IN-SERVICE VIDEO QUALITY MEASUREMENTS IN OPTICAL FIBER LINKS BASED ON NEURAL NETWORK

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Abstract: Video quality assessment plays a key role in evaluating and optimizing video systems. In this paper, objective image quality metric, appropriate for the fiber optic image transmission line without accessing to the original images, is evaluated by conventional neural networks. It allows an efficient continuous time scoring of the video stream efficiently by a mark on a scale of zero to five. The image database in this research has been collected in the Semnan University. The certainty of the trained network is above 81 percent. Simulation results show that the proposed method is highly correlated with experimental data collected through the subjective experiments.

Key words: *Digital video transmission link, single mode optical fiber, no reference video quality metrics, back propagation neural networks*

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1. Introduction

1.1 Image transmission noise measurement

Tremendous advances in computer and communication technologies have led to proliferation of digital media content. The digital systems are replacing all existing analog systems as a new carrier of the media service. However, noise occurs everywhere in video systems; cameras, video tape recorders, video tape, amplifiers, power supplies, cables and their connectors. On the other hand, every component in video signal generation, distribution, and transmission causes some noise in the video signal. But in this work only transmission line noise is considered. However,

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other parts' noise might appear on the final image in the computer, e.g. processing destroyer like blurring, shaking, blocking, etc.

Video transmission problems like attenuation, distortion and polarization changes are almost solved by utilizing optical fibers [1, 2]. Nevertheless, there are still some perturbations which create artifacts in the resulting images which degrade their quality. Fig. 1 shows some of these noise sources.

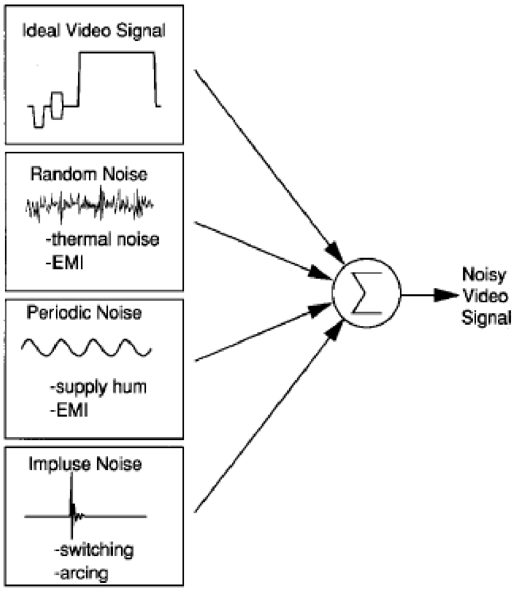

Fig. 1 *The noise sources of a video system.*

In video applications, the nominal luminance level ($L_{nominal}$) relative to the effective power of the noise (N_{rms}) is expressed as SNR which is given by equation (1) – for having high quality video signals, the SNR ratio should not be less than 54 dB.

$$SNR = L_{nominal}/N_{rms} \tag{1}$$

To address the noise issue, numerous noise measurement techniques have been developed. In some cases, these methods suffice, but they often require skills and equipments beyond those of standard video signal measurements. Nor they are suitable for identification of some image artifacts like blocking or blurring directly [3]. According to this gap we propose an automatic image quality measurement technique based on a learning algorithm.

1.2 Quality metrics

Quality metrics can be further classified into the following categories:

- Full-Reference (FR) metrics: FR metrics perform a direct comparison between the image or video under a test and a reference or "original". These metrics require the entire reference content to be available; this is an important restriction on the applicability of these metrics. Another practical problem with FR metrics is the alignment of the two images or videos under a test, especially in case of video sequences, in which it should be ensured that the frames and image regions being compared are exactly in correspondence.

- No-reference (NR) metrics: NR metrics look only at the image or video under a test and have no need reference information. It is then possible to measure the quality of any visual content, anywhere in the video frame and the transmission system. The difficulty here lies in taking apart the distortions from a regular content, a distinction that humans are able to make it from their experience.

