PhD Forum: Coverage Redundancy in Visual Sensor Networks

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ABSTRACT

When a network of cameras with adjustable zoom lenses is tasked with object coverage, an important question is how to determine the optimal zoom level for each camera. While covering a smaller area allows for higher detection likelihood, overlapping fields of view introduce a redundancy which is vital to fault tolerance and acquisition of multiple perspectives of targets. In our research, we study the coverage redundancy problem in visual sensor networks formalised as the k-coverage (e.g. [1, 3, 4]), where k represents the number of cameras covering a specific point. However, we are not trying to cover static points in the environment but rather mobile points that may change their position over time.

A visual sensor network (VSN) that we study, is composed of omni-directional cameras $C = \{c_1, c_2, \ldots, c_i, \ldots, c_n\}$ with 360-degree views, each equipped with an adjustable zoom lens. The circular field of view (FOV) of camera c_i has a range r_i that corresponds to current zoom level. The network is tasked to cover a set of moving objects $O = \{o_1, o_2, \ldots, o_j, \ldots, o_m\}$. We consider a point to be *covered* by a camera if it lies within the camera's FOV and is detectable by that camera. In order to address *detectability*, inspired by the work by Esterle et al. [2], we propose a resolution-based confidence model for our cameras. For a camera with a given resolution, the model identifies the classification success rate based on pixel density across all available objects within that cameras FOV. If the rate is above a certain threshold τ then the object is marked as *covered*. This enables each individual camera to identify the number of objects it covers at runtime. Before we describe details of our confidence model, we indicate a few important factors that affects the accuracy of the model; i) **current zoom level** has an inherent impact on the quality of the coverage. It invokes a trade-off between the size of area covered by the camera and the quality of acquired information. ii) **position of the object** the distance between the object and the camera affects the quality of obtained information. It is clear that the camera acquires more information on closer objects than further ones. iii) **size of the object** is also important and can affect the accuracy of the results. However, there are still some other factors such as camera type, environmental lighting, etc. that might lead to varying results. We factor out these issues in our profiling experiments. We propose the resolution-based confidence model using the template illustrated in Figure 1.

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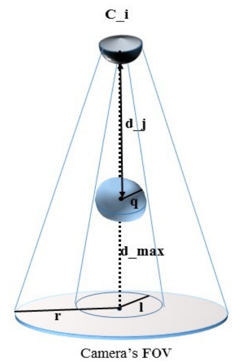

Figure 1: Demonstration of resolution-based confidence model template for an object o_j inside camera c_i's FOV.

We consider the size of object j to be equal to the radius q of its containing sphere, and the distance of the object from the camera as d_j. Using this information, we can calculate the resolution in terms of the number of pixels obtained by the camera for a given object, as shown in Equation 1.

$$\frac{q}{d_j} = \frac{l}{d_{max}};\ l = \frac{q \times d_{max}}{d_j};\ \frac{l}{r} = \frac{res_j}{res_i};\quad res_j = \frac{res_i \times q \times d_{max}}{r \times d_j} \tag{1}$$

where d_{max} and res_i are camera-dependent parameters defining the maximum distance at which a camera can still see an object with sufficient quality (visibility border) and the resolution of the camera based on the utilised sensor respectively. For a camera with a given res_i, the employed optical zoom levels and different distances between the object and the camera leads to varying pixel density over the region of interest. In this context, we conduct a set of profiling experiments where the region of interest (e.i. the object) is extracted from the image as a template for the detection algorithm. We use SURF keypoints to extract a set of features from each image. The classification success rate is calculated using Equation 2 :

$$\varphi(j) = \frac{f_{det}(j)}{f_{total}(j)} \tag{2}$$

where $f_{det}(j)$ is the number of successfully matched features between the template of object j and the current image, and $f_{total}(j)$ is the total number of features extracted from the template.

In order to determine the deviation in the confidence of cameras resulting from different pixel densities, we conducted a set of profiling experiments with 8 distinct objects. For each set of experiments we employed 6 discrete optical zoom levels and 10 equally increasing distances in the range of 1-10 meters (i.e. $1m$, $2m$, …, $10m$)

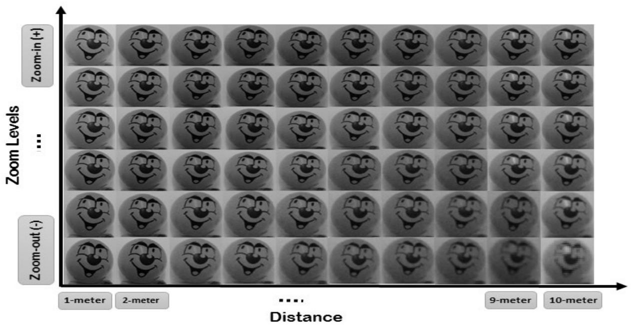

Figure 2: A mosaic of 60 different images of the same object. The x axis of image shows 6 employed optical zoom levels and the y axis demonstrates the distances in 1-meter steps and for 10 steps.

resulting in 60 different images with varying pixel densities. Figure 2 illustrates the *Ball* object. Applying the mean value which is shown as black dots, an approximation of the confidence is a 3-D surface plot demonstrated in Figure 3 .

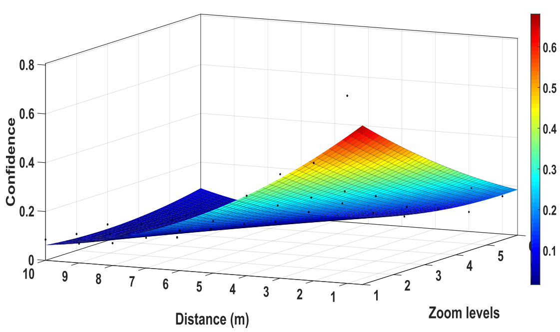

Figure 3: An approximation of the mean confidence obtained from the SURF-detection algorithm. The black dots indicate the mean confidence of the SURF-detection algorithm at different zooms and distances across all 8 objects.

In this study, for the purpose of the simulation, we assume a polynomial relationship between confidence and pixel density informed by these profiling experiments. Using the confidence value each camera is able to determine the correct number of objects it can detect and cover at every simulation time interval. This helps to increase the fidelity of a simulation tool by indicating the cameras behaviour in detecting and covering available objects across the network with higher level of accuracy. A higher level of accuracy can be achieved by incorporating more aspects of the network such as the object size, distance and the camera's current zoom.

Providing resolution based confidence model for our cameras, the next stage of our research focuses on the following research question:

- Is it possible for each camera to determine its own zoom level based on the local information in order to achieve the highest possible k-coverage for all objects in the system at all times?

Given the dynamic nature of the problem in which objects always move about, the challenge is in selecting an appropriate zoom for each camera such that the value of k is maximised over time.

Since, the global approaches such as Greedy algorithm require collection of the state information of all cameras, they introduce a significant communication overhead. Therefore, such approaches might not be appropriate for our problem area. As an alternative, we explore distributed approaches that solely operate on local information. These local approaches try to approximate the optimal solution (e.g. as studied in [5, 6]). In this regard, we are currently investigating the performance of some online redundancy managements approaches using reinforcement learning techniques in order to maximise the coverage redundancy across all available objects in the network.

KEYWORDS

visual sensor networks, smart cameras, online learning, machine learning approaches, decentralised systems

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