



## Chapter 9

# Object Localisation

### 9.1 Introduction

A method for localising multicoloured objects in images using MNS signatures, is proposed in this section. The idea is that an object of interest is likely to appear in the part of the image with the highest population of neighbourhoods with different colours, similar to the colours of the object. In our experiments, the object representation is computed from one or more example image regions.

The proposed algorithm was tested on localising objects in two video sequences showing sport events. The results obtained were acceptable, given the appearance variations of the sought objects and the relatively poor quality of the test sequences. A comparison with a well known localisation method called *histogram backprojection* was also performed. In both experiments, the MNS localisation success rate was higher than that obtained using backprojection.

### 9.2 MNS localisation

Assuming compact objects, we require that all image neighbourhoods with colours similar to the sought object lie in a relatively small image region. A template is placed over selected image pixels and the location with most neighbourhoods similar to the object inside the template region is returned as the object's expected position. Note, that the neighbourhoods considered

are exactly the representative neighbourhoods stored in the MNS signature. Therefore, properties like the area occupied by each colour (i.e. the density of each measurement in the image) are not exploited in the reported experiments.

The MNS localisation algorithm is as follows: Let  $S_i, i = 1..n$  be the set of neighbourhoods in the test image MNS, with similar measurements to the example measurements. Here, similar are those neighbourhoods from the image signature giving measurements that *matched* with a measurement of the example image during the matching process (described in Chapter 3). We denote the centre of a neighbourhood as  $S_i^c$ . The localisation algorithm is as follows:

*Algorithm 5: Object localisation*

1. Select a rectangular template  $R$  with dimensions  $r_x, r_y$ .
2. For every image pixel  $p$  in a selected subset  $P$  of all image pixels, calculate the cardinality  $k_p$  of the set
 
$$s = (i \in S_i : S_i^c \in R_p),$$
 where  $R_p$  is the template centred at pixel  $p$ .
3. Find the pixel  $p_{object}$  for which  $k_p$  is maximum.
4. Return pixel  $p_{object}$  as the object's position

For the reported experiments, the subset  $P$  was selected to be the centres of image neighbourhoods with measurements that *matched* a measurement of the object.

### 9.3 Histogram backprojection

The histogram backprojection (HB) method, computes the ratio of the colour histogram of the object example image ( $O_i$ ) and the image colour histogram ( $I_i$ ):

$$R_i = \frac{O_i}{I_i} \tag{9.1}$$

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For each image pixel, the probability of it belonging to the sought object is computed as the count of the  $R_i$  bin the pixel indexes into. Replacing each pixel with the corresponding probability, a greyscale image is computed. Object location is established as the pixel with the maximum spatial average over a circular neighbourhood centred on the pixel.

Both MNS and HB methods require a priori knowledge of the size of the sought object in order to choose an appropriate search template/neighbourhood. In addition, both methods are likely to fail to locate extended non-compact objects. Such objects can be localised using another localisation algorithm proposed in Chapter 10.

## 9.4 Experimental setup

Two experiments were carried out, using images grabbed off two video sequences of sport events. Example images of both sequences are shown in Fig. 9.2 and 9.3. Image resolution in both experiments was  $144 \times 176$  pixels.

**Experiment 1.** The first sequence covers a skating race, focusing on a skater wearing a body suit with distinctive colours. Appearance variations are due to changing object pose, scale and changing background. A single region was selected to represent object appearance (shown in Fig. 9.1)(a).

**Experiment 2.** The second experiment, involves locating a canoeist moving along a river. Compared to Experiment 1, the effects of changing background, object pose, viewpoint and illumination are much more apparent (see Fig. 9.1)(b).

For the comparison, the histogram backprojection method was implemented, exactly as described in [85], using  $8 \times 8 \times 8$  RGB histograms and a circular neighbourhood with radius 20 pixels. Regarding MNS, the default settings of the algorithm were used, identical to those used in other experiments described in this thesis. A template of size  $60 \times 40$  was selected for localising the skater and  $50 \times 40$  for localising the canoeist. The example regions selected for each object are shown in Fig. 9.1.

