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Novel Approach of Retrieving an Enhanced Frontal Face Image

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Abstract: **In bio-metric analysis system, such as face recognition, human computer interaction and so on, face is considered as one of the significant factor in remote life science. Images captured from inexpensive surveillances camera provides low resolution images. To avoid this problem, we need to retrieve a high-resolution image from those types of low-resolution video sequence. In order to provide a solution, Reconstruction based super resolution and Learning Based Super resolution algorithm was used for improving image quality. The employed LBSR algorithm in the existing system is Multi Layer Perception.MLP method use neural network for training the image. So it requires large memory space to store a huge amount of information, and they require large time for computation. Its improvement issue is limited. In this paper we are going to use Patch based classifier method. It will provide enhanced frontal face image compared to the existing method.**

Key Words: Face recognition, Super resolution, and Patch Based classifier.

I. INTRODUCTION

Face recognition has received important attention throughout the last two decades and lots of researchers study varied aspects of it. There are minimum of 2 reasons for this; the first one is a large choice of business and security applications and also the second is the availability of potential technology to develop and implement applications that demand well-build machine power. Today, automatic recognition of human faces could also be a field that gathers many researchers from whole completely different disciplines like pattern Recognition, PC vision, graphics, and science. Low resolution images are captured from inexpensive surveillance cameras. Therefore, having an automatic system operating with LR and low-quality face image is desirable. However, low-quality images don't have enough high-resolution (HR) details for facial analysis systems and using them directly in these systems isn't reliable. To overcome this problem we have to recognize a high-resolution image from the low-resolution video sequence. Super resolution (SR) could be a technique that aims to extend the resolution of an image or a sequence of images on the far side the resolution of the imaging system. SR algorithms area unit broadly classified into 2 classes: Reconstruction-based SR (RBSR, known as classical multi frame SR) [1] Learning-based SR (LBSR, referred to as hallucination, or example primarily based SR) [4]

RBSR algorithms typically work with over one LR input image. These LR inputs should have intra-image sub pixel misalignments. The algorithmic rule uses these misalignments to reconstruct the missing HR details of the inputs. These misalignments area unit thought of in an exceedingly registration step before beginning the reconstruction method. LBSR algorithms largely learn the relationship between some HR training images and their corresponding LR versions. They use this information to predict or perceive the missing HR details of the LR inputs. A training set, which is composed of variety of high-resolution images/video, is employed to later predict the details of lower resolution images/video. Each categories use extra priors to encourage generic image properties like smoothness, implicitly or explicitly.

In the existing system [13], they use both RBSR and LBSR Algorithm. Reconstruction based super-resolution formula, however, has 2 main problems: 1st, needs comparatively similar images with not an excessive amount of noise and second is that its improvement issue is limited. To contend with the primary problem we have a tendency to introduce a three-step approach, that produces a face-log containing faces of comparable frontal faces of the best attainable quality. To contend with the second problem, restricted improvement issue, we have a tendency to use a learning based super-resolution formula applied to the results of the reconstruction-based part to improve the quality. In LBSR algorithm they use MLP method [5]. It requires large memory space to store a huge amount of information, and it will take more time for computation because of the large number of two-dimensional matching operations. In the proposed system we are going to use patch based training method. It will provide enhanced frontal face image compared to the existing method.

II. RELATED WORK

The main idea in this paper is to recover a single high-resolution image from a set of low quality images from the video sequence. Several papers addressed the general super-resolution problem and suggested practical solution to this problem. SR algorithms area unit broadly classified into 2 classes: reconstruction-based SR and learning-based SR.

RBSR algorithms typically work with over one LR input image. These LR inputs should have intra-image sub pixel misalignments. The algorithmic rule uses these misalignments to reconstruct the missing HR details of the inputs. These misalignments area unit thought of in an exceedingly registration step before beginning the reconstruction method. The first RBSR system was a frequency domain algorithmic program planned by Tsai and Huang [2]. They used the shifting property of Fourier transform and also the spectral aliasing to reconstruct the HR details of the output.