- Reduced-reference (RR) metrics: RR metrics steer the middle course between these two extremes. They extract a number of features from the reference image or video (e.g. spatial detail, amount of motion). The comparison with the video under a test is then based only on those features [4]. The RR and NR video quality metrics are appropriate due to having in-service monitoring [5, 6].

1.3 Video quality measurement methods

Video quality assessment techniques have two kinds of approaches; the first one is an engineering approach which includes subjective metrics and the second is a psychological approach with objective metrics. These two methods have their own advantages and disadvantages: the former one is reliable but is tedious, expensive and cannot be conducted in real time. The later is easy and fast but is not always consistent with visual observation [7]. In addition, human observer can also perform an accurate quality measurement, known as HVS[1]-based objective measure [8, 9, 10, and 11]. However, it can also be considered as an objective metric in some manner. Ideally, such a quality assessment system would perceive and measure image or video impairments just like a human being, but it would be complex and time-consuming. So, it is not a suitable approach for in-service applications [7]. Another approach tries to exploit the properties of known artifacts, such as blocking, utilizes feature extraction and model parameterization. This class of measuring methods focus on the type of artifacts [12], [13] so it is simpler and normally more accurate than HVS.

For solving the mentioned difficulties and having an automatic quality measurement machine we propose a method based on the back propagation neural networks (BPNN) [14]. The inputs of BP-NN are six no reference gradient-based features, according to which good and bad images can be discriminated.

This paper is organized as follows: in Section 2, an explanation of quality metrics used in this paper is provided. The HVS model with neural network is described in Section 3. The results and other proposed methodologies are given in Section 4. Finally, Section 5 concludes and summarizes the paper.

[1]Human Visual System (HVS)

2. No Reference Gradient Based Metrics

Interestingly, human observers can easily assess the quality of distorted images without using any reference image but user-end application requires an estimation without having access to the original image, therefore NR quality metrics should be used. However, designing NR quality measurement algorithms is a very difficult task.

In this section six NR quality metrics are described, based on gradient; they are calculated by differential operators on the edges. All these metrics were implemented and tested to see if they are proper or not.

2.1 Blurriness

This NR-metric is based on analysis the spread of edges in an image. The algorithm is summarized as follows. First, an edge detector is applied to the luminance component of the image. The start and end positions of each significant edge in the image are defined as locations of the minimum and maximum local intensity closest to the edge. The distance between these two points is identified as a local blur measure for this edge location. The global blurriness for the whole image is estimated by averaging the local blur values over all significant edges found [8]. Another way for blurriness measurement is tested here. In this method, local min and max intensity of the image in an identified range at each row is needed. The difference between these two points' intensities is defined as the local blurriness. The global blurriness is obtained by averaging. It should be mentioned that the second method is faster and more reliable. So it is used for blurriness. It is first metric; if each m column is considered for local blurriness, the blurriness is given by:

$$if \left\{ \begin{array}{l} x = i \\ y \in [column_i, column_{i+m}] \end{array} \right.$$

$$local\_blurriness_i = \max(I(x,y)) - \min(I(x,y))$$

$$blurriness = \frac{1}{k} \sum_{i=1}^{k} local\_blurriness_i$$

According to several experiments we found that the appropriate number of columns for a 640 to 800 pixel image is 50. One more thing about this metric is that regarding to the definition of blurriness in [8] the image blurriness increases by decreasing the numeric amount of the blurriness metric.

2.2 Edge strength

After testing the edge metrics on a large number of images, we found that the edge strength in addition to the edge number and blurriness is required, so two efficient metrics, namely HES[2] and VES[3], are used. To implement these metrics, we first apply a canny edge detector to the input image. Then, the consequent edges dilate

[2]Horizontal Edge Strength
[3]Vertical Edge Strength

in order to have thicker edges. By multiplying this image to the input image, an image with its edges and around them is yielded. When the difference operation is applied to this image as vertically and horizontally, the vertical and horizontal edge strength metrics are obtained, respectively. The block diagram of this method is illustrated in Fig. 2.

