Neuro-Fuzzy approach to video transmission over ZigBee
H.B. Kazemian*, K. Ouazzane

Abstract
This research paper presents Neuro-Fuzzy applications to Moving Picture Expert Group (MPEG-4) video transmission in IEEE 802.15.4 ZigBee wireless. ZigBee can operate within 2.4 GHz frequency with a data rate of 250 kb/s, which may interfere with other wireless devices functioning within the same frequency band such as WiFi and Bluetooth. MPEG-4 Variable Bit Rate (VBR) video demands large bandwidth, and may cause data loss and time delay in the data rate limited ZigBee channel as a result of high variation in bit rate. Consequently, it is almost impracticable for MPEG-4 VBR video to be transmitted in the ZigBee channel. This paper introduces two new Neuro-Fuzzy schemes to monitor the input and the output of a data storage entitled traffic-regulating buffer. The input of the buffer is controlled by a Neuro-Fuzzy scheme to ensure that the traffic-regulating buffer neither flooded nor starved with video data. The output of the traffic-regulating buffer is observed by a second Neuro-Fuzzy scheme to make sure the departure-rate conforms to the traffic condition of ZigBee. The simulation results demonstrate that the proposed two Neuro-Fuzzy schemes reduce the excessive data loss and improve the picture quality, as compared with the conventional MPEG-4 VBR video over ZigBee.

1. Introduction

MPEG-4 VBR demands a significant data and a large bandwidth for a good quality video transmission. VBR offers variations in bit rate, which allows the video that requires still frames to use little data, and the video that needs many frames to use large data, in order to be able to provide a constant picture quality [1]. MPEG-4 VBR therefore presents uncertainty, excessive delay and data loss as a result of continuous variations in bit rate. IEEE 802.15.4 ZigBee is the only radio frequency standard developed to address the unique needs of low cost and low power wireless mesh networks for remote monitoring, personal and home control, smart energy, hospital care, toys, telecommunication and building automation network applications in industrial and consumer markets. But, the bandwidth in ZigBee is very limited, variable and unpredictable, due to interferences in radio-frequency environment, channel noises and portability of ZigBee devices. This research uses ZigBee 2.4 GHz frequency band, which has the highest bandwidth of 250 kb/s. However, ZigBee 2.4 GHz frequency might interfere with other neighboring wireless technologies operating within the same frequency range, such as Bluetooth and WiFi. It is therefore nearly impossible to transmit MPEG-4 VBR video over the ZigBee channel. This research consequently utilizes soft computing techniques to transmit MPEG-4 video in IEEE 802.15.4 ZigBee. Fuzzy Logic [2], Neural Networks [3] and Neuro-Fuzzy [4] techniques are able to deal with uncertainty, unpredictability and ill-defined systems, and have been applied to many wireless communication schemes, some of which are briefly outlined below.

Mar and Kao proposed an intelligent medium access control protocol based on fuzzy logic and compared it with a general packet radio system in Universal Mobile Telecommunications Systems (UMTS) priority scheme and the movable boundary wireless integrated multiple access in UMTS protocols. The resources of the wireless communication can be intelligently assigned for different types of mediums, using fuzzy logic control. The voice-video dropping probability and data packet delay were inserted into the fuzzy logic controller to optimally select the maximum number of voice/video slots [5]. Gomathy and Shanmugavel designed a fuzzy logic based priority scheduler to determine the priority of the packets in Mobile Ad hoc NETworks. The performance of the scheduler with the multicast routing protocols was evaluated in terms of the quantitative metrics such as packet delivery ratio and average end-to-end delay. The results were found to be encouraging and fuzzy logic improved the performance [6]. A fuzzy video variable bit rate control algorithm (RCA) with delay and quality constraints was proposed by Rezaei et al. for video streaming over Digital Video Broadcasting for Handheld terminals application. Computer simulation results on H.264/Advanced Video Coding (AVC) video coding standard showed that encoded bit streams by the proposed fuzzy video RCA improved the delay and quality constraints [7]. Gomes et al.
developed a quality of experience fuzzy routing protocol to determine the best routes for video streaming and multimedia, proposing a new variation of Optimized Link State Routing (OLSR) over Wireless Mesh Networks. Simulation results demonstrated the benefits of the proposed fuzzy logic routing, which determined the best routes for multimedia packets taking into account the user experience as compared with the existing versions of the OLSR [8].

Mohamed Rubino proposed random neural networks to automatically quantify the quality of video and audio flows at the receiving end to offer better performance. The real-time applications of random neural networks to H263 video transmission over IP networks produced significantly better performance than the standard transmission [9]. Yip used an artificial neural network to rectify face and eye gaze in video conferencing using one camera. The experimental results demonstrated that neural network provided significant improvement in the face and eye. In another work an adaptive error control mechanism for wireless video service was proposed by Wen et al. to globally optimize throughput with equal error protection. A recurrent neural network was introduced to decide the state transfer as a mechanism. The computer simulation results using the error resilient scheme demonstrated a major improvement in image quality and transmission efficiency for video over drastic time-varying wireless channel conditions [11]. Chen et al. introduced an image restoration method based on Hopfield neural network to repair video degradation during the image formation and transmission process over general packet radio service wireless communication system. The simulation results showed that this method can restore vague video images effectively [12].

