An algorithm for recovering camouflage errors on moving people

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Outline

- Definition of the problem
- Related works
- The proposed algorithm
- Experimental results

Detecting Moving Objects

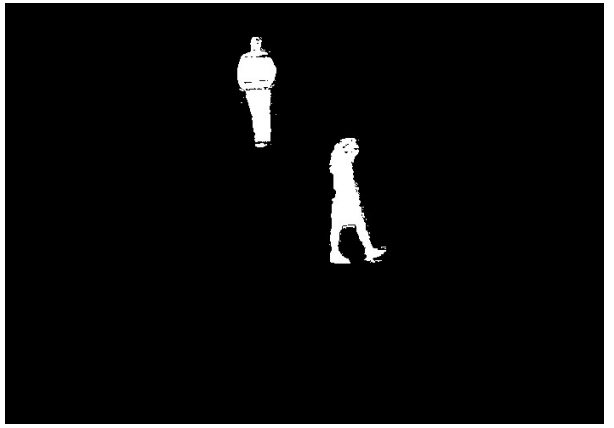
The most popular approach: *Background Subtraction*

Current Frame

-

Background

=



Foreground Mask

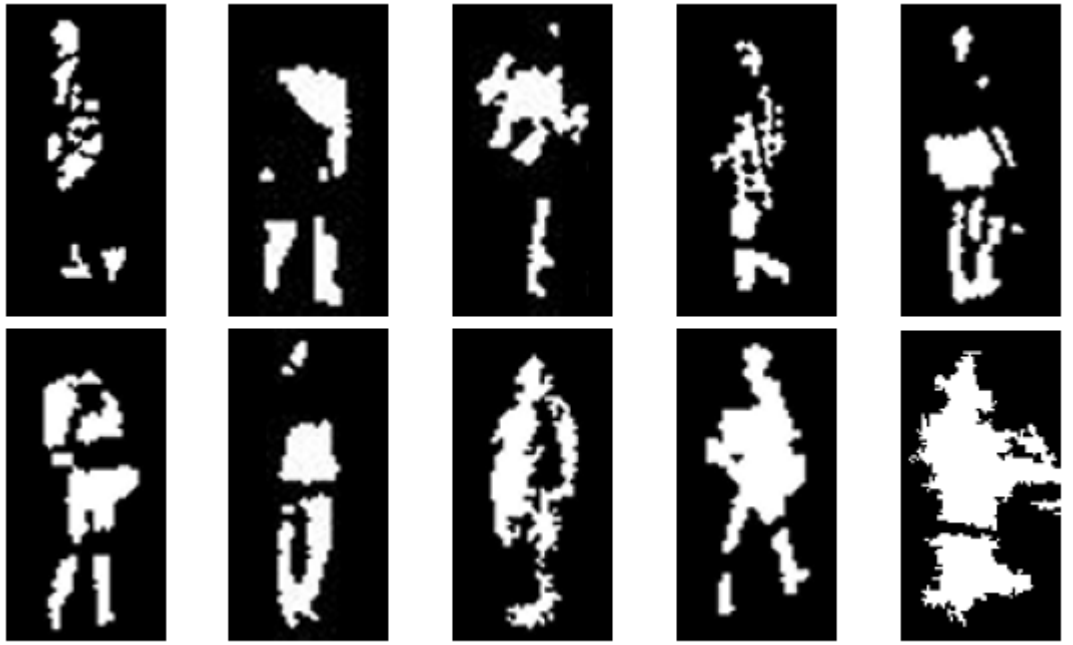
Moving Objects

The camouflage problem 1/2

- Background subtraction technique is subject to a set of well known problems, categorized in [9]
- One of this is the *camouflage*

The camouflage problem 2/2

- The effect of camouflage consists in a (random) fragmentation of the actual object in the scene



Related Works

- Camouflage has received less attention than the other problems
  - Some methods (e.g. [4]) involve the use of depth information to detect camouflaged objects
    - High computation cost and impracticable with legacy cameras
  - Other methods (e.g. [3, 8, 10]) propose some techniques to detect camouflaged objects by exploiting properties (e.g. color) of pixels belonging to a camouflaged object.
    - A single camouflaged pixel is unrecognizable without analyze its neighborhood

The proposed algorithm

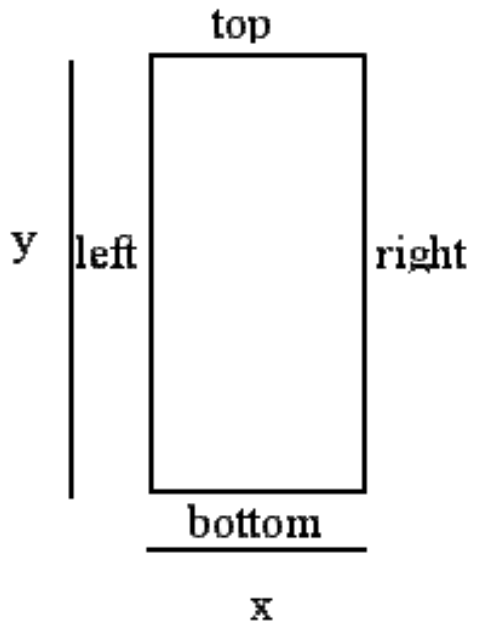
- We define

1. a model of the desired object(s)

