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### Introduction

Challenges in video processing for visual surveillance such as shadows, reflections, illumination changes, occlusions, and weather conditions as well as moving objects and camera motion and vibration are common and induce variability for each pixel in an image. Current computer vision approaches rely on controlling the huge number of parameters involved in scene variability, by addressing those challenges by creating extra add-on modules in their processing pipeline. We believe a new strategy may be required underpinned by the realisation that scene variability should be the expected norm rather than an inconvenience to control.



Analogy between (a) Cell duplication and (b) video capture by a surveillance system.



PROFILE HIDDEN MARKOV MODELS FOR FOREGROUND OBJECT MODELLING

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Insertion: Change in camera angle and/or position revealing previously occluded data, more details in common field of view (zoom in), Deletion: Change in camera angle and/or position introducing new occlusions, less detail in common field of view (zoom out),

Foreground identification process. A foreground object, Fa, is visible in all scanlines that are analysed, occluding various background regions.

**Segment-based clustering:** Given a set of foreground object segments, a phylogenetic tree is built encapsulating the similarity among segments. Families of segments in the tree can be discovered by finding groups characterised by significant intra-group similarity.

**P-HMM generation:** For each family of segments, a profile is built encapsulating multiple correspondences across all members and it is used define the architecture, as well as, the parameters of an HMM, i.e. transition and emission probabilities.

**ROI scanning:** Resulting segment profiles are scanned over regions of interest. An illustration of a subtree calculated with the proposed Foreground: The final foreground segmentation consists of the overlay between the method. In this example, the subtree consists of segments from the jeans jacket of the moving object initial and the detected foreground segments obtained with P-HMMs. shown above.

Foreground

Non-matching regions Best region matches

Gap regions





# **Conclusion & future work**

## References

Computer Vision (2011): 1583-1590.



• A bioinformatics-inspired pipeline for the generation of novel object descriptors and the detection of associated objects within a video.

• Added value demonstrated by evaluation performed on a standard video dataset comprising a variety of scenes and camera motions.

• Usage of those object descriptors for direct foreground detection in unseen frames to be investigated in future work.

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