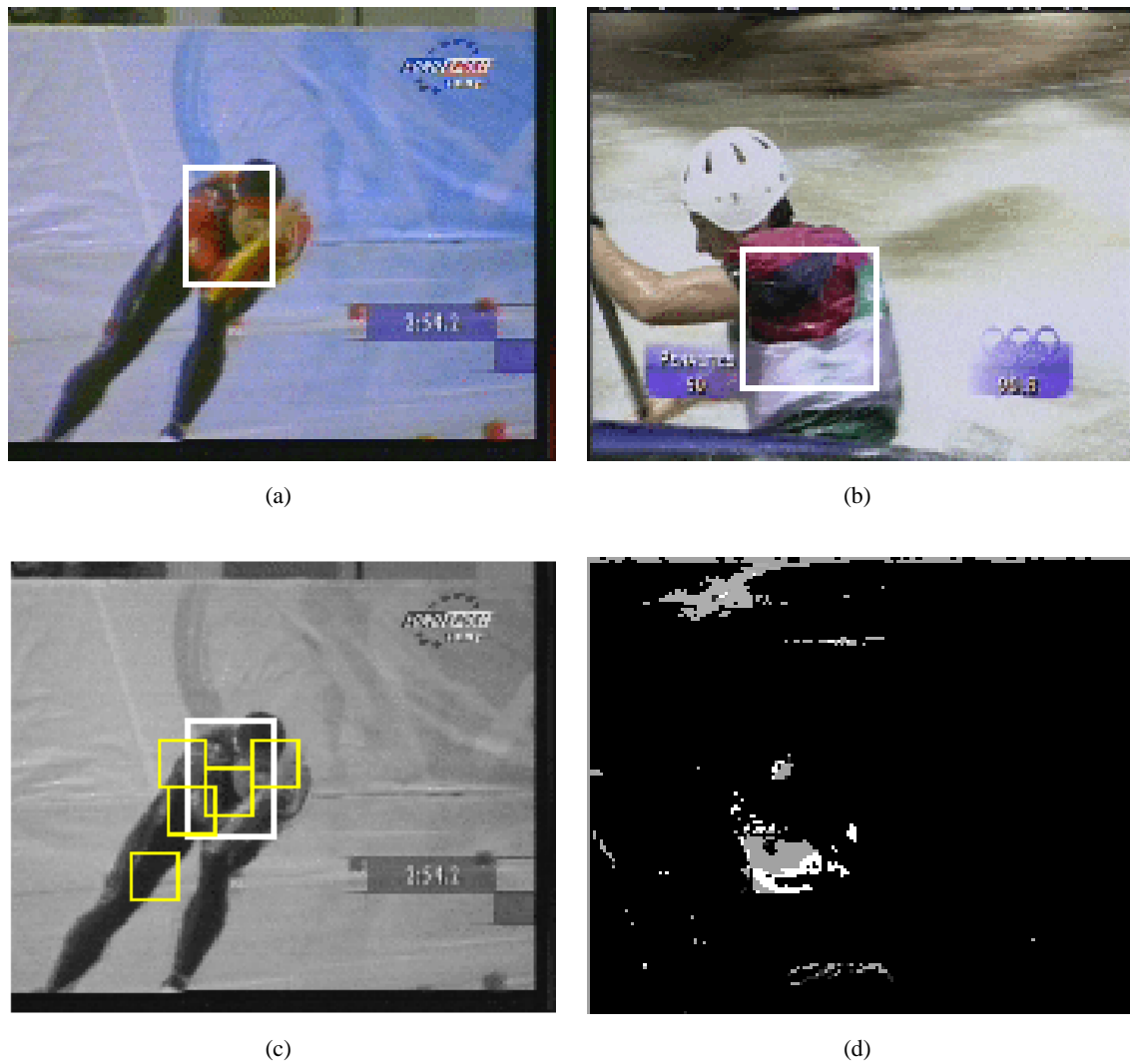


Figure 9.1: Example regions selected for localising (a) the skater and (b) the canoeist. Example of (c) matched regions used for MNS localisation for the image in (a) (d) the probability image produced by histogram backprojection for the image in (b)

## 9.5 Results

We use the success rate (or ratio)  $S$  to measure localisation performance, exactly as proposed by Huang et al. in [45] for testing the correlogram localisation<sup>1</sup>.  $S$  is defined as the fraction of all test frames showing a significant part of the object within the selected template/neighbourhood centred at the estimated object location.

In Fig. 9.2 we present examples of successful localisation of the skater. The white rectangle is the template used, centred at the estimated object location. Localisation was successful in 125 of the 129 frames, achieving a success rate  $S = 97\%$ . Three out of the 4 failure frames were not showing the athlete due to total occlusion, however we considered them as errors. The average time to localise the skater using MNS was 9 milliseconds. The same figure for HB was 1.69 seconds, using the settings described in the previous section.