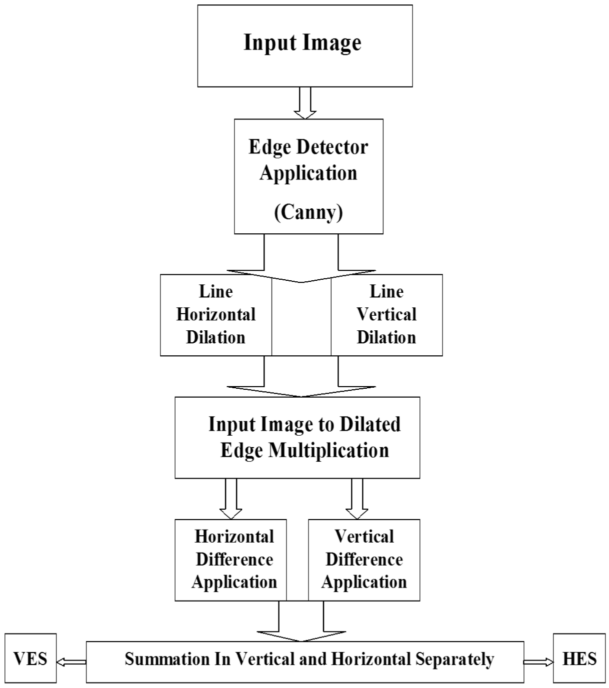

Fig. 2 *The block diagram of edge strength method.*

Testing this method on a large number of images, revealed impressive results. This way, the third and fourth reliable gradient based metrics are found.

2.3 Wavelet first level metrics

One effective way to examine both the blurring and blocking effects is to have some metrics in frequency domain [15]. Therefore, to make more accuracy in the case of edge numbers, vertical and horizontal subband of the first level of the wavelet domain were utilized as fifth and sixth quality metrics. The block diagram of this method is shown in Fig. 3.

To implement this metric Debitues wavelet is used and tested with kinds of edge detectors at the first level in the wavelet domain. Among the edge detectors-Sobel, Prewitt, Roberts, Log, Zerocross, and Canny-Zerocross and Log perform better because of their regular changes [16, 17, and 18]. Fig. 4 shows the curve of changes of this metric as the image artifacts increase is given in Fig. 4.

As shown in Fig. 4, the number of edges decreases with rise blocking and blurriness in the input image. We selected just Zerocross because it had more regular

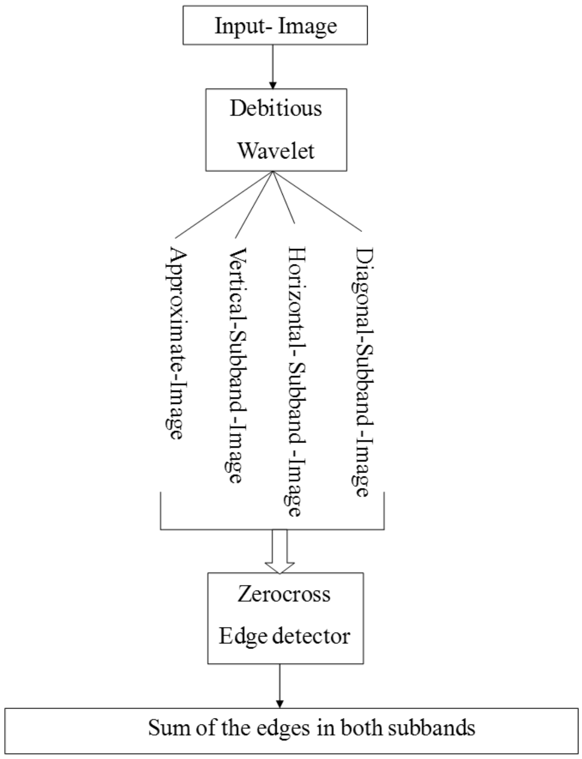

Fig. 3 *The block diagram of wavelet first level metrics.*

changes. The sum of the edge pixels in the horizontal and vertical areas in the wavelet domain is calculated and the sixth metric is made.