Abdennour presented a Neuro-Fuzzy short-term predictor for MPEG-4 video. The system was based on Adaptive Network Fuzzy Inference System (ANFIS) and performed single-step predictions for the I, P and B frames to smooth signals of the video sequences. It was concluded that Neuro-Fuzzy was capable of providing accurate prediction using long entertainment and broadcast video sequences as compared with those obtained using linear predictors [13]. Shahriari et al. proposed an adaptive error concealment method based on radial Neuro-Fuzzy scheme to H264/AVC video transmission over a wireless lossy channel. The simulation results showed that the proposed algorithm can produce better performances in quality and precision of error resilience over the traditional standard method introduced in the H.264/AVC video CODECS [14]. Khan et al. proposed an application of ANFIS to prediction of video quality over Wireless Local Area Networks (WLANs) and Universal Mobile Telecommunication Systems (UMTS). The research contributed in the development of a reference-free video prediction model and QoS control methods for video over UMTS/WLANs. The proposed models were validated using unseen video data set. The preliminary results demonstrated a good prediction accuracy using the models [15]. Zainaldin et al. presented a low bit-rate adaptive rate control video transmission over IEEE 802.15.4 ZigBee Networks. Transform-expand-sample methodology was utilized to model the rate MPEG-4 video. The ns-2 simulator was used to test and validate the MPEG-4 video over ad hoc ZigBee Networks. Zainaldin et al. state that transform-expand-sample methodology will enable a large number of applications for network surveillance purposes [16]. This paper takes the research further by applying two Neuro-Fuzzy schemes to video transmission over ZigBee and further introducing various noise levels to the wireless channel and its surrounding environment. ZigBee wireless standard currently does not support video data sources. The two new Neuro-Fuzzy schemes do facilitate the video transmission over ZigBee and this is where the novelty of this research lies.

The rest of the paper is organized as follows. Section 2 describes MPEG-4 video and ZigBee wireless technology, which are used in the paper. Section 3 outlines the two Neuro-Fuzzy schemes utilized in this research. Section 4 presents the computer simulation results and Section 5 provides the overall conclusion.

2. MPEG-4 video in ZigBee

2.1. MPEG-4 video

Video compression allows using, transmitting, or manipulating video data easier and faster. The main goal in video compression is to minimize the size of the files and maximize the quality of the reconstruction at the receiving end. An obvious way to reduce the amount of data is to avoid redundant data. In order to avoid superfluous data, the MPEG encoder introduces three main components, temporal model, spatial model and entropy encoder [17].

The principal of the temporal model is to fully encode the first frame as a reference and then encode the difference between the subsequent frames and the reference frame. If the difference value is 0, the process will understand that this frame is the same as the reference frame and subsequently it will not be encoded. If the difference value is not 0, the decoder already has the reference frame and it will add the difference to generate the current picture [18].

The video quality is affected by spatial compression model. Therefore, an appropriate balance needs to be struck between the video quality and the compression degree. Video transmission speed is also a critical factor in choosing a suitable configuration for the spatial compression, the video quality and the compression degree. Discrete Cosine Transform (DCT) is widely used as the first stage of spatial compression of digital video signal. A video signal is composed of many component cosine waveform frequencies. By removing some of the higher frequency components one can send less information at the expense of some deterioration in image quality. In essence, the DCT provides a frequency domain representation of the image. This process maps each 8 x 8 block of points (pixels) into frequencies, amplitudes and colors. Two-dimensional DCT is used in this research and the following equation represents

\[ l_j = \sum_{n=0}^{N-1} f_{n0} \cos \left( \frac{\pi}{N} n \right) \cos \left( \frac{\pi}{N} l \right) \]

where \( l \) and \( q \) are the horizontal and the vertical frequency indices that are 0, 1, 2, ..., \( N - 1 \) and 0, 1, 2, ..., \( N - 1 \) respectively.\( f_{n0} \) is the n1n2 element of the image, represented by the matrix.\( \gamma_j \) and \( \lambda_j \) are calculated using:

\[ \gamma_j = \left\{ \begin{array}{ll} \sqrt{\frac{1}{N}} & \text{for } \gamma = 0 \\ \sqrt{\frac{1}{N}} & \text{for } \gamma \neq 0 \end{array} \right. \]

\[ \lambda_j = \left\{ \begin{array}{ll} \sqrt{\frac{1}{N}} & \text{for } \lambda = 0 \\ \sqrt{\frac{1}{N}} & \text{for } \lambda \neq 0 \end{array} \right. \]

Compression schemes are designed to eliminate as much redundancy as it is possible. One way to achieve this is to use statistical predictability in signals. The information content or entropy of a sample is a function of how different the signal is from the predicted value. It is important to mention that most signals have some degree of predictability, such as sine wave. For entropy, ‘Huffman Coding’ algorithm is used, implementing the same principle discussed in Abid and Qaisar [19].

