"DESIGN AND DEVELOPMENT OF MULTI TASKING MACHINE USING NEURAL NETWORK FEATURE EXTRACTION FOR DISASTER MANAGEMENT"

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Abstract: In recent years, there has been a lot of interest in keeping tabs on how people behave in challenging settings. The majority of the methods used today use video cameras that are fixed to structures or pylons, and persons are identified and tracked in these video streams. The proposed strategy is meant to support this work. Aerial image sequences captured by camera systems mounted on aircraft, helicopters, or airships are used to watch people. This imagery is distinguished by a very broad coverage that offers the chance to see how individuals are distributed across a broad field of view. The method demonstrates initial results for automatic people detection and tracking from image sequences.

KEYWORDS: Tasking machine, Disaster Management.

I. INTRODUCTION:

Over the past few years, there has been an increase in interest in keeping track of how people behave in crowd settings and complex contexts. The pope's visit and an increase in major events including concerts, festivals, sporting competitions, and religious gatherings have raised awareness of the importance of crowd control. There is a novel method for identifying and following people in aerial image sequences. The behavior of the people is analyzed in order to identify uncommon events, such as panic situations or brawls, in addition to defining motion trajectories. Utilizing video cameras positioned on buildings to find and follow people in video streams is a common element of current methods. It is possible to locate human persons in terrestrial image sequences. Modern methods based on so-called sensor networks are capable.

The work of presents a system for detecting and analyzing events in airborne video feeds utilizing two modular building parts. While the second module uses the computed trajectories to recognize predefined scenarios, the first module finds and follows moving objects in a video stream. Another system for recognizing events is built on the basis of two related modules: tracking and event analysis. In these modules, complicated events are identified using logical and Bayesian approaches. Events focused on interactions between a small number of people are detected utilizing video streams from close-range surveillance cameras. A social force model (SFM) has been effectively used to replicate the phenomena in moving crowds, such as lane forms in corridors. The SFM takes into account interactions between pedestrians and with obstructions.

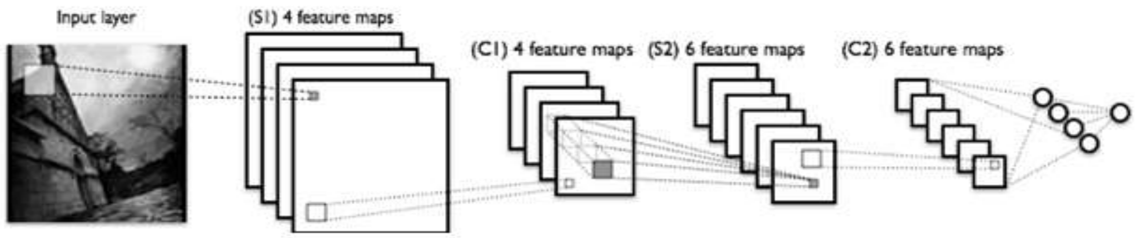
Aerial camera systems installed on airplanes, unmanned aerial vehicles (UAVs), helicopters, or airships are used to observe people. The given image sequences provide a wide field of view and enable for the examination of human population density, dispersion, and motion patterns. However, because the frame rate of these image sequences is typically significantly lower than that of video streams (just a few Hz), more advanced tracking techniques must be used. Additionally, compared to previous event detection systems, the interpretation of scenarios in such large-scale visual sequences must include a greater number of moving objects. So, rather than just alerting to a generic anomalous event inside a monitored area, the strategy aims to establish a wider range of recognized scenarios.

II.PROBLEM DEFINATION AND METHODOLOGY:

The achievement of image recognition is a difficult task. Applying metadata to unstructured data is a useful way to think about how to do it. hiring human professionals to perform manual tagging.The task of organizing music and movie libraries may seem daunting, but it becomes nearly impossible when faced with problems like teaching a driverless car's navigation system to distinguish between pedestrians and various other vehicles or filtering, categorizing, or tagging the millions of videos and photos that users upload on a daily basis to social media.