3. Neural Network Scheme

As mentioned before, the method used in this paper, is based on correlating a viewer's subjective opinion with the video measurements, called PEVQ[4]. PEVQ provides an overall objective quality video model that correlates with ratings obtained from subjective tests [4]. Designing such a model is not straightforward and the implementing of these models is computationally complex. To overcome such difficulties, a learning algorithm is usually employed [7].

The mapping function $y = F(x)$ is established during a training phase, in which the network learns to correctly associate the input vector to the output vector. The Back Propagation Neural Network[5] is one of the multi-layer feed-forward neural networks, in which the transfer-function of the output layer is a nonlinear sigmoid function and therefore its output is a continuous variance range from 0 to 1. Hornik and Stinchombe have shown that "a single hidden layer feed-forward network, with

[4]Perceptual Evaluation of Video Quality
[5]Back Propagation – Neural Network (BP-NN)

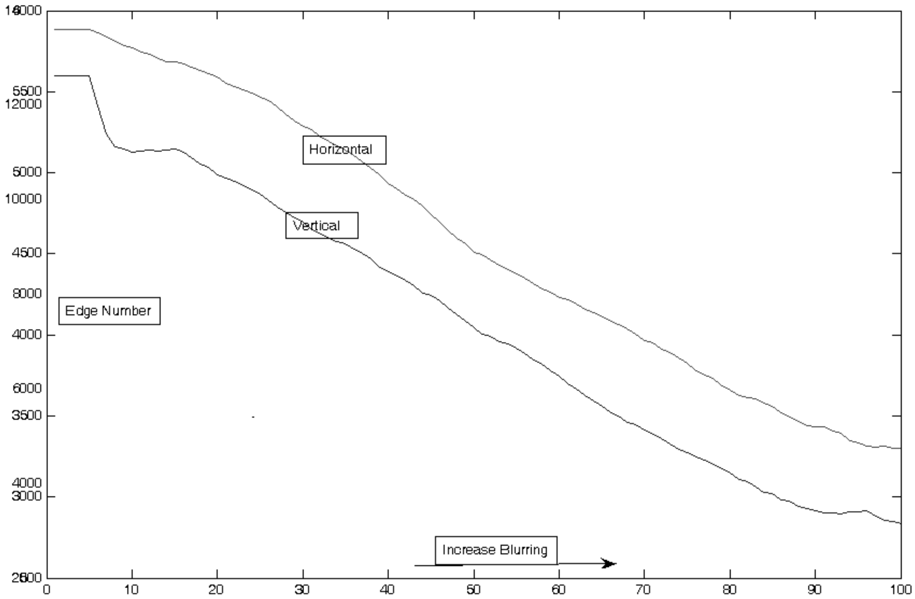

Fig. 4 *The changes of edge numbers detected by the Zerocross method with respect to the blurriness increase in the wavelet domain.*

arbitrary sigmoid hidden layer activation functions, can approximate an arbitrary mapping from one finite dimensional space to another one". So BP-NN seems to be an appropriate tool to mimic the human brain for assessment of image quality. For a given application, the critical aspect of designing a BP-NN is choosing an appropriate network size, which consists of the number of layers in BP-NN, the number of nodes per layer, and the number of connections. The network size would affect network complexity, training time and especially the generalization capability. In other words, a too simple structure cannot utilize the training set sufficiently and a too complicated structure may "over-fit" the training set. The number of input and output nodes is determined by the specific knowledge about the problem. The number of connections is determined by the correlation of the input signal, and the number of nodes in the hidden layers is determined by trial. Therefore, one has to train several networks with different sizes repeatedly, until an appropriate network is found [7].