2.2. ZigBee wireless protocol layers

ZigBee is a low-cost low-power technology, predominately used for wireless mesh networks and provides a highly reliable communication.
ZigBee operates in 868 MHz, 915 MHz and 2.4 GHz frequency bands. The 2.4 GHz frequency band is part of Industrial, Scientific and Medical (ISM) band—a band that has been globally dedicated to these purposes. This means, 2.4 GHz ISM band could be used for wireless network devices without the need to obtain a license. In this paper, ZigBee 2.4 GHz ISM frequency with the data rate of 250 kb/s is used supporting a distance of up to 30 m. There are some other Personal Area Networks (PANs) and Local Area Networks (LANs) technologies operating within 2.4 GHz ISM band, such as Bluetooth, WiFi (IEEE 802.11b,g,e), Cordless Phones and Microwave Ovens. ZigBee devices consume less power and they are cheaper than other 2.4 GHz frequency band technologies such as Bluetooth, WiFi, Cordless Phones and Microwave Ovens. The power consumption of ZigBee is around 10 mW. ZigBee can be activated that is triggered from sleep to active mode in 15 ms or even less. Because ZigBee can sleep most of the time, the average power consumption can be very low, resulting in long battery life and very low complexity. The basic channel access mode is ‘carrier sense multiple access with collision detection/avoidance’ (CSMA/CD). The CSMA/CD algorithm is very simple and the ZigBee software is designed to be easily developed on small and inexpensive microprocessors. Low power consumption, low cost, 2.4 GHz ISM frequency band and low complexity make ZigBee an ideal wireless technology for video transmission in PAN.

Fig. 1 outlines the IEEE 802.15.4 ZigBee wireless protocol layers, which has been utilized in this paper. The Medium Access Control (MAC) layer and the Physical (PHY) layer are defined by IEEE 802.15.4 standard [20]. IEEE 802.15.4 only defines the specifications for MAC and PHY layers, but it does not provide specifications for higher layers. The ZigBee standard defines the Application Layer and the Network Layer. The ZigBee Application Layer consists of the application support sub-layer (APS), the ZigBee Device Objects (ZDO) and the manufacturer-defined Application Objects (AOs). The APS sub-layer connects two devices together based on their services and requirements. The ZDO is responsible for describing the role of the device in the network. The ZDO starts connections, responds to binding requests, provides a secure communication between devices, discovers devices on the network, and determines which application services they provide. The APS provides an interface between the Network Layer and the Application Layer through a general set of services that are utilized by both the ZDO and the manufacturer-defined AOs [21–22]. There are three roles that any ZigBee device can perform, ZigBee coordinator, ZigBee router and ZigBee end device. ZigBee coordinator starts the root of the network tree and connects to other networks and there is one ZigBee coordinator in each network. ZigBee router can run an application function and the router can act as an intermediate router, passing on data to other devices. ZigBee end device contains just enough functionality to talk to the parent node, either the coordinator or a router. ZigBee end device cannot relay data from other devices. This relationship allows the node to be asleep a significant amount of the time thereby saving energy consumption.

3. Two Neuro-Fuzzy schemes

Fig. 2 presents the overall structure of two Neuro-Fuzzy control schemes for a traffic-regulating buffer in 2.4 GHz ZigBee wireless. The diagram comprises of Neuro-Fuzzy 1, Neuro-Fuzzy 2, MPEG-4 encoder, token bucket and traffic-regulating buffer. The arrival-rate Neuro-Fuzzy scheme 1 and the departure-rate Neuro-Fuzzy 2 scheme control the input and the output of the traffic-regulating buffer. MPEG-4 encoder coverters the Audio Video Interleave (AVI) video to MPEG-4. Generic cell rate algorithm or token-bucket is part of ZigBee and is a rule by which video data streams are assessed for compliance with the terms of the traffic contract [23–25]. The token bucket is predominately used to prevent the overflow of data into the network. If video data floods the network, the electronic tokens will be taken and the surplus of video data will be kept in the bucket and flushed after some period of time. Because of its ability to flush excessive data, the token bucket is utilized for real time video transmission, which requires video data to be transmitted in sequence. However, token bucket does not accommodate for data loss and video quality. The token-bucket date rate policing therefore is typically inadequate to control the transmission of MPEG-4 video over 2.4 GHz ZigBee wireless. This research incorporates a traffic-regulator, and the input and the output of the buffer is controlled by two Neuro-Fuzzy schemes where the incoming signal is smoothed and manipulated to reduce excessive data loss and improve video quality. To be able to describe the two Neuro-Fuzzy schemes in Fig. 2, the rule-based fuzzy logic controllers in Neuro-Fuzzy schemes are first discussed.