Using neural networks would be one approach to solving this issue. Although traditional neural networks can be used to analyze photos in theory, doing so in practice will be quite costly from a computing standpoint. For instance, a typical neural network would still require 0.5 million parameters and 900 inputs to interpret a 30-by-30-pixel image. When the images are significantly larger (for example, 500*500 pixels), the number of parameters and inputs required rises to extremely high levels, yet a decently strong system can manage.

CONVOLUTION NEURAL NETWORK:



Convolution layer sub sampling convolution layer sub sampling layer fully connected MLP

Fig 1: Convolution neural network

- The real input image that is scanned for features. The filter that passes over it is the light rectangle. The Activation maps are arranged in a stack on the top of one another, one for each filter you use. The larger rectangle is 1 patch to be down sampled.
- The activation maps condensed via down sampling.
- A new group of activation maps generated by passing the filters over the stack that is down sampled first.
- The second down sampling – which condenses the second group of activation maps.
- A fully connected layer that designates output with 1 label per node.

MULTILAYER PERCEPTRON AND NEURAL NETWORKS

The multilayer perceptron is the most known and most frequently used type of neural network. On most occasions, the signals are transmitted within the network in one direction: from input to output. There is no loop, the output of each neuron does not affect the neuron itself. This architecture is called feed forward.

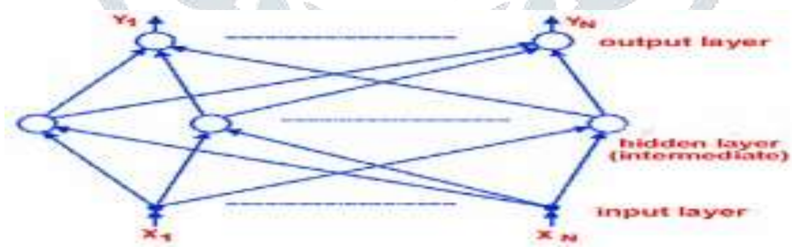
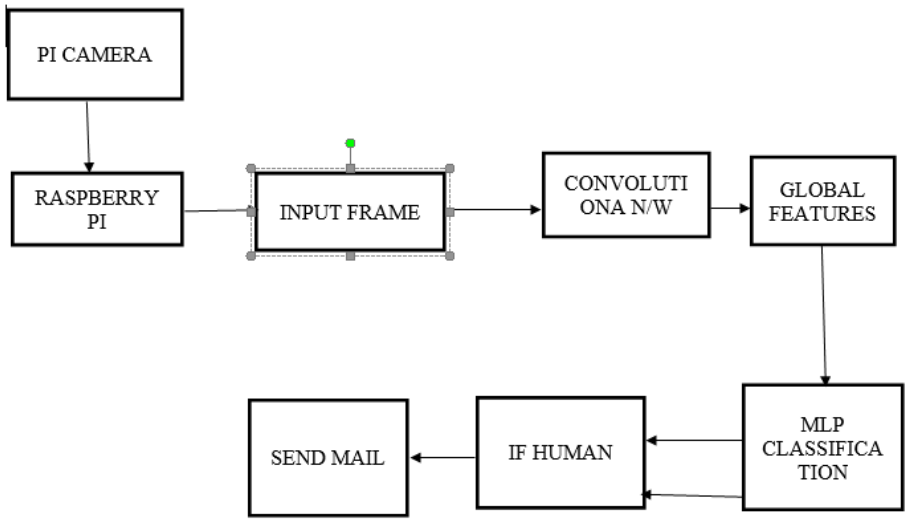


Fig 2: Neural network feed-forward multilayer.

The term "hidden" refers to layers that are not directly related to their surroundings. Since the input layer's primary job is to transfer input signals to the upper stratum without any input processing, there is some debate in the reference material on whether or not it should be considered an independent layer in the network. The inputs are clustered in the input layer, but in the following we will just count the layers made up of standalone neurons. Additionally, there exist feed-back networks that, thanks to reaction links within the network, are capable of transmitting impulses in both directions. These networks have a lot of power and can be highly complicated.