1. a procedure to suitably grouping obtained blobs (connected components detected in the background subtraction phase) so as to adequately fit the model

The proposed model

- We focused our attention to the detection of moving people
- The model must be carefully defined:
  - A too detailed model would result in many missed detection
  - A too general model would cause the generation of many false positive errors



$b_1 \le x \le b_2$

$h_1 \le y \le h_2$

b_1 and b_2 are minimum and maximum real width

h_1 and h_2 are minimum and maximum real height

The grouping procedure 1/2

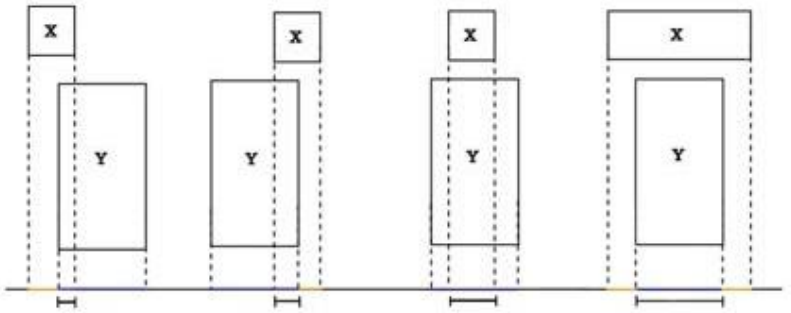
- Objective
  - grouping two or more blobs in order to form a unique blob representing the object defined with the model

- The procedure
  - repeatedly merging couples of blobs into larger ones until the new blob best fits the defined model

The grouping procedure 2/2

- Conditions to group two blobs (represented by their bounding boxes X and Y)

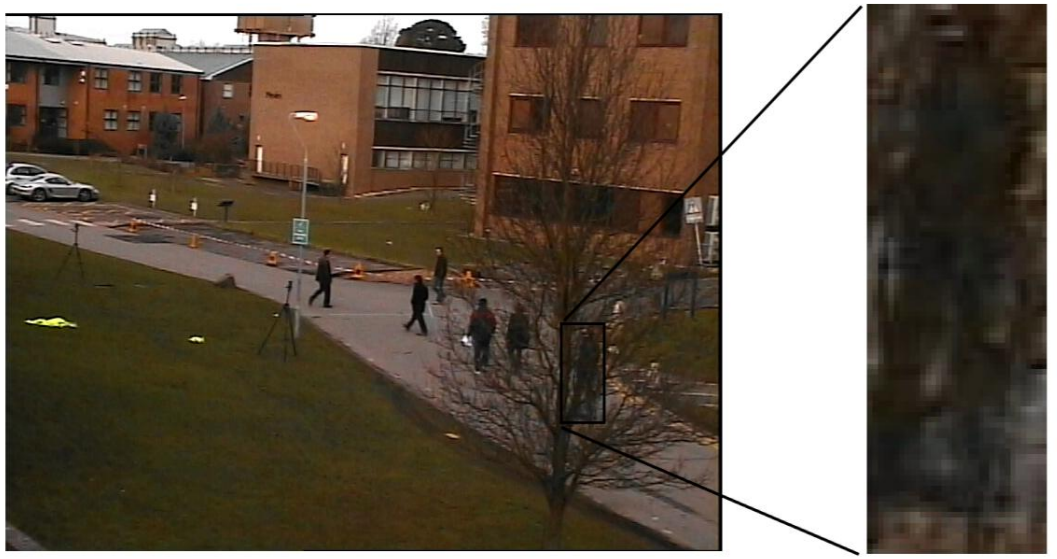
1. $right_p(X) \geq left_p(Y) \wedge left_p(X) \leq right_p(Y)$
   - The projection on the horizontal axis of the bounding boxes are overlapped
2. $height_r(Z) \in [h_1, h_2]$
   - The real height of the grouped box is included between h_1 and h_2
3. $width_r(Z) \in [b_1, b_2]$
   - The real height of the grouped box is included between h_1 and h_2