3.1. Design of Neuro-Fuzzy 1

Fig. 2 outlines the overall architecture of the proposed two Neuro-Fuzzy schemes. In this section the design of Neuro-Fuzzy scheme 1 of Fig. 2 is described in detail. Fig. 3 is the Rule-Based Fuzzy (RBF1) controller for the input or arrival-rate Neuro-Fuzzy scheme 1 to the traffic-regulating buffer. The initial fuzzy inputs are the fuzzified mean value of video data $\bar{\tau}(t)$ and the fuzzified standard deviation $\sigma(t)$ of data to RBF1. The initial fuzzy output from RBF1 is $R(t)$. The inputs in Fig. 3 have four linguistic codes for mean value $\bar{\tau}(t)$, Small, Intermediate, Large and Very Large, and three linguistic codes for standard deviation $\sigma(t)$, Small, Intermediate and Large. The output video arrival-rate $R(t)$ has seven linguistic codes, Very Small, Intermediate Small, Small, Intermediate, Large, Intermediate Large and Very Large. In order to reduce time delay for time sensitive video steam, the system is designed to have a minimum number of rules for a faster execution. There are twelve rules in the RBF1 altogether as a result of four mean values $\bar{\tau}(t)$ and three standard deviations $\sigma(t)$, which produce an optimum output.

Fig. 4 shows the structure of the proposed arrival-rate Neuro-Fuzzy scheme 1. The initial setting of this Neuro-Fuzzy controller is the same as the RBF1 controller. The fuzzified mean value $\bar{\tau}(t)$ has a generalized bell activation function [26]. The output from Neuro-Fuzzy scheme 1 is the required or desire arrival-rate $R_{d}(t+2)$ generated by the Neuro-Fuzzy, refer to Fig. 2. The bell activation function is also used for the departure-rate of the
Neuro-Fuzzy scheme 2. The activation function of a neuron is set to the membership function that specifies the neuron’s fuzzy set. The values of these activation functions and the exact shape of the bell are decided through the training of ANFIS. A rule neuron receives inputs from the respective fuzzification neurons and calculates the firing strength or the truth-value of the rule it represents. The generalized bell function depends on three parameters φ, ψ, and η given by:

$$f(x) = \frac{1}{1 + \left|\frac{x - \eta}{\psi}\right|^p}$$  \hspace{1cm} (3)

where the parameters φ and ψ both determine the shape of the membership function, and the parameter η locates the center of the curve. The parameter ψ is usually positive. The Neuro-Fuzzy schemes for the arrival-rate and the departure-rate are both developed on the Takagi–Sugeno–Kang method of fuzzy inference. Takagi–Sugeno–Kang method works well with optimization and adaptive techniques [27–28]. The output membership functions of the Sugeno method is a first-order and the general first-order Sugeno fuzzy model has rules of the form

$$\text{if } p \text{ is } A \text{ and } q \text{ is } B \text{ then } r = e^p + v^q + \kappa$$  \hspace{1cm} (4)

where A and B are the antecedents, while e, v, and κ are all constants. From Eqs. (3) and (4), the number of available parameters for training in the Neuro-Fuzzy scheme 1 is

$$4 \text{ MFs} \overline{\eta}(t) \times 3 \text{ params}/MF + 12 \text{ MFs} \overline{R}(t) \times 3 \text{ params}/MF = 12 \text{ params} + 36 \text{ params} = 48 \text{ params}$$  \hspace{1cm} (5)

where the input is \(\overline{\eta}(t)\) with 4 membership functions (MFs) and the output is \(\overline{R}(t)\) with 12 membership functions (MFs). There are three parameters (params) in Eqs. (3) and (4). In order to provide enough information for training these parameters, the number of input-output training pairs must be larger than the number of available parameters. The video data is based on Phase Alternate Line (PAL) and there are 25 frames per second in PAL. It is assumed that there are 24 frames in 1 s in this research and a Group Of Picture (GOP) contains 12 frames, therefore two GOPs per second. Therefore, each training loop must at least involve 48/12 = 4 GOPs. In the computer simulations, the parameters of membership functions of Neuro-Fuzzy 1 are changed once every 10 GOPs. Therefore, the training set for each training procedure contains 120 input–output pairs.

In this section the simulation have been done for the supervised Neuro-Fuzzy scheme 1 for the desired arrival-rate \(\overline{R}_{a}(t+2)\) generation. The desired arrival-rate \(\overline{R}_{a}(t+2)\) is calculated using

![Diagram 2: Two Neuro-Fuzzy schemes monitoring video from I/O of a traffic-regulating buffer for transmission over ZigBee.](image)
the following equation:

\[ R_d(t+2) = r_d(t+2) \times (R_{d,\text{max}} - R_{d,\text{min}}) + R_{d,\text{min}} \]  

(6)

where \((t+2)\) is the GOP encoded by the MPEG encoder, \(r_d(t+2)\) is the fuzzified \(R_d(t+2)\), min departure-rate is \(R_{d,\text{min}} = \min_{\text{estimated}} (t+1), R_d(f_{last})\), and max departure-rate is \(R_{d,\text{max}} = \max_{\text{estimated}} (t+1), R_d(f_{last})\). In Fig. 2—the Neuro-Fuzzy 1, \(R_{d,\text{estimated}}\) is an estimated data rate for an open loop algorithm, \((t+1)\) is the GOP in the process of going through the system to reach token-bucket and enter the ZigBee channel. \(R_d(f_{last})\) is the departure-rate of the last frame. The last frame departure-rate \(R_d(f_{last})\) values are fed back to the Neuro-Fuzzy scheme 1 to adjust the membership functions of the rules and to rectify the subsequent transmission in order to improve the picture quality. The fuzzy output of MPEG-4 video is arrival-rate \(R_a(t+1)\). The arrival-rate \(R_a(t+1)\) of the traffic-regulator is controlled on a GOP by GOP basis using the Neuro-Fuzzy scheme 1. \(R_a(t+1)\) is the GOP in the process of going through the system to approach token-bucket and enter the ZigBee network. Table 1 summarizes the Neuro-Fuzzy scheme 1 notations used in Fig. 2.