SYSTEM DESIGN AND ARCHITECTURE

Block diagram of methodology



PI Camera

To fulfill the growing demand for camera modules that work with the Raspberry Pi. A revision C add-on camera module for the Raspberry Pi has just been made available by the team, and it is fully compatible with the original. It improves optical performance compared to the earlier Pi cameras and provides users with a much clearer and sharper image. Additionally, it offers the FREX and STROBE signals, which, when combined with the right camera driver firmware, can be used for multi-camera synchronize capture.
The board is quite little, measuring only 36mm by 36mm. The distinguishing feature of our module is that, in contrast to the official one, the Lens is removable, making it ideal for mobile applications and other uses where size and image quality are crucial. A brief ribbon cable is used to connect it to the Raspberry Pi. The CSI bus, a higher bandwidth connection that transfers pixel data from the camera back to the processor, is used to connect the camera to the BCM2835/BCM2836 processor on the Raspberry Pi. The ribbon cable from the camera board to the Raspberry Pi is traversed by this bus.

Fig 3: Pi camera

Features:

- High-Definition video camera for Raspberry Pi Model A/B/B+ and Raspberry Pi 2
- Omni vision OV5647 sensor in a fixed-focus module with replaceable Lens
- Lens holder: M12x0.5 , CS mount or C mount
- 5MPixel sensor

Raspberry pi:

- Meant to be a very inexpensive, open computer to help give kids access to computers that they could experiment with, like many of us did in the 1980's.
- Hooks up to TV's, USB KB+mouse, powered off cell phone power adaptors – things many of us have already!
- SD storage so easy to reflash if you screw it up
- Linux based OS, so easy to get in and see how it works.
- Also has GPIO so possible to use for robotics!
- HUGE community following! (Not true of many of these types of devices…) Think Arduino popular… (>1M units sold in the first year…)
- Default is 700Mhz, but most will overclock to ~1Ghz

Frames:

Currently, summing frames is a technique used to detect single pixel targets in order to increase the signal and decrease the background noise. In flight system applications during acquisition, the noise is often an uncorrelated mixture of focal plane noise, system noise, thermal noise, target motion, and kinematics motion. Any dynamic system application, including UAV, UGV, product tracking, and process control, follows a similar procedure. Signals are distinguished from the natural or uncluttered backdrop by choosing pixels that are K sigma or more above a threshold. This method of distinguishing signal from background results in a frame delay and decrease in frame rate due to the summing. Dim indications that could be important are concealed below the threshold floor.

Method and Approach:

Data from cooled, 256-pixel square HgCdTe and InSb focal plane arrays (FPA) were obtained for the mathematical experiments described in this study. In noisy photos, each signal is represented by a single pixel, but the information is most often dispersed across multiple pixels. This study describes a number of algorithms for the detection of small unresolved features in such noisy images.

Data:

An unresolved point spread function is scaled to a specific signal to noise ratio and randomly positioned in the FPA backdrop scene by a computer program to add the signal to the background. It is typically defined as a point spread function from an optical system created to have a two pixel full width at half maximum, or an Airy disk. Due to the signal's non-stationarity in the field of vision, it is dispersed across a number of pixels. The complete width at half maximum of the signal would be two pixels if motion is not introduced. Figure 1 shows an illustration of imagery. Large data sets were then created after experimentally obtaining background data in a lab.

Two types of target imagery are studied:

1. Targets that tend to dwell in a small number of pixels and follow a predictable path in the field of view.
2. Targets that tend to move randomly in the field of view and whose extent is not predictable .
   The studied data's particular components have a maximum linear motion per frame that ranges from 3.5 to 12.0 pixels. Due to motion effects, some target smearing can be seen in every frame. The direction of the smear will probably stay the same for multiple frames in situations when the camera footage is not motion adjusted. To provide data that meets these requirements, a scene generating tool was created. A common image and a close-up of the signal

