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2-D OBJECT RECOGNITION USING SURVEILLANCE VIDEO PROCESSING ON DAUBECHIES WAVELET DECOMPOSITION

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ABSTRACT

The project suggests effective motion recognition built on background subtraction using dynamic threshold approach with mathematical morphology. Here the techniques frame differencing, dynamic threshold based detection will be used. In addition to dynamic threshold, mathematical morphology is also used within ability of greatly attenuating color dissimilarities has generated by background motions while still highlighting moving objects. After the object foreground detection, the parameters like velocity motion, speed will be determined. Finally the simulated results will be shown that used background subtraction with daubechies wavelet decomposition approach is effective rather than previous background subtraction methods.

Keywords: video, frame separation, difference generation, multi threshold with connected component analysis, parameter analysis.

INTRODUCTION

For object tracking, a camera is frequently used to obtain information of object motion which can then be working in coordination controls. Real-time tracking of animals, particularly for crossing border area from forests to human life habitation of multiple targets in formations, still suffers from limitations imposed in computation resources. Camera is used in a tracking system for animals to detect their color-tags and shape analysis on object track. The digital camera has become a widespread sensor for monitoring and surveillance systems. With the enhancement of the semiconductor technology, present digital cameras with high pixel number can provide more image aspects in various implementations. A digital image sensor usually employs an array consisting of the charged-couple device (CCD) or CMOS. By passing light through the lens and color filter array (CFA), the real image is changed into the RGB image projected on the digital image sensor array. The raw RGB image then is rebuilt intoa meaningful image for human perception by de-mosaics king and color correction. For sensing applications, anextra image processing technique to extract object is required for every image pixel. Moreover, it should be eminent that imaging processing utilizes a lot of memory space and most of computation resources in a computer system.

Figure-1. Input video (Person walking.avi).

The detection of moving object is an important task in the image sequences of the area which is in surveillance to study wild life animals, for efficient video compression to track moving object, remote sensing, image processing, medical imaging and robotics. The moving object recognition is the initial step in object recognition. The aim of moving object recognition is at detecting moving objects that are of interest in video sequences with back-ground which is either stationary or moving. The algorithm mostly uses either temporal or spatial information in the image sequences to do moving object detection, and the most generally used approach is pixel intensity. The algorithms for moving object detection have been suggested in the literature, most of them can be categorized into three most popular approaches. Some of them can do moving object detection in real-time, they comprise background subtraction. There are basically two difficulties one is processing speed and second is consistency of the moving object detection, and also the size of quality related algorithm of two main indexes. The moving object detection can be categorized in to 3, comprising optical flow, frame difference and background subtraction methods.

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LITERATURE SURVEY

Visual surveillance in reality, particularly for humans and vehicles, is one of the most active research topics in computer vision. It has a wide range of favorable applications, including access control in special areas, human recognition at a distance, crowd change statistics and congestion analysis, detection of irregular behaviors, and interactive surveillance using multiple cameras, etc. In common, the processing framework of visual surveillance in lively scenes includes the following stages: molding of environments, detection of motion, classification of moving objects, tracking, explanation and understanding of behaviors, human identification, and union of data from multiple cameras. An evaluation on new developments and general approaches of all these stages. Finally, it is examined in possible research directions, e.g., occlusion handling, a combination of two and three-dimensional tracking, a mixture of biometrics and motion analysis, anomaly detection and behavior prediction, content-based recovery of surveillance videos, behavior understanding and usual language description, combination of information from multiple sensors, and remote surveillance.

Finding moving objects from a video sequence is a essential and critical job in many computer-vision applications. A common method is to do background subtraction, which recognizes moving objects from the portion of a video frame that deviates from a background model. There are many problems associated in developing a good algorithm for background subtraction. First, it must be tough against changes in illumination. Second, it should avoid detecting moving background objects such as wavering leaves, rain, snow, and shadows by moving objects. Lastly, the internal background model should respond faster to changes in background such as initial and ending points of vehicles. In this paper, various background subtraction algorithms are compared for distinguishing moving vehicles and pedestrians in traffic video sequences. Changing from simple techniques for example frame differencing and adaptive median filtering, to more sophisticated modeling techniques are considered. While difficult techniques regularly produce superior performance, this experiments display that simple techniques for instance adaptive median filtering can produce good results with much reduced computational difficulty.