3.2. Design of Neuro-Fuzzy 2

As stated, the departure-rate Neuro-Fuzzy scheme 2 is also shown in Fig. 2 diagram. In this section the design of Neuro-Fuzzy scheme 2 of Fig. 2 is explained in detail. The initial condition of the RBF2 controller is shown in Fig. 5. The fuzzy inputs are the fuzzified capacity of the traffic-regulator or queue length \(X(f)\) and the fuzzified available tokens from the token-bucket \(Y(f)\), and the fuzzy output is \(R_d(f)\) the normalized video departure-rate from the traffic-regulator, where \(f\) is a frame. The departure-rate \(R_d(f)\) is controlled frame by frame using the Neuro-Fuzzy scheme 2. The inputs in Fig. 5 have three linguistic codes for \(Y(f)\), Empty, Average and Full, and four linguistic codes for \(X(f)\), Empty, Average, Full and Saturated. \(R_d(f)\) has five linguistic codes, Very Small, Small, Medium, Big, Very Big. RBF2 has twelve rules overall.

Fig. 6 represents the structure of the departure-rate for the Neuro-Fuzzy scheme 2. The queue length \(X(f)\) and the token-bucket \(Y(f)\) have both generalized bell activation functions. Therefore from Eq. (3) and (4), the number of available parameters for training in the Neuro-Fuzzy scheme 2 is

\[
3 \text{ MFs } Y(f) \times 3 \text{ params/MF} + 4 \text{ MFs } X(f) \times 3 \text{ params/MF} = 9 \text{ params} + 12 \text{ params} + 36 \text{ params} = 57 \text{ params}
\]

(7)

where the inputs are \(Y(f)\) and \(X(f)\) with 3 and 4 membership functions (MFs) respectively. The output is \(R_d(f)\) with 12 membership functions (MFs). Using the same analysis as Neuro-Fuzzy 1, each training loop must at least involve 57/12 ≈ 5 GOPs. The departure-rate \(R_d(f)\) is calculated using the following equation:

\[ R_d(f) = r_d(f) \times (R_{d,\text{max}} - R_{d,\text{min}}) + R_{d,\text{min}} \]  

(8)

where \(r_d(f)\) is the fuzzified departure-rate \(R_d(f)\), and the min departure-rate is \(R_{d,\text{min}} = \min_{\text{estimated}} R_d(t+1), r_{\text{bandwidth}}\) and the max departure-rate is \(R_{d,\text{max}} = \max_{\text{estimated}} R_d(t+1), r_{\text{bandwidth}}\). \(r_{\text{bandwidth}}\) is the actual data-rate. \(r_{\text{bandwidth}}\) is the speed in which MPEG-4 video is transmitted. Table 1 further summarizes the Neuro-Fuzzy scheme 2 notations utilized in Fig. 2.

### Table 1

<table>
<thead>
<tr>
<th>Notations</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(m(t))</td>
<td>Normalized mean queue length in the traffic-regulating buffer</td>
</tr>
<tr>
<td>(\sigma(t))</td>
<td>Normalized standard deviation of queue length in the traffic-regulating buffer</td>
</tr>
<tr>
<td>(\hat{R}_a(t+2))</td>
<td>Desired arrival-rate</td>
</tr>
<tr>
<td>(R_a(t+1))</td>
<td>Arrival-rate at the traffic-regulating buffer</td>
</tr>
<tr>
<td>(Y(f))</td>
<td>Normalized available memory space in the token-bucket</td>
</tr>
<tr>
<td>(R_{d,\text{estimated}}(t+1))</td>
<td>Estimated data rate for an open loop algorithm</td>
</tr>
<tr>
<td>(R_d(f))</td>
<td>Departure-rate</td>
</tr>
</tbody>
</table>

1st Neuro-Fuzzy scheme – GOP rate=2 GOPs per second

Frame \(f\) of GOP \(t+2\) starts at MPEG-4 encoder

During transmitting of GOP \(t\) to ZigBee

Frame \(f\) of GOP \(t+1\) leaving MPEG-4 encoder for the traffic-regulating buffer

For GOP \(t+2\)

Frame \(f\) of GOP \(t\) has entered the ZigBee channel

For GOP \(t+1\)

At the beginning of frame \(f\)

Frame \(f\) of GOP \(t+1\)

Frame \(f\) of GOP \(t\)

Frame \(f\)
4. Results

The two novel Neuro-Fuzzy schemes were applied to two video clips entitled, 'Chicago' and '007 Die Another Day' [29] using computer simulation with presence of noise. The initial frame sizes for 'Chicago' had been 480 × 240 pixels and for '007 Die Another Day' had been 480 × 352 pixels. However, in real time transmissions smaller frame sizes are used for the low bandwidth ZigBee wireless. For computer simulations, these two video clips were resized by deleting all the pixels on the even rows and the even columns. The actual video clips sizes are outlined in Table 2.

