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OPTIMISED BLURRED OBJECT TRACKING USING ANFIS

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ABSTRACT

Many promising applications need to track the blurred images in the videos. In most of the object trackers, implicit assumptions are made that the video is blur free. However, in real time videos, motion blur is very common. If severe blur is present in a video the performance of the generic object trackers may go down significantly. The proposed method uses GLCM algorithm for feature extractions from the blurred object and then ANFIS (Adaptive Neuro Fuzzy Inference System) for tracking those blurred objects in the videos. The ANFIS model is trained with the parameters of blurred objects. The input video is imported and GLCM (Gray-Level Co occurrence Matrix) method is used to extract features from the frame. Now the ANFIS data is loaded and compared with the frame. Then the blurred object is detected and tracked by the ANFIS model. The proposed algorithm robustly tracks challenging scenes and severely blurred videos. The speed and performance is improved in this proposed method.

Keywords: blur image, GLCM, ANFIS.

1. INTRODUCTION

Object tracking is important for various visual applications like interaction of human-computer, video surveillance, augment and vehicle navigation reality. Many object tracking and generic tracking method has been proposed [1]. Various efforts were invested to plan generic tracking method on handling background illumination change, noises, occlusion, clutter etc. The generic object tracker implicit assumption is blurring free [2]. Due to quick moving object and low speed camera, blur motion occur in common video. The generic object tracker performance may fall extensively when severe blur motion presents in videos. Precisely locating and verifying image sequence involves in object detection [3]. During video sequence, object tracking is used to monitor temporal changes and objects spatial including its size, shape and position etc. [4] Using ANFIS the features appearance of object extracted and using GLCM object abrupt motion estimated and tracked. Traditional tracking methods deal with blurred videos [5]. Due to quick moving object and low down speed camera motion blur invasive in real videos and by destroying target critical features and observation model they bewilder visual tracking task [6]. In object tracking, to overcome motion blur issue before tracking extract the input image. The robust filter approach has been developed and it gives excellent performances. The tracking of blurred object is getting prevented because of two disadvantage is occurring by tracking, those are mentioned as: computation cost and feature appearance. The tracking algorithm speed is very slow, so it may be high within the computational cost and the illumination could change the target the feature representation by extracting [7]. Before tracking, it's not suitable to use ANN method as pre-processing. Tracking needs shape or location object in each frame [8]. In video analysis, three key paces is used, first is moving objects detection and filtering with pre-process to smoothing the image and reduce the noise. Second is feature extraction of object detection and third is object tracks analysis [9]. Canny blur object detection is used for trace and detecting object. For tracking high accuracy object we using ANFIS algorithm and it utilize training set among object also subtract the background. Using GLCM algorithm the object will track. In this paper from multiple surveillance cameras track the object with more accuracy and efficiency.

2. RELATED WORK

The human motion tracking and detection for security system were formulated in this paper. From live video the object detected and using subtraction of background this system proposed real time security. It's mostly applicable in military, jeweler, shops and banks etc. Using background subtraction method object detection made efficiently and to reduce system frame rate the DML Bayesian method is used on the skin color white and black video can used when background is same then try to identify the object. The system reduces total time and cost consumed and increase efficiency. In various applications real time security efficiently tracking object modeled as Maximum Weight Cliques issue in object segmentation [10] simultaneously in all the video frames. When region comparison is calculated the object shape is not calculated in adjacent frames. For quick moving objects the performance of segmentation is degraded. Our method overcomes this issue combining co-clustering with tracking related adjacency graph. In motion [11] motion predicted shape and appearance similarities used to achieve object extractions in the video sequences. The objects characterize by trajectories smooth motion and spatially cohesive. To predict object shape and position our method using co-clustering substitutes motion estimation. Baldini *et al*. proposed [12] robust and simple approach in outdoor scene for tracking moving targets which may include background movements. For subtraction of background probabilistic based motion detection [13], by motion detection technique matching based tracking found data with those establish with block matching. In various weather conditions algorithm applied to different image sequences [14]. In this paper novel

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tracking approach proposed that integrates OF and FIR filters with ANFIS arbitration rules. AFOA efficiently and effectively calculated target object position in real-time manner. For tracking FIR filter used, it showed high level error for finite number. The AFOA technique has been rewarded over the weakness to the UFIR filter process for switching to track technique of assisted with PLKOF with region of interest for so many turn. By comparing AFOA, FIR filter and KF approaches experiments were demonstrate in terms of time and error. The AFOA system demonstrates error decrease with reasonable calculation burden [15]. This paper efforts to learn and gives brief information about various image classification methods. The most common methods for classification of image categories as unsupervised and supervised or nonparametric and parametric or object-oriented or spectral classifiers, spectral-contextual classifiers and contextual classifiers or soft and hard classification.

