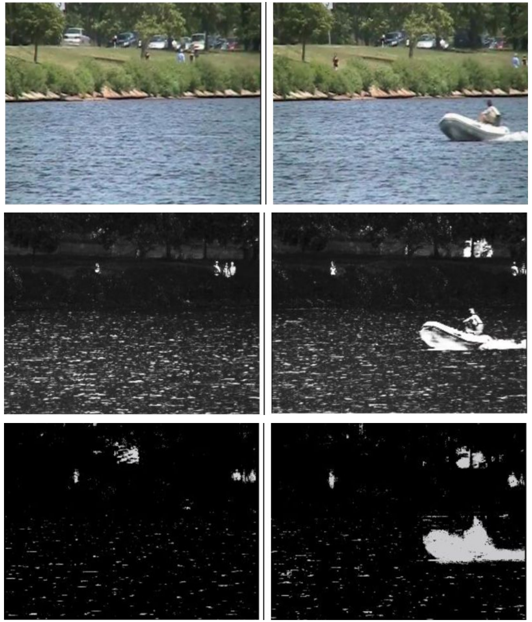
- The non adaptive models generate a lot of noise.
- They are unable to perform robustly even over small environmental changes (such as lighting condition changes etc).

# Adaptive Models

- These models assume the time series of individual pixels come from mixtures (shaped like ellipsoids (Gaussian) or cylinders) and that clusters evolve **slowly** over the time.
- The pixels that fall into the clusters are considered as background while the rest is considered as foreground.

# Adaptive Models : Results

- **AGMM** is possible capable of capturing static and slightly dynamic backgrounds. But it fails at aquatic scenes.
- **ACMM** is able to capture backgrounds most cases including aquatic scenes.
- Since the noise generated from water is of same shape and size, spatial filters could be used to get rid of that noise.

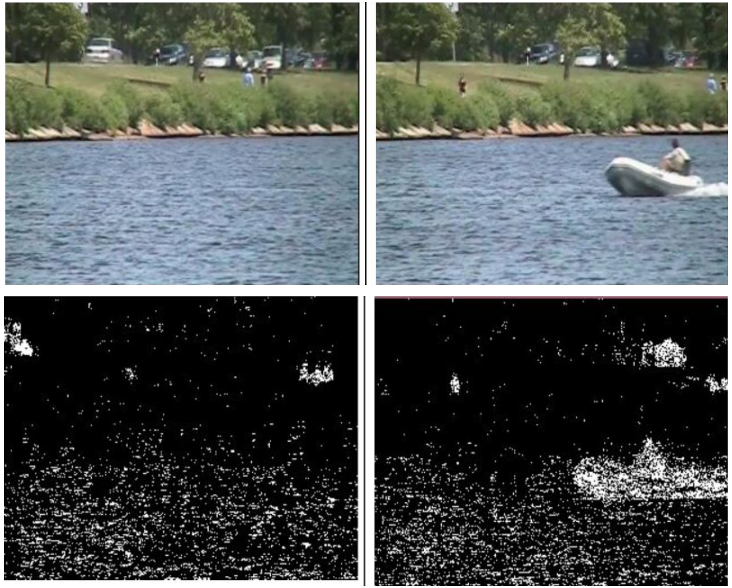


Row 1: Input frames
Row 2: AGMM results
Row 3: ACMM results

# Pixel Based Adaptive Segmentation

This approach models the background by “remembering” the colours taken by a pixel at the last few time points. This model depends on the pointwise approximation of the background model in contrast to the (Gaussian or cylindrical) distribution idea in mixture models.

# Pixel Based Adaptive Segmentation : Results

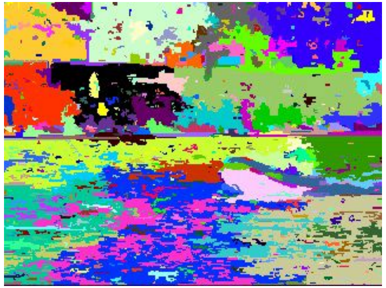


Row 1: Input frames
Row 2: PBAS results

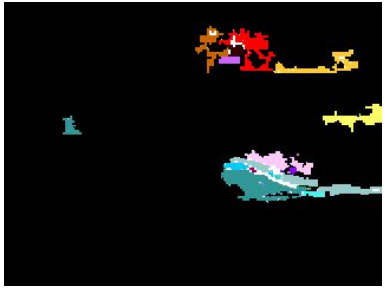
- Ripples in the water considered as foreground.
- Some pixels in the boat still considered as background.
- Considerable noise