In this paper the maximum allowable data-rate or contracted data-rate used for video transmission is 210 kb/s. Having two buffers to monitor the video data may cause delay which is not acceptable for time sensitive MPEG-4 streaming. A token-bucket with large buffer storage will lead to a potential delay. Therefore, a token-bucket size of 24 bits is used in this paper. When the contracted data-rate at the token-bucket is 210 kb/s, the token-bucket produces a maximum acceptable delay of 24/210 = 0.11429 ms, which amounts to 2.8 video frames approximately.

In the simulation an absolute value is introduced to guarantee the actual data-rate \( r_{\text{bandwidth}} \) is always below the contracted data-rate, refer to Figs. 7 and 9. Furthermore in Figs. 7 and 9, by keeping the values of the traffic-regulator departure-rate \( R_{\text{t}}(f) \) between the arrival-rate \( R_{\text{a}}(t+1) \) and the actual data-rate \( r_{\text{bandwidth}} \) there will always be video data in the system so long as \( R_{\text{a}}(t+1) \neq 0 \). The actual data-rate \( r_{\text{bandwidth}} \) at which ZigBee transmits data varies according to interferences encountered by the ZigBee channel and the neighboring 2.4 GHz ISM frequency bands. To reflect this in the computer simulation, the collective interferences in the ZigBee wireless is presented by the Gaussian distributed noise. In the computer simulation, \( g(M, S^2) \) kb/s is used as a Gaussian distribution, where, \( M \) is the mean value, and \( S \) is the standard deviation [30]. The mean value of the Gaussian noise is zero [31]. In this paper low-level noise is used to represent local interferences in the ZigBee channel. The low-level noise has a standard deviation of 10/3 = \( \sqrt{11.11} \), such that 99.7% of the actual data-rates \( r_{\text{bandwidth}} \) are within the range of [200–210] kb/s. 10 is the difference between 200 and 210, and 3 is the maximum allowable frame delay in the token-bucket. The medium-level slow-changing noise is introduced to simulate a scenario where a WiFi or Bluetooth is operating in the neighboring area. The medium-level noise has a standard deviation of 20/3 = \( 
\sqrt{44.44} \) where 99.7% of the actual data-rates \( r_{\text{bandwidth}} \) are within the [190–210] kb/s range. The high-level rapid-changing noise represents the situation where an interfering device like microwave switches on and off from time to time as well as general low-level noise. The high-level rapid-changing noise has a standard deviation of 50/3 = \( \sqrt{277.77} \) where 99.7% of the actual data-rates are within the [160–210] kb/s range.

The 'Chicago' and '007 Die Another Day' video clips are used to present two different scenarios. The two Neuro-Fuzzy schemes can either reduce the data loss significantly or modestly, depending on the real-time applications and the requirements at the receiving end of the devices. The simulation results are presented in sections 4.1. 'Chicago' and 4.2. '007 Die Another Day', which demonstrate the two different scenarios.

### Table 2

<table>
<thead>
<tr>
<th>Video clips sizes used in computer simulations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Width (pixel)</td>
</tr>
<tr>
<td>Resized Chicago</td>
</tr>
<tr>
<td>Resized 007 Die Another Day</td>
</tr>
</tbody>
</table>

### Table 3

<table>
<thead>
<tr>
<th>Simulation results</th>
<th>Two Neuro-Fuzzy schemes – three different noise levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low-level noise ( g(0, 11.11) )</td>
</tr>
<tr>
<td>Mean value of actual data-rate ( r_{\text{bandwidth}} ) (kb/s)</td>
<td>205.42</td>
</tr>
<tr>
<td>Standard deviation of output rate from MPEG-4 encoder (kb/s)</td>
<td>14.87</td>
</tr>
<tr>
<td>Standard deviation of output rate from traffic-regulating buffer (kb/s)</td>
<td>8.47</td>
</tr>
<tr>
<td>Percentage of data loss at token-bucket</td>
<td>0.19</td>
</tr>
<tr>
<td>Percentage of data loss at traffic-regulating buffer</td>
<td>0.76</td>
</tr>
<tr>
<td>Total percentage of data loss</td>
<td>0.95</td>
</tr>
</tbody>
</table>

### Table 4

<table>
<thead>
<tr>
<th>Simulation results</th>
<th>Two Neuro-Fuzzy schemes – three different noise levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low-level noise ( g(0, 11.11) )</td>
</tr>
<tr>
<td>Standard deviation of output rate from MPEG-4 encoder using open loop VBR system (kb/s)</td>
<td>64.79</td>
</tr>
<tr>
<td>Percentage of decrease in standard deviation of video output rate using Neuro-Fuzzy schemes</td>
<td>86.93</td>
</tr>
<tr>
<td>Percentage of data loss using open loop VBR system</td>
<td>8.63</td>
</tr>
<tr>
<td>Percentage of decrease in data loss using Neuro-Fuzzy schemes</td>
<td>88.99</td>
</tr>
</tbody>
</table>
of 205.42 kb/s, 201.21 kb/s and 189.98 kb/s respectively. The different noise levels are here to represent that the actual data rate $r_{\text{bandwidth}}$ changes according to the level of interferences in the ZigBee channel and the neighboring devices. The higher is the noise the lesser bandwidth will be available for data transmission.

