Anomaly Detection in Surveillance Footage
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ABSTRACT

Given surveillance footage, develop an abandoned object detection system. The framework is based on Background Subtraction techniques, with pre-processing involving a dual-time background subtraction algorithm, which maintains two backgrounds, one updated with a relatively high frequency, and the other at a low frequency. We have implemented an algorithm based on the Approximate Median model, and another using the Running Averages foreground analysis extraction mechanism. Results show that the system is fast, and robust in both moderately and sparsely populated areas. As the system does not use expensive filters and statistical calculations, it is less intensive computationally, and at the same time delivers good detection results.

Motivation

Monitoring of public places for terrorist attacks. Online analysis and prediction of events needed as part of Automatic threat detection system. Detect a person abandoning a bag at a crowded metro station. Detect a fight, a person jumping a fence, an accident. The retail industry loses billions of dollars per year to thefts and shoplifting. For efficient large-scale monitoring, it is critical to design a system based on intelligent video analysis.

Works and Approaches

Prior research on background subtraction (BGS) used several parametric BGS techniques, such as running average, running Gaussian average, approximate median filter, and Gaussian Mixture Model. These parametric techniques determine the foreground and update the subsequent background based on the distribution of intensity value. Aside from these techniques, other studies have introduced nonparametric models that detect foreground and background based on the intensity of statistical properties. Other nonparametric models include a kernel density estimator and mean shift estimation. We do background subtraction, then blob detection and tracking. Affinity propagation clustering algorithm is applied. We prevent small blobs from getting identified as objects and thus, reduce false positives.

Methodology: First Algorithm

- Segment live video stream into individual images.
- Extract a region of interest and convert to a 3D intensity matrices (height * width * intensity value of each pixel).
- These matrices are fed as input to the Background Subtraction module.
- The first frame of the incoming video is initialized as ‘Current Background’.
- Subsequently, the intensity of each pixel of this current background is compared with the corresponding pixel of the next frame. If it is less, then the intensity of that pixel of current background is incremented by one unit, otherwise it is decremented by one unit. In case of equality, the pixel intensities remain unchanged.
- Every 20 seconds, update Buffered Background. All those pixels which do not belong to the prospective abandoned objects set are made equal to that of ‘Current Background’. Difference of the two backgrounds is represented as a binary image with the white portion representing foreground.

Methodology: Modified Algorithm

- We maintain both prolonged background BufferedBackground and temporarily static CurrentBackground.
- A queue data structure is maintained to keep a moving average of nframe number of frames, by default the last 100 frames.
- When 100 frames have been read, the Current background is initialized to the average of the 100 frames. Buffered Background is initialized to the Current Background at that point.
- The Current Background is a moving average of the last 100 number of frames, as opposed to the approximate median.
- If the intensities of about 30% to 40% of the pixels change abruptly by a considerable amount, then we change the Buffered Background by a proportion of the change. This intelligent updating helps with changing lighting conditions, and is done dynamically, as opposed to the regular time updating in the basis algorithm.
- Take the difference of the Current Background and the Buffered Background.
- Find contours in the difference image.
- Store the centres of contours in an array.
- Apply affinity propagation clustering algorithm. This is done to make sure that
- The large clusters are abandoned objects. For detecting one abandoned object, take the largest cluster.

RESULTS AND DATASETS

We chose various videos from the AllAbandoned Objects DATaset (ABODA) dataset which are challenging for abandoned-object detection. The situations include crowded scenes, marked changes in lighting condition, night-time detection, as well as indoor and outdoor environments.

STRENGTHS

- Model is adaptive and dynamic, non-probabilistic, and intuitive in nature.
- It is non-probabilistic, and intuitive in nature. Two different reference frames are used for self-adaptability resulting in less computation due to non-inclusion of any complex mathematics.
- Having two backgrounds has an added advantage that the user can adjust the time interval between the update of reference background frames to suit different needs and environments.
- The Buffered Background is updated intelligently, only when it is necessary.
- Using affinity propagation clustering algorithm avoids detection of false positives.
- Moving crowd/objects, and unnecessary details like shadows, reflections on floors and walls are filtered off efficiently.
- Parameters can be tweaked as per needs of different surveillance scenarios.

FUTURE WORK

- Tracking
- Occlusion detection needs to be incorporated.

CONCLUSIONS

- The algorithm works in real time, and has a high success rate, and low false positive rate.
- In a few cases a very still person was detected for a short amount of time, till that person moved again.
- The algorithm works well even at a low resolution of 160 by 160.
- Processing speed was found to be somewhat inversely proportional to the video resolution as well as the frame rate.

REFERENCES