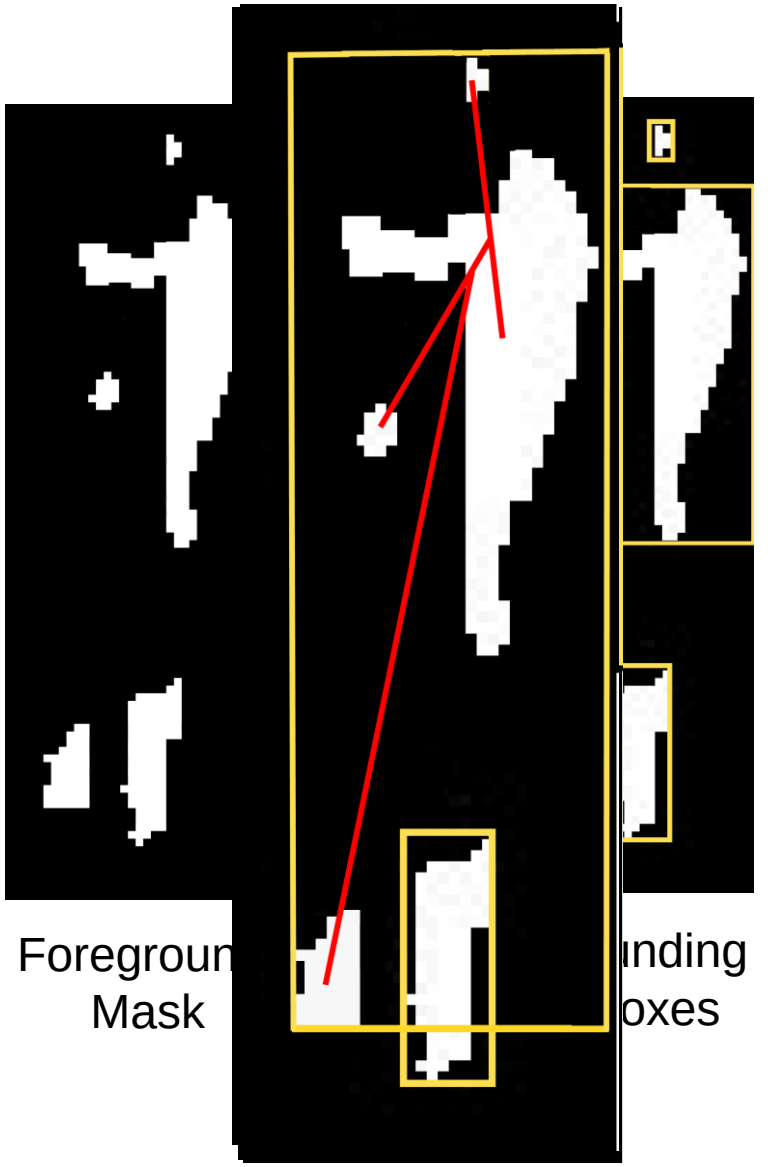
The grouped box Z is built starting from X and Y pixels coordinates

Inverse Perspective Mapping is applied in order to determine its real size

An Example



Source image and a detail of a person



Experimental Results 1/4

- The proposed method
  - is independent from the foreground detection algorithm used
  - is used as a postprocessing on the output of four well known foreground detection techniques
    - *Mixture of Gaussians* [5] (MOG)
    - *Enhanced Background Subtraction* [2] (EBS)
    - *Self-Organizing Background Subtraction* [7] (SOBS)
    - *Statistical Background Algorithm* [6] (SBA)

Experimental Results 2/4

- Performance index

$$f\text{-}score = \frac{2 \cdot precision \cdot recall}{precision \cdot recall}$$

$$precision = \frac{TP}{TP + FP} \qquad recall = \frac{TP}{TP + FN}$$

Fuzzy definition for True Positive, False Positive and False Negative

$$TP = \sum_{g \in G} \sum_{d \in D} \frac{|g \cap d|}{|g \cup d|} \qquad FP = \sum_{d \in D} \frac{|d| - max_{g \in G} |d \cap g|}{|d|} \qquad FN = \sum_{g \in G} \frac{|g| - max_{d \in D} |d \cap g|}{|g|}$$

where
G set of bounding boxes of the ground truth
D set of bounding boxes detected by the algorithm
$|\cdot|$ area of a bounding box

Experimental Results 3/4

- Dataset

videos acquired in different lighting and weather conditions

NA1

NA2

NA3

Public database
(PETS Conference)

http://www.cvg.rdg.ac.uk/PETS2006/

PETS

Indoor sequence
(presented in [7])

MSA

Experimental Results 4/4

Video ID	EBS			MOG			SBA			SOBS		
	bef.	aft.	imp.	bef.	aft.	imp.	bef.	aft.	imp.	bef.	aft.	imp.
NA1	.671	.673	0.3%	.657	.668	2.0%	.220	.304	38.5%	.530	.573	8.0%
NA2	.775	.875	12.9%	.671	.676	0.7%	.256	.278	8.5%	.434	.510	17.4%
NA3	.555	.693	24.7%	.644	.649	0.7%	.204	.227	10.9%	.287	.420	46.4%
PETS	.773	.801	3.6%	.753	.651	-13.4%	.645	.635	-1.5%	.582	.606	4.0%
MSA	.847	.904	6.6%	.520	.539	3.5%	.163	.206	26.4%	.850	.850	-

Conclusions and Future Works

- We presented a new model-based method for removing camouflage errors in video surveillance applications
- Experimentations confirmed the effectiveness of the method
- **Future improvements**
  - Refining the model
  - Definitions of suitable models for other objects of interest