Table 3 also outlines the standard deviations for the video output rate from the MPEG encoder and the traffic-regulating buffer. For the 'Chicago' video clip, the standard deviations of the output rate from the MPEG-4 encoder gradually increases as noise level increases. This demonstrates that noise level directly contributes

![Figure 7](image.png)

**Fig. 7.** Chicago—output bit-rate using two Neuro-Fuzzy schemes with three different ZigBee noise levels. (i) Two Neuro-Fuzzy schemes with low-level noise within range of 200–210 kb/s. (ii) Two Neuro-Fuzzy schemes with medium-level noise within range of 190–210 kb/s. (iii) Two Neuro-Fuzzy schemes with high-level noise within range of 160–210 kb/s.
to the higher standard deviation which results in more burstiness in the video throughput and hence more data loss. The two Neuro-Fuzzy schemes decrease the standard deviation of output rate from the traffic-regulating buffer considerably, resulting in less burstiness and a significant reduction in data loss and time delay. Comparing the standard deviation of output rate from the MPEG encoder with the standard deviation of output rate from the traffic-regulating buffer, the standard deviation from the traffic-regulating buffer is much lower at low-level noise, medium-level noise and high-level noise. Table 3 further shows the percentage of data loss at the token-bucket, the traffic-regulating buffer and the total data loss using the two Neuro-Fuzzy schemes. The data loss increases as the noise level increases.

The data loss is predominately at the traffic-regulating buffer with a little loss at the token-bucket. However, the total percentage of the data loss in the proposed system for 'Chicago' video clip is lower than '007 Die Another Day' video clip [30].

In this research traffic regulator is used to make sure that video data is predominately lost at this buffer where the two Neuro-Fuzzy schemes can control and reduce the loss. The idea is that the overall video data loss between the traffic-regulating buffer and the token-bucket in the proposed system should be smaller than when the conventional native token-bucket is operating on its own. In Table 4, the standard deviations and the MPEG-4 video data loss are compared with the conventional open loop VBR system that is a ZigBee transmitter which only has a token-bucket. Table 4 shows that the standard deviations using the conventional open loop VBR system are much higher than the two Neuro-Fuzzy schemes for low-level noise, medium-level noise and high-level noise, by 86.93%, 85.40% and 81.89% respectively. These figures are based on the standard deviation of output rate from the MPEG-4 encoder using the open loop VBR system 64.79 kb/s and comparing them with the standard deviations of output rate from the traffic-regulating buffer using the two Neuro-Fuzzy schemes. These figures further demonstrate that the two Neuro-Fuzzy schemes are capable of dealing with interferences, such as low-level noise at the ZigBee device, various other 2.4 GHz ISM wireless devices operating in the neighboring area and the microwave rapid-changing noise, which further shows the suitability of the proposed design for real-time applications. Table 4 also shows the percentage of data loss using the conventional open loop VBR system for the three noise levels and comparing the results with the total percentage of data loss from Table 3. The percentage of decrease in data loss using the two Neuro-Fuzzy schemes for low-noise, medium-noise and high-noise are 88.99%, 78.40% and 66.94% respectively, demonstrating an improvement in the picture quality at the receiving end. The percentage of decrease in data loss using the two Neuro-Fuzzy schemes are in a sliding scale, which illustrates as the noise level increases the proposed system will be less capable of reducing the data loss. Furthermore, the data loss is directly proportional to the

![Fig. 8. Chicago—probability density comparison of GOP size for VBR system and two Neuro-Fuzzy schemes.](image)