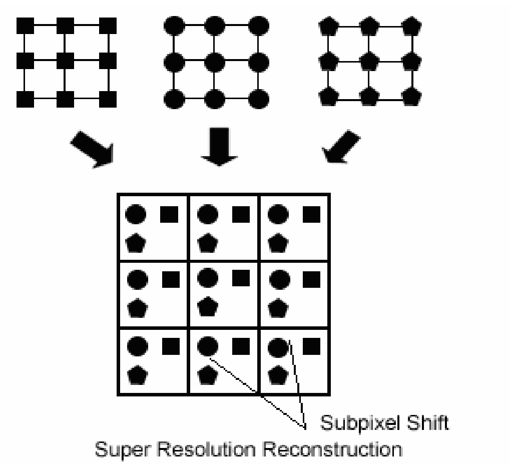

Fig 1: Illustration of super resolution reconstruction;

Spatial domain solutions for RBSR were later developed [3]. These ways have higher concerns for noise and blur than the frequency domain approaches. Many ways are planned for spatial domain RBSR. These ways chiefly take issue in 3 points: the used registration algorithmic program, the used technique for getting the ultimate response of the system and also the regularization technique. For getting the ultimate response of the system, Irani et al. [3] used an iterative back projection based mostly technique almost like what's utilized in computer aided tomography.

LBSR algorithms largely learn the relationship between some HR training images and their corresponding LR versions. They use this information to predict or perceive the missing HR details of the LR inputs.

III. PROPOSED WORK

The proposed system during this paper deals with the real world issues of a SR system operating with faces coming back from a surveillance video sequence. Such a system has many problems: the slight-motions restriction of the objects, ill-posed and ill-conditioned nature of the HR response, slow convergence of the system and little magnification factors. Feeding all frames of a surveillance video sequence to any SR system is not possible, as a result of there are several face images in such a sequence that don't seem to be helpful attributable to issues like not facing the camera blurriness ,uneven illumination and so on.

Including all such images within the computations reduces the convergence speed of the system and makes the ultimate response incorrect and unreliable Therefore, there's a requirement for a mechanism to assess the standard of the detected faces and discard the useless ones. Furthermore, faces given to RBSR system have to be terribly like one another. Thus, the faces selected by the assessment algorithmic rule have to be somehow classified based their similarity. To this end we tend to introduce a three-step approach that produces a face log containing images of comparable faces of the best attainable quality. Within the commencement, we tend to classify face images in terms of head position. In steps 2 and 3, we tend to prune this first face log supported variety of quality and similarity measures, severally, and find yourself with a refined face-log on that the SR algorithms will operate. Rather than using reconstruction or LBSR algorithms with their inherent issues, we tend to use a mixture of each style of these algorithms. This will improve the quality of the image.

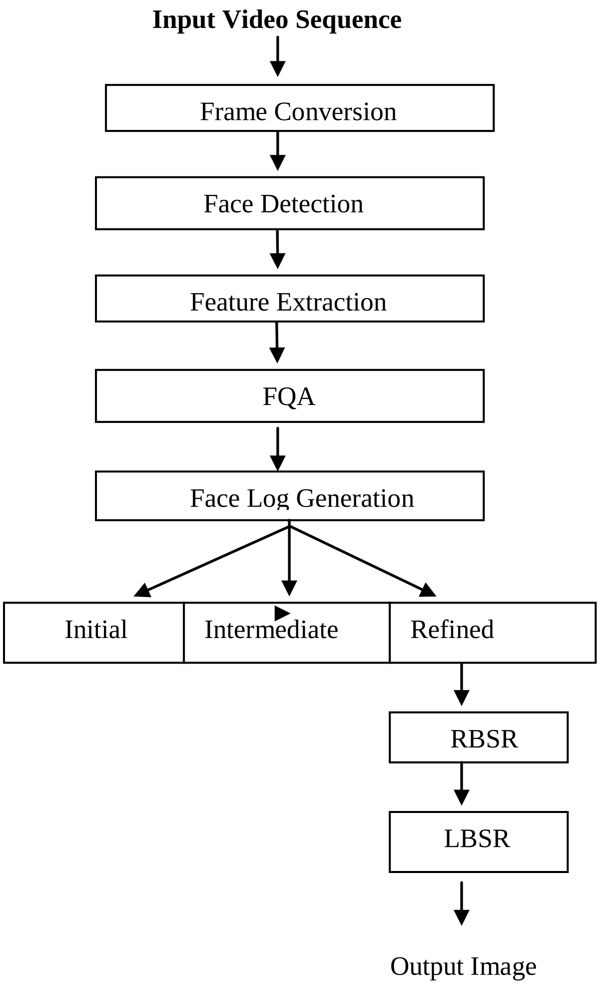

Fig 2: Block Diagram of Proposed System

The block diagram of our system is shown in the above figure (Fig 2). In the first block of the system, face-log generation, the input video sequence is summarized to at least one [up to a few face-log(s)]. The images within the face-logs area unit terribly the same as one another and area unit of higher quality compared to the other images of the sequence. It means that they're smart inputs to successive block of the system that may be a cascaded SR. In this block, an RBSR is applied to the generated face-log(s) and produces an HR image. The quality of this HR image is improved compared to the LR images in the refined face-log. This HR image is then fed to an LBSR to enhance it even a lot of.