4. Experiments

4.1 Making image dataset

The image dataset used in this project was collected in the Semnan University. The setup was used for preparing these images, which is shown in Fig. 5.

As shown in Fig. 5, a camera makes a stream of images and sends them to the optical fiber modem. Images are transferred through the single mode optical fiber

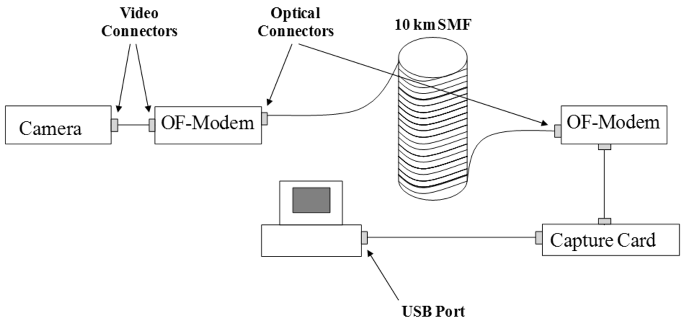

Fig. 5 *Image dataset providing setup.*

to another modem on the other side, the destination indeed. The resulting video signal from the optical modem is digitalized by an external capture device and is transferred to a PC via the USB port.

The images shown in this paper were provided in different situations such as vibration, bending, and twisting in order to build a set of noisy images as neural network inputs. These images were given to an image processing expert to be scored in a zero to five in terms of visual quality from the experts' point of view. Averaging the experts' scores reveals the targets of neural network. In Fig. 6, six images are shown to illustrate how the experts score them,.

In Fig. 7, the quality of the image according to the given-score is donated.

The main characteristics of the devices in the image database is provided below:

Optical Fiber Modem:
BER $<10^{-9}$
SNR: 67dB min
Wavelength: 1310/1550 nm
Optical output power: -5 dBm
Bandwidth: 5 MHz - 10 MHz
Optic Connector: ST standard – Loss: 0.319 dB
Video Connector: BNC connector

Single Mode Fiber:
Length: 10 km
Loss: 0.346 dB/km at 1310 nm
Critical Bending Radius: 75mm
Chromatic Dispersion $\leq$ 3.2 ps/(nm.km) at 1285 $\sim$ 1330 nm

4.2 Experimental Results

The six obtained image quality metrics with the provided-dataset are used as neural network inputs the training phase. This process is shown in Fig. 5.

(a)

(b)

(c)

(d)

(e)

(f)

Score (a) = 0; Score (b) = 1; Score (c) = 2;
Score (d) = 3; Score (e) = 4; Score (f) = 5;

Fig. 6 *Scoring images from the experts' point of view.*

The neural network inputs have 6 characteristics: Edgnum, Blurriness, Horizontal and Vertical edge detection of the first level of the wavelet domain, Horizontal-strength, and Vertical-strength, and the neural network has one hidden layer and six nodes. There are tangent sigmoid transfer function and linear functions in the input and output layers, respectively. The convergence curve of the trained network is shown in Fig. 9.