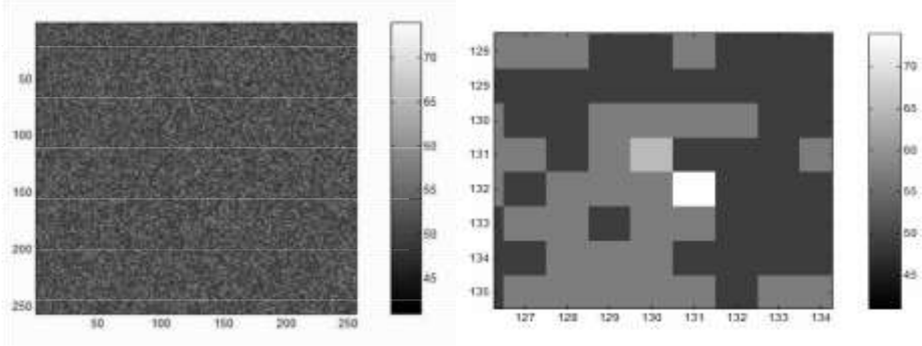


Fig 4: Typical Input imagery used for algorithm

The data gathered in hardware during the loop simulation, where an optical system was out of alignment and there were faults in the focal plane array resembling those found in practical applications, served as the inspiration for this experiment. Below is a table of the experiment's data. As can be observed in Figure 2 below, the horizontal striping is standard readout noise from an Indigo ROIC, the vertical white bar is a flaw in the focal plane, and the diagonal fringes represent an optical misalignment among components. The huge thermal bloom at the bottom and top of the picture obscures the unresolved concentric rings of single pixel target signals while being of no strategic importance.

III. DETECTION AND TRACKING:

Segmenting a region of interest from a video scene and tracking its motion, placement, and occlusion are the objectives of object tracking. Prior phases for tracking an object in a series of photos are object detection and object categorization. To confirm the presence of items in video and to precisely pinpoint that object, object detection is conducted. The identified object can then be categorized into other groups, including people, cars, birds, clouds in the sky, swaying trees, and other moving objects. Object tracking involves keeping track of an object's presence, position, size, shape, and other characteristics as they change over time and in space in a video sequence. Numerous applications, including video surveillance, robot vision, traffic monitoring, video in paintings, and animation, use object tracking

The first stage in many computer vision applications, such as event detection, video surveillance, and robotics, is often the identification of regions of interest. It may be beneficial to have a broad object detection method, however it is quite challenging to handle unknown items or objects with considerable variations in color, shape, and texture. Because of this, many viable computer vision systems presuppose a stationary camera environment, which simplifies the object detection process. Two complementary sets of pixels are used to divide an image, which is typically from a video clip. The foreground object-corresponding pixels are in the first set, while the background object-corresponding pixels are in the second, complementary set. This product or outcome is frequently shown as a binary picture or as a mask.

Following are the basic steps for tacking an object

1. Object Detection

Object detection is the process of locating objects of interest in a video clip and grouping their pixels together. Various methods, including frame differencing, optical flow, and background subtraction, can be used for object detection.

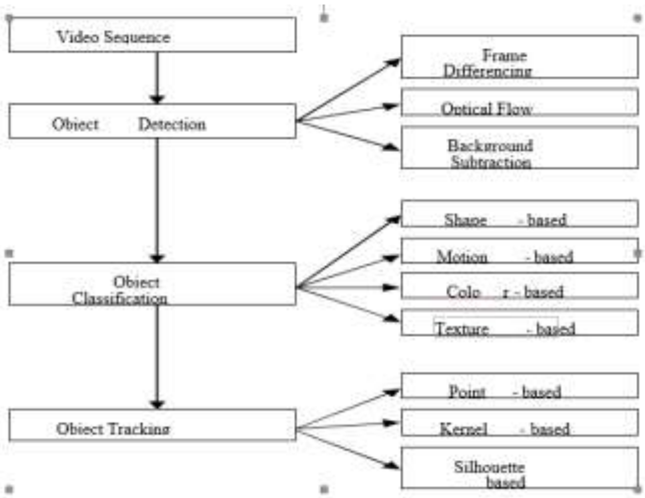
2. Object Classification

Vehicles, birds, soaring clouds, swaying trees, and other moving items fall under the category of object. Shape-based classification, motion-based classification, color-based classification, and texture-based classification are the methods used to categorize the items.

3. **Object Tracking**:

The challenge of roughly estimating an object's path in the image plane as it moves across a scene is known as tracking. The methods for tracking the objects are silhouette, kernel, and point tracking.