A. Face Detection

The entire video sequence is to be converted to frames and stored in a readable format. We use the Viola and Jones [6] idea of employing Haar -like features of the integral images of the input video sequence to detect face images. Haar-like features are digital image features used in object recognition within the detection section of the Viola–Jones object detection framework, a window of the target size is stirred over the input image, and for every section of the image the Haar-like feature is calculated. This dissimilarity is then compared to a learned threshold that separates non-objects from objects.

B. Feature Extraction

We need completely different LR face images of an individual against one another instead of having actual numerical values for his or her facial expression. We've got used three face expression Head-Pose estimation, Sharpness, Brightness.

1. Head –pose estimation

There are lots of ways for head-pose estimation in the literature [7]–[9].These methods are either local or global. Local methods use a set of facial components like eyes, eyebrow and lips to estimate the head-pose.. Global methods use the entire face image to estimate the head-pose to be able to work with LR images. Head-pose in this database is determined by pan and tilt angle.

2. Sharpness

To calculate the sharpness of the image

$$Shxi = avg(abs(Xi - lowpass(Xi))) \quad (1)$$

$Shxi$ - Sharpness,

low pass - simple 3 × 3 mean filter.

3. Brightness

It is necessary to assess the brightness of the face images of a given video sequence. It's the mean of illumination element of the face in YCbCr color area.

C. Face Quality Assessment

To compare a face image of a selected person with the other face images of a similar person from a video sequence, we want to assign a high quality score to every face. To do so, we've combined the normalized worth of the above-explained features into a quality score for every face.

$$Q1Xi = Pmin / P_{xi} \quad (2)$$

P_{xi}- Head-pose value

P_{min}- minimum value of the head-pose

The above equation (2) is user to normalize the head-pose value. For normalizing the other 3 features, we've used

$$Qjxi = Fxi / Fmax \quad (3)$$

xi - *i*th face image,

$Qjxi$- *j*th quality score of *Xi*, *j* = {2, 3, 4},

Fxi - value of the current feature of *Xi*,

$Fmax$ - maximum value of the current feature

Having normalized the above feature values, we use a Weighting system to combine them into a quality score for each face.

$$Nxi = \sum_{j=1}^{4} WjQjXi \ / \sum_{j=1}^{4} Wj \quad (4)$$

N_{Xi} - normalized quality score

QjXi - jth quality score

Wj - Weight of this score

D. Face Log Generation

We need to construct three face logs. Initial face-log Intermediate face-log, Refined Face-log

1. Initial Face-Log

Based on the value of head pose value, we classify face images of the input video sequence into three face-logs containing frontal, left side-view, and right side-view face images. These face logs are denoted as **initial face-logs**. If the head-pose of a face is between −15° and 15° it will be added to the initial frontal face-logs, if it is more than15° it will be added to the right side-view initial face-log and if it is less than −15° it will be added to the left side-view initial face-log.

2. Intermediate Face -Log

Suppose that the initial frontal face-log contains m1 face images. The FQA technique reduces its size to m2 images, such that m2< m1. This reduced face-log contains the m2 best images of the initial face-log and is denoted intermediate face log. The image with the highest quality score in this intermediate face-log is found and considered as the reference image (best image).

3. Refined Face Log

Two similarity measures are calculated between the reference image and the other face images in the intermediate face-log. These two similarity measures are correlation coefficient and structural similarity measure [11]. For calculating these similarity measures, we need to change the size of the images to the same size as the reference image and convert them to grayscale. $s1xi$ is the first similarity measure between these two images.

Structural similarity measure takes into consideration contrast, luminance and therefore the structure of the images between the ith face image within the intermediate face-log and the reference face image

$$Sxi = (s1xi + s2xi)/2 \quad \textbf{(5)}$$

The mean of these two similarity measures [see (5)] is then considered as a similarity factor between current face and the reference face. Based on this similarity factor, m3 (m3<m2) most similar images are chosen and considered as a refined face-log. This refined face-log is used as the input to the RBSR algorithm.