# Hierarchical graph segmentation

Input frame



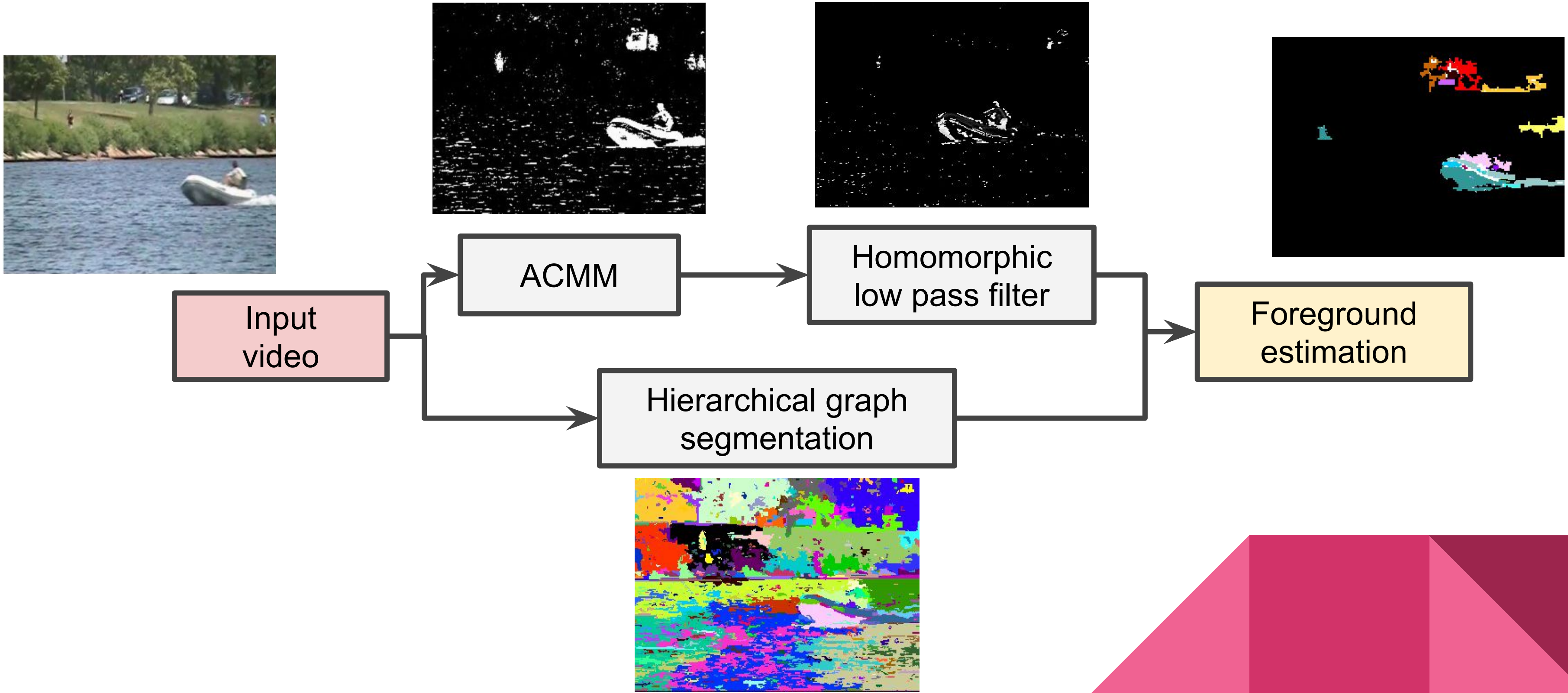
Graph segmentation



Fused with Background subtraction

- Graph segmentation algorithms are used to cluster objects in images.
- Image segmentation is  performed by imposing a soft limit on spatial and temporal pixel distances.
- Hierarchical segmentation performs image  segmentation herachically from larger to smaller segments to optimize performance.
- The proposed pipeline uses graph segmentation as a post-processing step to remove small articles in the image and identify specific objects as they

# Algorithm aggregation pipeline



# Comparative performance

**Input frame**

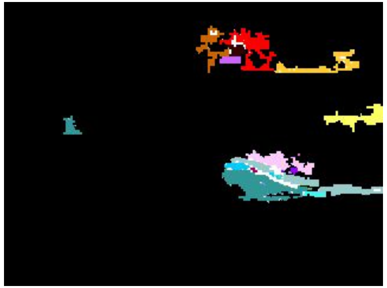
PBAS

GMM

**Ground truth**

AGMM

ACMM



**Proposed**

# Conclusions

- Adaptive mixture models outperform non-adaptive mixture models at all times.
- Cylindrical model outperforms Gaussian model when it comes to aquatic scenes.
- PBAS works only when the background is slightly dynamic.

# References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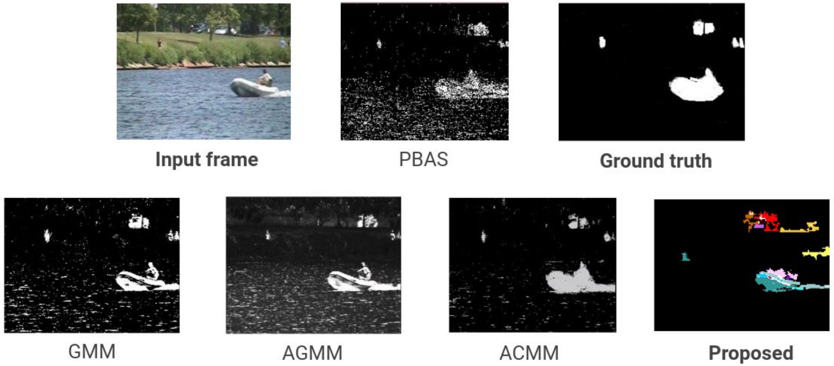
# Summary

- Background subtraction (=foreground estimation) in videos. Trivial in static backgrounds. Non trivial in dynamic backgrounds.
- Analysis on videos with land, aquatic, humans, vehicles, plants.
- Algorithms : Mixture models (adaptive and non adaptive, Gaussian and cylindrical), PBAS, RPCA, graph segmentation.

## Comparative performance




# Thank you!