An algorithm was developed for tracking and segmenting the piglets. It is verified on sequence of 200 images of 10 piglets moving on a straw background. The capture rate of images was 1 image/140msec. The segmentation technique was a mixture of image differencing with respect to a median background and a Laplacian operator. The blob edges are tracked in the segmented image. During tracking, the piglets were modeled as ellipses initialized on the blobs. The piglets can be tracked in an elliptical window by finding blob edges about the piglet's position, which was projected from its previous two positions.

One of the common methods for real-time moving regions segmentation of image sequences comprises either background subtraction or thresholding the error between the current image and estimate of the image without moving objects. The many methods to this problem vary in the kind of background model used and the process used to update the model. In this paper each pixel is modelled as a combination of Gaussians and an on-line approximation to update the model. The adaptive mixture model contains Gaussian distributions are then calculated to determine which are resulted from a background process. Every pixel is categorized based on whether the Gaussian distribution which describes it most efficiently is considered part of the background model.

A novel method for detecting and tracking multiple moving objects built on discrete wavelet transform and identifying the moving objects with their color and spatial information is suggested in this paper. Many tracking algorithms have enhanced performance under static background but background with fake motions the results get poorer. Therefore, most of the tracking algorithms use indoors instead of outdoor environment. As discrete wavelet transform has a nice property that it can split a frame into four different frequency bands without the loss of the spatial information, it is implemented to solve the problem of the fake motions in the background can be placed into the wavelet sub-band that has high frequency. In tracking multiple moving objects, most of the applications have problems when objects pass across each other. Spatial information and color are used in the paper to solve the problem of objects passing against each other. The experimental results prove the probability and usefulness of the proposed method.

PROPOSED METHOD

Videos captured from a camera are input to the background sub tractor. Pre processing stages are used to filter and to change the input video to a processable format. In this method daubechies wavelet technique is used. In this wavelet technique each image frame is divided into four sub-bands .In first sub-band we evaluate the image qualities, in the second subband each image is segmented horizontally, in the third sub-band the images are segmented vertically and finally in the fourth sub-band the images are segmented diagonally. The values obtained from each sub-band are compared to a threshold value.

Frame separation

For processing and to detect video the input video (.avi) file is changed into still images. These sequences of images gathered from video files by finding the statistics about it through ‘aviinfo’ command. The command ‘frame2im’ is used to convert the frames into images and name is given to each images and this process is done for all the video frames. The above diagram represents the process flow of this separation

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Figure-2. Frames obtained from the input video.

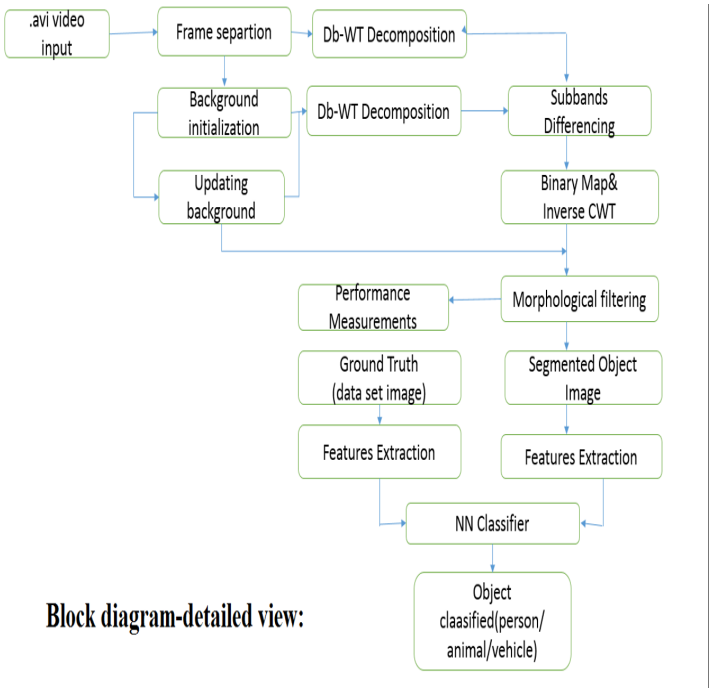

Figure-3. Object tracking using Background Subtraction Model-Block diagram.