E. Reconstruction Based Super Resolution

To apply the RBSR to the images in the refined face-log we resize all of them to 46×56 pixels after face quality assessment. The RBSR produces a HR image of size 92×112 from the LR images of the refined face-log. Then, the proposed system feeds this image (of size 92×112) to the learning-based part to improve its quality even more. Before applying the RBSR, the images in the refined face-log need to be first registered to compensate for their mis-alignments.

In order to reconstruct the HR image from the LR images of the refined face-log we use the imaging model. Based on the imaging model every LR image has been created by warping, blurring and down- sampling the HR image. This methodology improves the quality of the LR images in the refined face-log. For more improvement of this HR image, it's fed to subsequent step of the system that's an LBSR algorithm.

F. Learning Based Super Resolution

In the proposed system we are going to use patch based training method. For training this technique we've used around five images. Need a high and low resolution source as inputs for training a patch based classifier. We must extract the average value of image and down sample each image. Convert the image RGB space to YIQ color space. Separate the image into overlapping patches and process on the Y-Component (luminance). Find the mean and gradient features for each sub patches. Compute weight matrix by reconstructing nearest appearance neighbors of each patch. The nearest appearance patch will be determined by distance measures, local covariance and regularization parameters. These patches will again be converted to RGB color space. Finally the nearest reconstructed high resolution patches will be combined to project the image

IV. RESULT ANALYSIS

To show the efficiency of the proposed system in real-world situations, it has been tested using three different videos. The three videos are taken from NRC-IIT [12] database, is a publicly available database containing 22 low-resolution video sequences of 11 test-subjects. People in this database are sitting on a movable chair in front of a camera to see their similarity. $s2xi$ is the second similarity measure

and change their head-pose, facial expressions, and distance to camera. The average length of the videos of this database is around 14 s.

Fig (3) shows the initial face log .it contain the frontal face images of the given video sequence. Fig (4) shows the intermediate face log. Fig (5) shows the refined face log of the given video sequence and fig 6(a) shows the output of the RBSR algorithm. Finally Fig 6(b) shows the output of proposed system.

Here we are using SSIM (structural similarity Matrix) for calculating the quality of the image. From Fig (7) the Patch Base Classifier provided better result compare to the Multi Layer Perception (MLP).

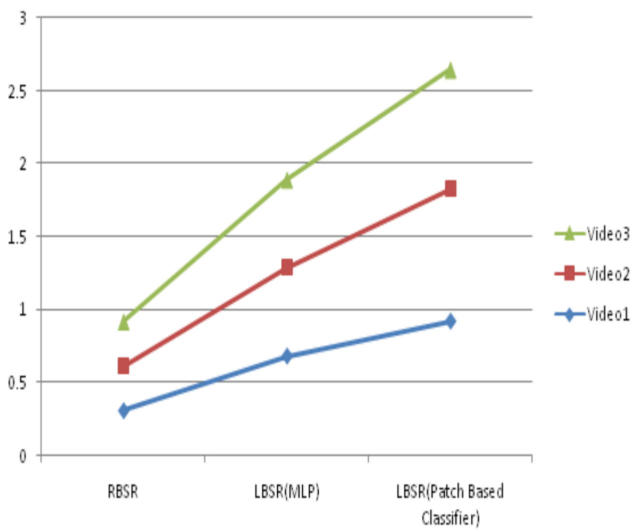

Fig (7) Comparison between Existing and Proposed

V.CONCLUSION

Facial analysis applications need high quality frontal face images; but the inexpensive surveillance cameras provide low resolution videos. Therefore, there's a necessity for a mechanism to bridge between low quality, low-resolution face images from video sequences and their applications in facial analysis system. Super-resolution is one amongst these mechanisms. The projected system during this paper deals with the real-world issues of super-resolution systems operating with surveillance video sequences. So we are using Both RBSR and LBSR algorithm for improving the resolution of the image. The patch based Classifier further improves the quality of the image and reduces the computation time and memory consumption.

Fig 3: Initial Face Log

Fig 4: Intermediate Face Log

Fig 5: Refined Face Log

Fig 6(b) Output of RBSR

Fig 6(b) Output of LBSR

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