Basic steps for tracking an object



The motion estimation and detection, background subtraction, shadow removal, and occlusion detection-based object tracking approach is used when there are numerous humans involved. In the lab, video sequences have been recorded and run through the suggested algorithm. When there is occlusion in the video sequences, the algorithm performs well. This work presents a tracking technique for tracking moving objects in videos using adaptive background reduction. First, the median filter is employed to create the movie's backdrop image and denoise the video sequence. Then, moving object detection and tracking are performed using an adaptive background removal approach.
Adaptive background subtraction is effective in both identifying and tracking moving objects, and the background subtraction algorithm runs more fast, according to the results of the Raspberry Pi simulation. attempts to identify moving things in static, single-camera video sequences captured by security systems by removing the background images. It intends to enhance background subtraction methods for applications involving indoor video surveillance. Various indoor video sequences are generated and tested using the unique automated threshold updating (ATU) algorithm, which provides greater efficiency. Also covered are the statistical and temporal differencing approaches. The unique approach is then contrasted with the current approaches. presents a new background-subtraction-based technique for recognizing moving items from a static backdrop scene. a trustworthy background update model.

Background subtraction

Background modeling is the first step in background subtraction. The algorithm for background subtraction is built around it. The background modeling technique must be perceptive enough to detect moving things. Reference models are produced from background modeling. This reference model is employed in the background subtraction technique, which compares each video sequence to the reference model to identify any potential variations. The differences in pixel count between the current video frame and the reference frame indicate the presence of moving objects. Currently, background modeling is accomplished using mean filters and median filters often. The background subtraction method, which has a straightforward methodology but is extremely sensitive to changes in the external environment, uses the difference method of the current image and the background image to detect moving objects.

Tracking of People

It is difficult to track hundreds or thousands of individuals from an airborne platform in a congested area. Visually distinguishing between persons gets difficult at too high a population density. Additionally, there aren't many traits in a single person's spectral signature in an aerial image to distinguish them from nearby people. Due to the movement of the flying platform and the shifting influence of shadows, clouds, or nearby people, the appearance aspects can change considerably in a short amount of time.

To connect recognized regions in successive images, a semi-global optical-flow tracking technique is used, which compromises local features with global smoothness restrictions.
Segments from the prior detection phase serve as the tracking algorithm's input data. The displacement vectors between two subsequent images are computed using these segments as input into an optical flow algorithm. To narrow the search space for flow computation, typical human maximal motion characteristics are used. If the estimated movement is reasonable given the local object density and there is a segment in the second image at the expected place, both segments are linked to represent the motion of a single individual. Because the results of the optical flow computation are impacted by both changing illumination conditions and object motion

Without explicitly matching their unstable appearance, object regions can be linked thanks to the global smoothness requirement of optical flow. The suggested method's disadvantage is that it relies on accurate and comprehensive object detection results in each image. Images are processed in addition to being two frames apart to avoid scenarios where a single individual could not be spotted in one image of the sequence or when a link could not be created. While the person's location in the bridged image is interpolated, these linkages are used to fill in any gaps between the three consecutive photographs. The entire sequence is subject to the introduced procedure.
Trajectories reflecting the motion of people through the image sequence are the tracking algorithm's output.

APPLICATION

- To rescue survivals in the disaster area
- To detect the wild life's in the forest

IV. CONCLUSION

This experiment illustrates the detection and tracking of humans from aerial image sequences. Additionally, the accomplishments in trajectory interpretation show the power of event detection. It is interesting to see the following new advancements and investigations: The object detection component will eventually be enhanced using hear-like characteristics and AdaBoost classification. Along with detection, tracking may also be made better. Although the algorithm can handle cases in which a person is missed in a single frame, it entirely fails when it occurs in two or more succeeding frames. The suggested optical-flow algorithm cannot overcome this issue. The ability to construct longer trajectories, whose completeness greatly increases with the current results, would be made possible by connecting more than one image.

V.FUTURE SCOPE

This experiment illustrates the detection and tracking of humans from aerial image sequences. Using aerial sequences, persons can be found and followed in video broadcasts. There is ground-breaking research on human individual tracking in terrestrial image sequences. These photographs offer in-depth data to track the catastrophe area's characteristics, and the related image signals are sent to the appropriate individual. The outcomes of the trajectories may increase the likelihood of rescue.

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