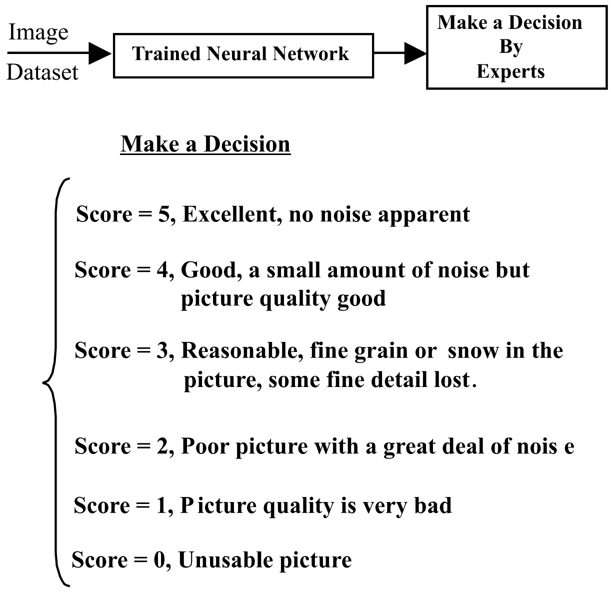

Fig. 7 *The operation of making a decision at the quality measurement system.*

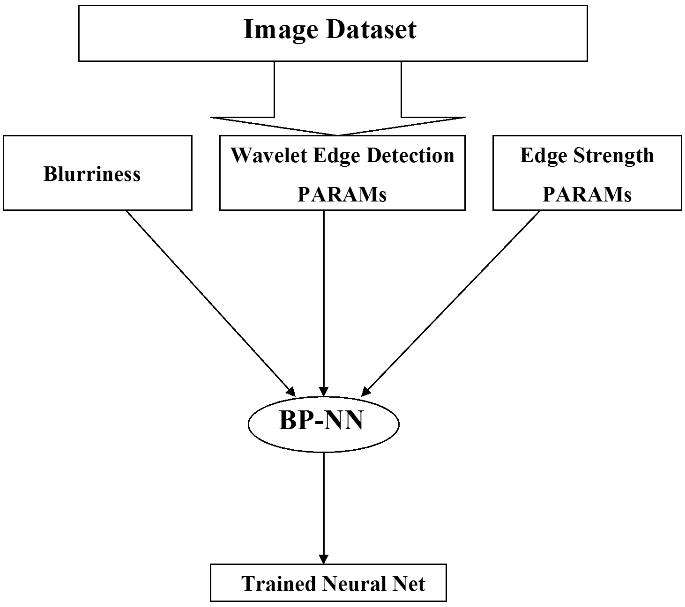

Fig. 8 *The training phase of the image quality measurement system.*

The results approved the prominence of this method about eighteen percent increase with the help of the BP-NN and six gradient based NR-metrics.

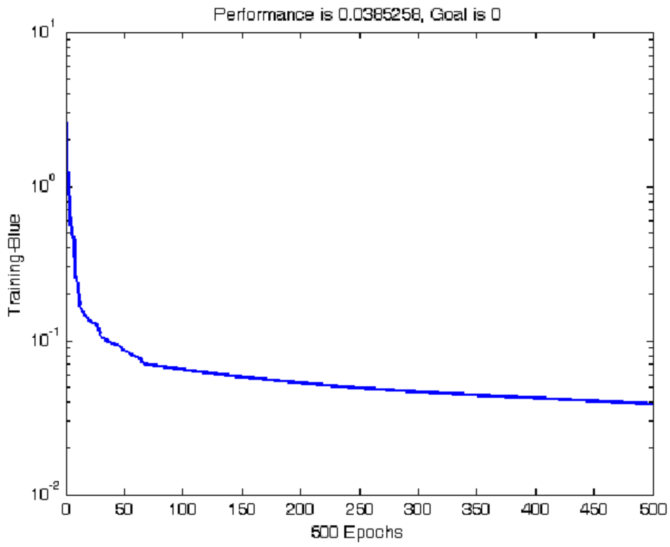

Fig. 9 *Training process of the proposed neural network.*

5. Conclusion

Since there is degradation such as attenuation, distortion and vibration in images which are transferred through the optical fiber, we proposed an image objective quality measurement metric with the help of a neural network. Because user-end application requires an estimation without having access to the original, six NR quality metrics were used. All of them were implemented, tested, and evaluated. The experimental results showed that this method was highly correlated with the experimental data collected through the subjective experiments. Simulation results approved the reliability of more than 81% for this method.

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