3. PROPOSED WORK

The tracking and detection algorithm was implemented atmospherically humiliated video sequences also compare with state of art approach for tracking and detecting moving objects. In the proposed work, the ANFIS is trained with the blurred images and the input video is extracted into frames. The Textural features such as color, size, correlation, texture, blurriness are extracted from each frame. Then it is compared with the ANFIS dataset for blurred images. Now if they match, the blurred object is detected and tracked in a rectangular box whose size is mentioned in the MinimumBlobArea in the Blob Analysis method. The system is trained with the new images also because the ANFIS method is an adaptive technique. In this proposed method certain statistical values like Energy, Entropy, PSNR and Mean are calculated. The Elapsed time in processing each frame is also calculated. Finally the elapsed time is reduced thus increasing the system speed and the Psnr is increased thus improving the performance. Figure-1 shows the steps involved in the tracking of the blurred object from the given video file.

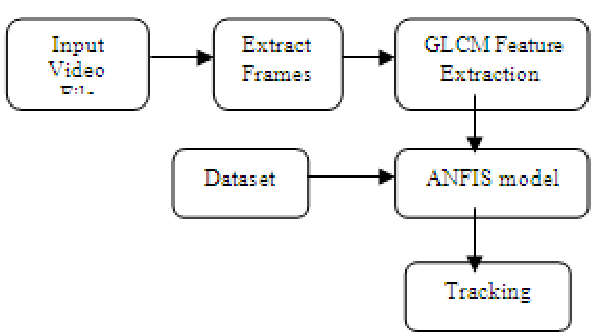

Figure-1. Proposed method block diagram.

A. Input video file

The input video file is provided as audio video files or the user can record video with the help of Web camera. A video signal is a sequence of two dimensional (2D) images projected from a dynamic three dimensional (3D) scene onto the image plane of a video camera. The color value at any point in a video frame records the emitted or reflected light at a particular 3D point in the observed scene. The image from the surveillance consider as an input image. The input image may blur in order to remove blurriness from an image we introduce pre-processing technique. The preprocessing method suppresses unwanted distortions and enhances the features of an image. It considers the redundancy of the image and corrects the degradation.

Figure-2. Input video file.

B. Extracting frames

The video file is need to be converted into frames. The number of video frames can be specified based on the requirement. The frames are the images of the video at number of steps. The frames are helpful to process the video .We have taken 20 frames for processing. Filtering is technique to enhancing or modifying image. It removes the unwanted noise from an image. Filtering include smoothing, sharpening and edge detection. Filtering helps to reduce image noise, contrast, image size, pixel values, etc. this technique processed to convert into original and reliable input image object.

C. GLCM feature extraction

The method to reduce the amount of information required to represent a large set of data accurately is called the feature extraction. Gray-level Co-occurrence matrices (GLCM) algorithm is used to capture accurate textural characteristics of the image by considering scales and multiple orientations. It is a matrix where the rows and columns of this matrix represents the gray levels of an image. Texture features can be determined to capture granularity and regions repetitive patterns within image. In statistical view, textures consider as convoluted pictorial patterns as of statistics for characterization function. Statistics examples extracted from image region or image are standard deviation, mean gray level, and entropy. By counting gray levels occurrences at given angle and displacement characterize texture contain GLCM. The function hsvhistogram is included to find the histogram equalization values. The color autocorrelation helps to find the color values of the objects in each frame. Also the color values changes when any object enters in the video frame. The color frame has to be converted into gray image so as to apply the blob analysis method. This method helps to mention the minimum blob area to surround the detected object with a rectangle. This size can be increased to track larger objects. The dataset is created and sent to classifier to detect the blurred object. Statistics such as energy, entropy, psnr and mean are calculated from GLCM to get texture features.

