BACKGROUND MODELING USING OCTREE COLOR QUANTIZATION

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Abstract—By assuming that the most frequently occurring color in a video or a region of a video belongs to the background of the image, I propose a new algorithm for detecting foreground objects in a video. The process of detecting the foreground objects is complicated because of the fact that there may be swaying trees, objects of the background being moved around or lighting changes in the video. To deal with such complexities many have come up with solutions which heavily rely on expensive floating point operations. In this paper I used a data structure called Octree which is implemented only using binary operations. Traditionally octrees were used for color quantization but here in this paper I used it as a data structure to store the most frequently occurring colors in a video as well. For each of the starting few video frames, I constructed an Octree using all the colors of that frame. Next I pruned all the trees by removing nodes below a certain height and gave the leaf nodes a color which is dependant on the topological path from that node to its parent. Hence any two leaf nodes in two different octrees with the same topological path from themselves to the root will represent the same color. Next I merged all these individual trees into a single tree retaining only those nodes whose topological path to itself from the root is most common among all the trees. The colors represented by the leaf nodes in the resultant tree will be the most frequently occurring colors in the starting video frames of the video. Hence any color of an incoming frame that is not close to any of the colors represented by the leaf node of the merged tree can be regarded as belonging to a foreground object.

As an Octree is constructed using only binary operations, it is very fast compared to other leading algorithms.

Index Terms—Background modelling, Octree color quantization, moving object detection

I. INTRODUCTION

Due to the advancement of technology and heavy reduction in costs of FPGA development, traditional video surveillance equipment has evolved from merely capturing video from a static vantage point and transmitting it to performing some preliminary analysis such as extracting objects of interest from the scene and then transmitting it.

For most of the analysis that is done on a surveillance video, the first crucial step is to detect the foreground pixels of the video. This is done by first constructing a background model and matching each individual frame with this model. Any pixel of a frame which deviates significantly from this model is marked as a foreground pixel in that image.

Several techniques for construction of this background model have been proposed. The most trivial of this techniques is to average the first 20 or so frames and use the averaged frame as the background model. This adequately takes care of the lighting changes but this technique fails when the background of the scene contains swaying leaves, clocks or part of the background is constantly moved around the scene etc.

Wren et al.[1] tried to solve this problem by fitting a Gaussian distribution for all the colors occurring at each pixel location of a frame using the past N frames. Any pixel value from the input frame which is sufficiently close to the mean of the Gaussian distribution for that pixel location is marked as a background pixel and the Gaussian distribution is updated. This technique fails when the histogram of pixel values at any given location is bimodal or has multiple peaks.

Stauffer et al.[2] attacked the short comings of the previous work by using multiple (about 3 to 5) Gaussian distributions per pixel locations. Each input frame pixel is matched with a corresponding Gaussians at that location. Any pixel which is in the range of 2.5 of the mean of a Gaussian for that pixel location is marked as a background pixel and that Gaussians parameters are updated. The problem with this technique is its heavy usage of floating point operations and its huge memory requirement. Also the error rate is very high.

The wallflower principles and practises [3] a pioneering work by Microsoft research team, not only came up with a background modelling technique but also surveyed all the recent background modelling techniques and listed out all the common problems that a background modelling techniques would face. It views the process of constructing the background model at pixel level, segment level and frame level. The pixel level algorithm attacks the problems with leaf swaying and background motion problems. In this work I provide a better alternative to their pixel level algorithm. The frame level and the segment level techniques listed out in the wallflower paper could be used with this paper as well.

In this paper I tackle the problem by constructing an octree[5] which is discussed in section 2. The octree is constructed by iterating over each individual pixel location of each individual frame of the training video. The colors found are quantized and form a leaf node in the octree. Each pixel of the incoming frame is quantized similarly and checked to see if a corresponding leaf node exists in the already constructed octree. This is shown in section 3. If a node does exist it is marked as a background pixel. In section 4 I show a method of merging multiple octrees a technique to be used...
when we don’t have a training video or as the wallflower paper calls it, the bootstrapping problem.

II. OCTREE COLOR QUANTIZATION

An octree is a tree data structure in which each internal node has exactly eight children. Octrees are most often used to partition a three dimensional space by recursively subdividing it into eight octants. Octrees are also used for color quantization. The octree color quantization algorithm, invented by Gervautz and Purgathofer in 1988, encodes image color data as an octree up to nine levels deep.

In computer graphics, color quantization or color image quantization is a process that reduces the number of distinct colors present in an image, usually with the intention that the new image should be as visually similar as possible to the original image. Various methods are available for color quantization such as the median cut algorithm, popularity algorithm. Octree\[5\] is the leading color quantization technique as it executes in $O(N)$ execution time and barely occupies memory of the order $O(K)$. Here $N$ being the number of pixels in the image and $K$ is a number which is proportional to the number of unique colors present.

For a picture whose colors we wish to quantize, we consider each color and store it in a octree using the store color algorithm. Next we prune the octree. By pruning the octree we hope to group together colors which look visually same. Few methods of pruning have been covered in \[14\] and \[15\]. In this paper I followed a simple pruning algorithm that is to remove few levels from the bottom of the tree. Since each color at a level $N$ is constructed using $N$ most significant bits of the red, green, blue values of the color, the newly exposed leaf nodes will have $N$ bits of the original color that they represented. One way to assign a new color to these newly exposed leaf nodes is to use their $N$ original bits and fill out the remaining bits with 0’s. This way if any two colors had the same parents till the height of pruning will now be represented by the same color. This new color could be used to redraw the image. Fig 2 shows the same image redrawn using an octree pruned at different levels.