Background subtraction

Main background subtraction approach to moving object recognition is its extreme sensitivity to active scene changes due to light and unnecessary events. Although these are usually detected, they leave behind "holes" where the newly exposed background images varies from the well-known background model (ghosts). While the background model eventually adjusts to these "holes," they produce false alarms for a short time of time. Therefore, it is highly necessary to build a method to motion recognition based on a background model that automatically adjusts to changes in a self-organizing manner and without a previous knowledge. Background subtraction then uses the video frame to calculate and update the background model. Foreground detection is where the pixels that show a significant difference to those in the background model are identified as foreground.

A foreground mask can then be output in which pixels are assigned as foreground or background. The foreground detection stage can be described as a binary classification problem whereby each and every pixel in an image is assigned a label to the class of background or foreground. Formally, for every pixel p in image K, a label pl is assigned where K € {0, 1} where 0 = background and 1 = foreground. After this mask is obtained, background pixels are usually fixed to white or black to allow focus on the foreground object. Many simple decision rules to classify each pixel have been suggested, each of which can be carried out in any one of a number of color spaces. Many background subtraction algorithms reduce down to the simple subtraction of the pixel in the expected background image from the pixel in the observed image and any significant change indicates that an object of interest has been recognized.

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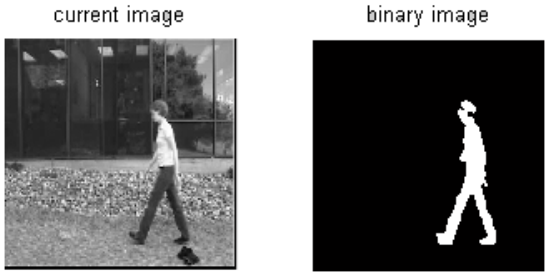

Figure-4. Comparison of current image and binary image.

Target selection

Another constraint one would in most cases like to mix into the energy function is the reason that targets cannot appear or disappear within the tracking area. Nevertheless, only a soft constraint is forced, since otherwise one would have to explicitly model entry/exit locations and long term obstruction.

Object tracking

The output of the change detection segment is the binary image that covers only two labels, i.e., '0' and '255', representing as 'background' and 'foreground' pixels correspondingly, with some noise. The main aim of the connected component analysis is to identify the large sized connected foreground region or object. This is one of the important operations in motion detection. The marking operation scans the image moving along the row until it comes to the point P, for which S = {255}. When this is true, it checks the four neighbors of which Based on that information, the labeling of P occurs as given below,

If all four neighbors are '0' assign a new label to P, and increment the label,
Else
If only one neighbor has S = {255} assigns its label to P
Else (i.e., more than one of the neighbors has S = {255})
Assign one of the labels to P. Here, note that the relation between the pixels that are expressed through a "label value" in the considered image rest on the value of the label. That means the two pixels from Background, labeled as l_B is not necessarily to be connected, but the two pixels labeled l_P from the foreground region are to be connected. After this process, the desired region will be localized by rectangular bounding box which is chosen from image processing toolbox. The bounding parameters are evaluated by 'region props' function which provides a height and width of an object.

CONCLUSIONS

The project presented an efficient object detection based on background subtraction using frame difference with threshold and mathematical morphology. It will be improved with futures of connected component analysis and morphological filtering for tracking moving objects. After the foreground detection, the parameters like velocity of the motion, speed was estimated and performance of object recognition will be measured with sensitivity and correlation using ground truth frames. Finally the proposed method will be proved that it is effective for background subtraction in static and dynamic texture scenes compared to prior methods.

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