D. ANFIS (Adaptive network based fuzzy inference system)

ANFIS model is initially trained by blurred images. Some images are captured and then blurred to train the model with blurred images for further comparison. The pixel value of blurred image has drastic changes over the neighborhood. To combine best features like Neural Networks and Fuzzy Systems i.e. prior knowledge representation constraints set (network topology) to minimize optimization investigate space from Fuzzy System and back propagation adaptation toward structure network to mechanize neural networks parametric fine-tuning. Hybrid optimization technique is an arrangement of back transmission gradient descent and least-squares technique. Two steps of Hybrid learning algorithm are given below:

1. Forward pass
2. Backward pass

In forward pass, assertion constraints are fixed and to update consequent parameters least square evaluation is used. In backward pass, subsequent constraints are fixed and also to update assertion constraints back transmission gradient descent technique is used. For FIS system assertion and subsequent constraints are identified by repeating backward and forward passes. The features extracted from the GLCM are used to create a dataset which contains histogram values, Autocorrelogram values, color values, Texture values and wavelet moments. The output parameters like energy, entropy and psnr also calculated. The object is detected and the number of objects in the each frame and the name of the object is displayed in the output. Thus the ANFIS is trained with the dataset. Later it is compared with the input video frames to detect and track the blurred objects.

4. RESULTS AND DISCUSSIONS

A. Structure of an ANFIS model

The ANFIS model has inputs, membership functions for input and output, rules and output. The inputs are the values or the parameters to be trained. The fuzzy rules are the statements specifying how the output should be for a given set of inputs and the condition.

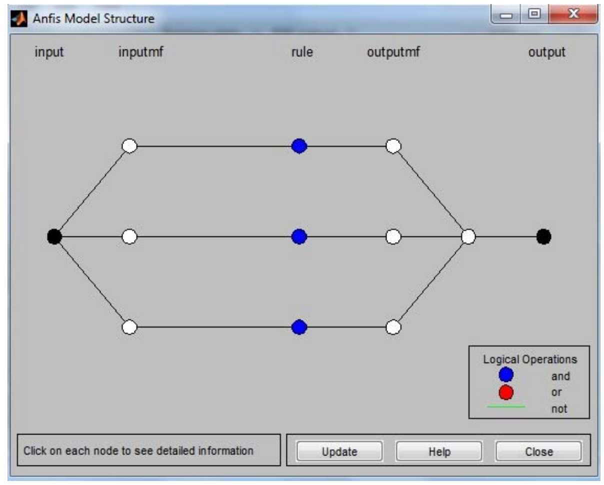

Figure-3. Structure of an Anfis model.

Figure-2 shows logical operation. In this ANFIS model structure logical operation, AND is performed on inputs. Based on input value membership function the output performs.

B. ANFIS editor

ANFIS editor can be used to load the training data from workspace or file by using load data option. The file contains blurred object details. Then the rules for the fuzzy inference system should be specified. Then Generate FIS generates the FIS system. Then the FIS should be trained using the option Train Now. Then the data should be tested with either Training data or Testing data and checking data. Figure-3 shows Training data.

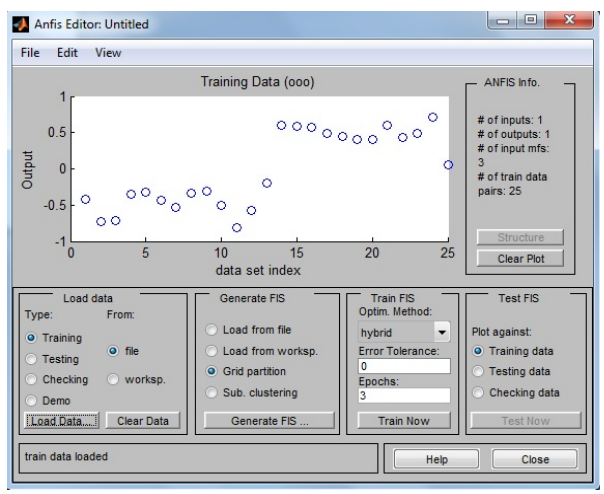

Figure-4. Training data for the ANFIS.

C. Membership functions and fuzzy rules

After loading data, generate Fussy Inference System to define fuzzy rules and membership functions. These rules specified using Rules Editor window. In this proposed method three rules major rules have been specified. Then the program starts reading the input video.

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It converts the video into number of frames. Then the system checks the data with the trained data and the blurred object is detected. Once the FIS is generated, we have to train the system to identify the blurred objects. Here the training error will be generated. The checking error is the difference between the checking data output value, and the output of the fuzzy inference system corresponding to the same checking data input value, which is the one associated with that checking data output value. The system can be trained using two methods like Hybrid method or Back propagation method. Here we use the hybrid method to train the system. Then the last step is to test the system. Testing is done with the training data available in the anfis.dat file. Figure-4 shows the Training Data output of the ANFIS model.