Algorithm 1 Store color

1: \[\textbf{procedure} \text{STORE COLOR}( \text{Color, Root, Number of Levels})\]
2: \hspace{1em} \textbf{if} Root is NULL \hspace{1em} \textbf{then}
3: \hspace{1em} root \leftarrow \text{create node}();
4: \hspace{1em} \text{node temp} \leftarrow \text{root}.
5: \hspace{1em} \textbf{for} $i$ := MSB to Number of Levels \textbf{do}
6: \hspace{1em} \text{index} \leftarrow \text{Color.red}[i] + \text{Color.green}[i] + \text{Color.blue}[i];
7: \hspace{1em} \textbf{if} \text{temp.child}[index] \neq \text{NULL} \textbf{then}
8: \hspace{1em} \text{temp} \leftarrow \text{temp.child}[index]
9: \hspace{1em} \textbf{else}
10: \hspace{1em} \text{temp.child}[index] \leftarrow \text{create node}();
11: \hspace{1em} \text{temp} \leftarrow \text{temp.child}[index]
12: \hspace{1em} \textbf{End If}
13: \hspace{1em} \textbf{End For}

III. CONSTRUCTING AN OCTREE CONTAINING ONLY THE BACKGROUND COLORS OF AN IMAGE

If we assume that the most frequently occurring color in a video usually belong to the background, we can construct an octree only containing the background colors. We construct an octree for each frame of a video or a group of frames and prune it using the technique presented in the previous section. Each octree obtained this way will hold the quantized representation of all the colors in each frame or a group of frames. By using the merging procedure shown below we could merge together multiple octrees to obtain a single octree which will contain the most frequently occurring colors in a quantized way. This octree could be thought of as containing all the colors of the background.
Our assumption that the most frequently occurring colors in a video usually belong to the background is invalidated in the case when a foreground object stays static for a while and suddenly starts to move. Since that object’s color has appeared in most frames it would be treated as belonging to the background of the video. This could happen when a person sleeping in front of a camera suddenly starts to move. To remedy this, we could subdivide a video into multiple regions and obtain an octree for each of these regions.

Algorithm 2 Merge multiple octrees into a single octree

1: procedure MERGE TREES( Roots[], Threshold, numberOfTrees, Number of Levels)
2:     for i := 1 to 8 do
3:         count ← 0
4:         for j := 1 to numberOfTrees do
5:             if roots[j] ≠ NULL and roots[j].child[i] ≠ NULL then
6:                 count ← count + 1;
7:         End if
8:     End For
9:     if count/numberOfTrees ≥ threshold then
10:        result.child[i] ← New Node();
11:     End if
12:     End For
13:     for i := 1 to 8 do
14:         if result.child[i] ≠ NULL then
15:             for j := 1 to numberOfTrees do
16:                 tempRoot[j] ← root[j].child[i];
17:             End For
18:             Result.child[i] ← Construct Tree(tempRoot, threshold, numberOfTrees, Number of Levels);
19:         End if
20:     End For

Algorithm 3 Check color

1: procedure CHECK COLOR( Color, Root, Number of Levels)
2:     if Root is NULL then
3:         return False
4:     else
5:         node temp ← root
6:         for i := MSB to Number of Levels do
7:             index ← Color.red[i] + Color.green[i] + Color.blue[i];
8:             if temp.child[index] ≠ NULL then
9:                 temp ← temp.child[index]
10:             else
11:                 return False
12:         End If
13:     End For
14:     return True

IV. FOREGROUND PIXEL DETECTION AND OCTREE UPDATE.

To identify the foreground pixels in a video, we run the procedure shown in the previous section on the first few seconds of the video or the first 100 frames or so of the video. Once we constructed an octree containing the background colors, the process of identifying foreground object locations in an incoming frame is pretty straightforward. For each pixel color of the incoming frame, we use the check color procedure to see if it is present in the octree. If it is not, it is labelled as a foreground pixel.

In case we subdivided the video into multiple regions when checking if a pixel belongs to foreground or background, we use the octree of that region in conjunction with the procedure below to ascertain if it is foreground or background.

V. EXPERIMENTAL RESULTS

The following results are obtained on a second generation i5 laptop running at 2.3 GHz with 4 GB of ram on Windows 7 SP1 and JRE 7 with no updates installed. The datasets for these experimentation is from the wallflower paper.

Fig. 3. A video with waving trees in the background

Fig. 4. Result of motion detection using frame on frame differencing
The $F_0$ scores for different leading algorithms (CB[6], IMOG[8], LBPH[9], STBS[11]) on different datasets is given below in comparison with Octree. The $F_0$ scores are calculated using the formula given below.

$$F_0 = 2 \frac{P_0 \times R_0}{P_0 + R_0}$$

Where $P_0 = \frac{T_n}{T_n + F_p}$ and $R_0 = \frac{T_n}{T_n + F_p}$.

$T_n, T_p, F_n, F_p$ stand for True negative, True positives, False negatives and False Positives.
|      | EE  | SW     | IND  | WK   | Avg   |
|------|-----|--------|------|------|-------|
| CB   | 0.973 | 0.984  | 0.996 | 0.997 | 0.9875 |
| IMOG | 0.984 | 0.995  | 0.995 | 0.999 | 0.99325 |
| LBP | 0.991 | 0.997  | 0.999 | 0.996 | 0.999325 |
| STBS | 0.992 | 0.993  | 0.99  | 0.998 | 0.99325 |
| OCTREE | 0.992 | 0.999  | 0.999 | 0.991 | 0.99525 |

**TABLE I**

**COMPARISON OF $F_0$ SCORES ON DIFFERENT DATASETS**

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