Fig. 9.3 shows examples of localisation of the canoeist. In many cases, the dramatic variation in appearance did not affect significantly MNS localisation. Success rate was 65%. The main causes of errors were small instances of the canoeist significantly occluded by waves or computer generated captions or viewed under dramatically different illumination. HB performance was lower than MNS, with a success rate  $S = 56\%$ .

Sought Object	Success Rate	
	Mult. Neighborhood Signature	Histogram Backprojection
Skater	0.97	0.94
Canoeist	0.65	0.56

Table 9.1: Localisation results

## 9.6 Summary

In this chapter, the proposed MNS method was applied to object localisation i.e. to establish the location of the projection of a sought object in an image. Assuming compact objects of known shape and with fairly distinctive colours, an algorithm was proposed, based on the idea

<sup>1</sup>A comparison with that method was not attempted in this work

that the object is most likely to appear in that part of the image with the highest population of neighbourhoods with colours similar to the colours of the sought object.

In the experimental section, localisation of objects in the presence of a wide range of appearance variations is shown. Given the relatively low quality of the images and the appearance variations present, MNS performance was acceptable. In two reported experiments, localisation success rate was 97% and 65% respectively. Performance was compared to histogram backprojection, a well known method based on colour histograms. In both cases, MNS outperformed backprojection.



Figure 9.2: Examples of the localised skater

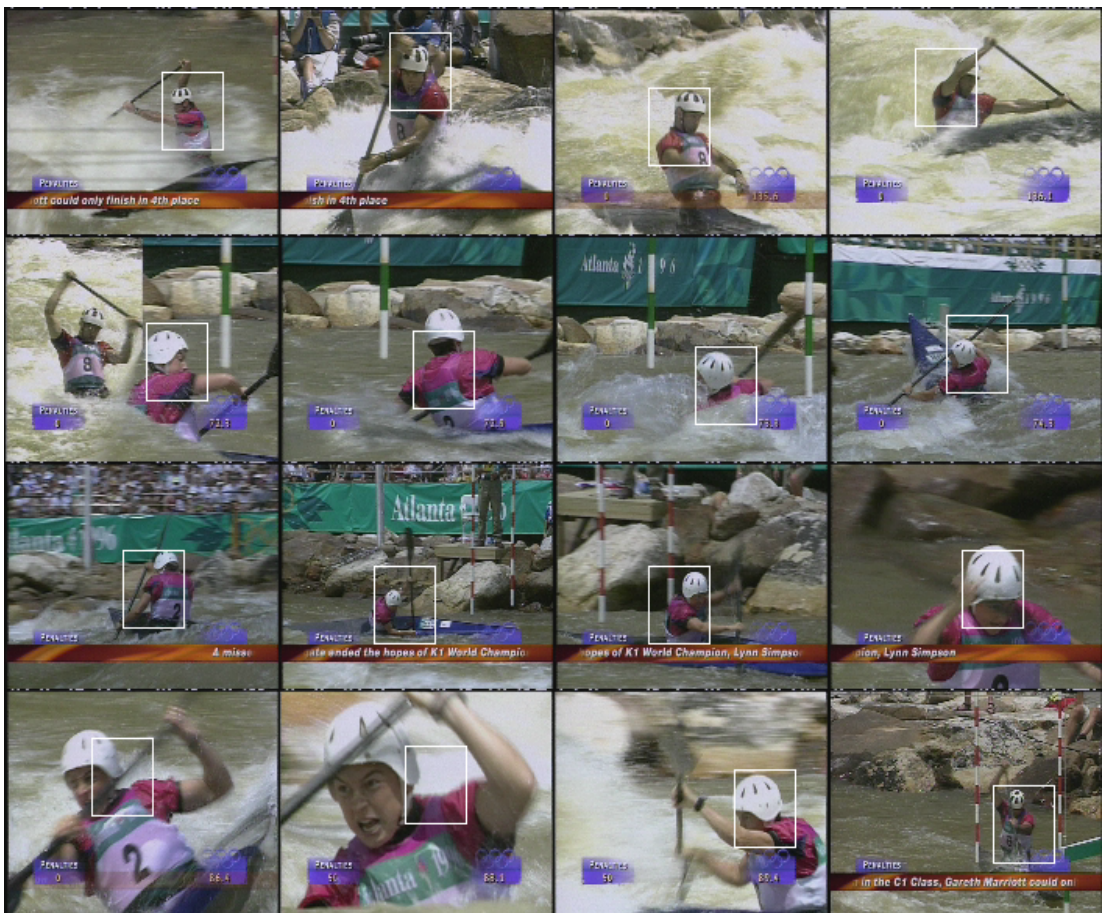


Figure 9.3: Examples of the localised canoeist