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A novel approach to recognition of the detected moving objects in non-stationary background using heuristics and colour measurements

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Abstract

Computer vision has become a growing area of research which involves two fundamental steps, object detection and object recognition. These two steps have been implemented in real world scenarios such as video surveillance systems, traffic cameras for counting cars, or more explicit detection such as detecting faces and recognizing facial expressions. Humans have a vision system that provides sophisticated ways to detect and recognize objects. Colour detection, depth of view and our past experience helps us determine the class of objects with respect to object's size, shape and the context of the environment. Detection of moving objects on a non-stationary background and recognizing the class of these detected objects, are tasks that have been approached in many different ways. However, the accuracy and efficiency of current methods for object detection are still quite low, due to high computation time and memory intensive approaches. Similarly, object recognition has been approached in many ways but lacks the perceptive methodology to recognise objects.

This thesis presents an improved algorithm for detection of moving objects on a non-stationary background. It also proposes a new method for object recognition. Detection of moving objects is initiated by detecting SURF features to identify unique keypoints in the first frame. These keypoints are then searched through individually in another frame using cross correlation, resulting in a process called optical flow. Rejection of outliers is performed by using keypoints to compute global shift of pixels due to camera motion, which helps isolate the points that belong to the moving objects. These points are grouped into clusters using the proposed improved clustering algorithm. The clustering function is capable of adapting to the search radius around a feature point by taking the average Euclidean distance between all the feature points into account. The detected object is then processed through colour measurement and heuristics. Heuristics provide context of the surroundings to recognize the class of the object based upon the object's size, shape and the environment it is in. This gives object recognition a perceptive approach.

Results from the proposed method have shown successful detection of moving objects in various scenes with dynamic backgrounds achieving an efficiency for object detection of over 95% for both indoor and outdoor scenes. The average processing time was computed to be around 16.5 seconds which includes the time taken to detect objects, as well as recognize them. On the other hand, Heuristic and colour based object recognition methodology achieved an efficiency of over 97%.

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