Then the file has to be saved using the fis extension. Then training the Fuzzy Inference system is completed. Now the program starts reading the input video. It converts the video into number of frames. Then the system checks the data with the trained data and the blurred object is detected. This is repeated for all the consecutive frames.

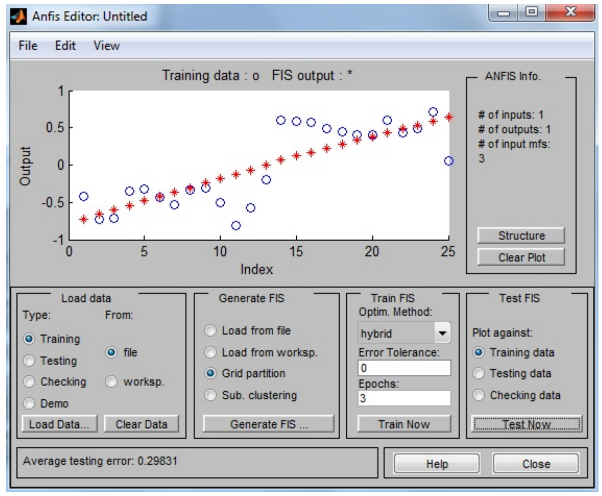

Figure-5. Output from the ANFIS model.

Figure-6. Tracking of blurred objects.

Figure-5 shows Tracking of blurred objects in one of the frame. Once the blurred object is detected, a rectangular box is drawn covering the blurred object. Also the name of the object and number of blurred object is also shown in the output video.

D. Performance calculation

Table-1 shows Elapsed time, Entropy value, Energy value, PSNR and Mean value of the detected object in each frame using ANFIS.

Table-1. Performance calculation.

Frame	Elapsed time (sec)	Entropy value	Energy value ($*10^{-1}$)	PSNR	Mean
Frame1	1.6485	3	1.78	1.222 $*10^{-1}$	1.99 $*10^{2}$
Frame2	0.6148	2	2.7	1.22 $*10^{-1}$	5.9 $*10^{1}$
Frame3	0.3865	2	2.68	1.191	6.325
Frame4	0.3125	2	2.69	1.179	187
Frame5	0.3267	3	1.8	1.099	244

E. Comparison table and graph

The proposed system has been compared and analyzed for time taken in processing the video and training the system. It is found that ANFIS takes less time compared with the existing techniques.

Table-2. Shows the elapsed time of different techniques.

Technique	Elapsed time (Sec)
KF	1.87
FIR	1.85
AKOA	1.94
AFOA	1.98
ANFIS	1.64

Figure-6 shows the graph of Elapsed time of different techniques. When compared to other techniques ANFIS has less elapsed time which shows this method takes less time for processing and the speed of the system is increased.

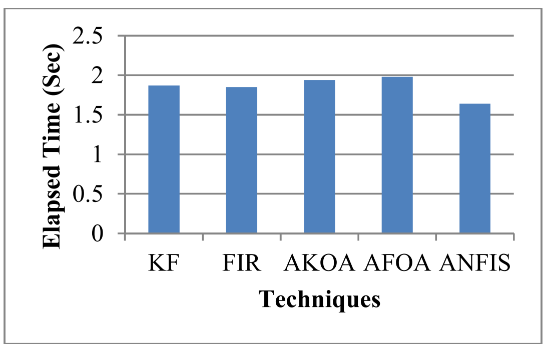

Figure-7. Elapsed time for different techniques.

5. CONCLUSION AND FUTURE ENHANCEMENT

An extensive review of tracking methods and object detection is presented in this project. For detection and tracking system, object shape illustration and recognition is important. Feature selection and object tracking is presented insight in this project. Image processing techniques like pre-processing and filtering produces enhanced image from the blurred input video. GLCM algorithm and ANFIS has been extensively used for feature extraction and tracking the blurred object. GLCM is one of the most effective algorithms which is used for feature extraction. ANFIS supports the proposed system to obtain high performance and speed of tracking. The Elapsed Time, Entropy, Energy, PSNR and the mean are calculated and displayed for each frame. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. The PSNR and Mean are observed to be effective for this proposed method of object tracking. In future development, using Principal component analysis (PCA) technique the shape and size of human images in a challenging blurred scenes can be detected.

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