<table>
<thead>
<tr>
<th>Simulation results</th>
<th>Two Neuro-Fuzzy schemes – three different noise levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low-level noise (G(0, 11.11))</td>
</tr>
<tr>
<td>Mean value of actual data-rate from MPEG-4 encoder (kb/s)</td>
<td>205.42</td>
</tr>
<tr>
<td>Standard deviation of output rate from MPEG-4 encoder (kb/s)</td>
<td>18.79</td>
</tr>
<tr>
<td>Standard deviation of output rate from traffic-regulating buffer (kb/s)</td>
<td>12.15</td>
</tr>
<tr>
<td>Percentage of data loss at token-bucket</td>
<td>0.49</td>
</tr>
<tr>
<td>Percentage of data loss at traffic-regulating buffer</td>
<td>1.54</td>
</tr>
<tr>
<td>Total percentage of data loss</td>
<td>2.03</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Simulation results</th>
<th>Two Neuro-Fuzzy schemes – three different noise levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low-level noise (G(0, 11.11))</td>
</tr>
<tr>
<td>Standard deviation of output rate from MPEG-4 encoder using open loop VBR system (kb/s)</td>
<td>79.81</td>
</tr>
<tr>
<td>Percentage of decrease in standard deviation of video output rate using Neuro-Fuzzy schemes</td>
<td>84.78</td>
</tr>
<tr>
<td>Percentage of data loss using open loop VBR system</td>
<td>14.29</td>
</tr>
<tr>
<td>Percentage of decrease in data loss using Neuro-Fuzzy schemes</td>
<td>85.79</td>
</tr>
</tbody>
</table>
Fig. 9. 007 Die Another Day—output bit-rate using two Neuro-Fuzzy schemes with three different ZigBee noise levels. (i) Two Neuro-Fuzzy schemes with low-level noise within range of 200–210 kbps. (ii) Two Neuro-Fuzzy schemes with medium-level noise within range of 190–210 kbps. (iii) Two Neuro-Fuzzy schemes with high-level noise within range of 160–210 kbps.
standard deviation. Comparing Table 4 with Table 3, the standard deviations for the conventional open loop VBR system is much higher than the two Neuro-Fuzzy schemes, hence the data loss is higher. Therefore, the two Neuro-Fuzzy schemes reduce the standard deviations and the burstiness and subsequently reduce the data loss. Fig. 7 shows the arrival-rate $R_a$, the departure-rate $R_d$ and the actual data-rate $R_{bandwidth}$ for low-level noise, medium-level noise and high-level noise. As noise increases within the range of 200–210 kbps to 190–210 kbps and 160–210 kbps, there will be less bandwidth available for MPEG-4 video transmission. The proposed two Neuro-Fuzzy schemes are capable of dealing with the three noise levels by reducing the burstiness of the signal. Fig. 7 demonstrates that the burstiness of the departure-rate $R_d$ is significantly reduced as compared with the arrival-rate $R_a$ for all three noise levels using the two Neuro-Fuzzy schemes. Reduction in burstiness of VBR data decreases the data loss and the excessive time delay, which provides an image quality enhancement. The probability density and histogram graph for ‘Chicago’ video clip is plotted in Fig. 8. The graph in Fig. 8 shows that the video density is greater and there is more GOP size (bit) as compared to the conventional VBR scheme. This in effect demonstrates that there is slightly more data for transmission and consequently reducing data loss by using the proposed two Neuro-Fuzzy schemes.

4.2. ‘007 Die Another Day’

The numerical values for the applications of the two Neuro-Fuzzy schemes to a MPEG-4 video clip entitled ‘007 Die Another Day’ are outlined in Table 5. Since the noise levels are the same for both video clips ‘Chicago’ and ‘007 Die Another Day’, the mean values of actual date-rate $R_{bandwidth}$ would be the same for both clips. The standard deviations for the video output rate from the MPEG encoder and the traffic-regulating buffer are also illustrated in Table 5. The higher is the noise levels the higher would be the standard deviations, resulting in more burstiness in the video output and more data loss. Comparing Table 3 ‘Chicago’ results with Table 5 ‘007 Die Another day’, the standard deviations of the video output rate from the MPEG encoder and the traffic-regulating buffer output rate for ‘007 Die Another Day’ are much higher than ‘Chicago’, because of the scene complexities of the ‘007 Die Another Day’ video clip. This is to demonstrate that more complex scene produces more data loss and less complex scene causes less data loss, hence the quality of video output could further depend on the video clip itself. The percentage of data loss at the token-bucket, the traffic-regulating buffer and the total data loss using the proposed Neuro-Fuzzy system are also presented in Table 5. The data loss is mainly at the traffic-regulating buffer with some loss at the token-bucket. Comparing Table 3 with Table 5, the percentage of data loss at the token-bucket, the traffic-regulating buffer and the total data loss are much higher for ‘007 Die Another Day’ than ‘Chicago’ as the standard deviations and burstiness are much higher for the ‘007 Die Another Day’ clip. Furthermore, there are more pixels per frame for the resized ‘Die Another Day’ than resized ‘Chicago’, hence there are more burstiness and data loss for the ‘007 Die Another Day’ video clip. The standard deviations and the data loss from the two Neuro-Fuzzy schemes are compared with the conventional open loop VBR system in Table 6 for the ‘007 Die Another Day’ video clip. The standard deviations using the conventional open loop VBR system is much higher than under the two Neuro-Fuzzy schemes for low-level noise, medium-level noise and high-level noise by 84.78%, 83.70% and 80.34% respectively. The figures are based on the standard deviation of output rate from the MPEG-4 encoder 79.81 kbps from Table 6 and comparing them with the standard deviations of output rate from the traffic-regulating buffer of Table 5. Comparing Table 6 the standard deviation of output rate from the MPEG-4 encoder using the open loop VBR system with its counterpart in Table 4, demonstrates that the standard deviation of ‘007 Die Another day’ is higher due to the complexity of the video clip. This standard deviation has a subsequent impact in obtaining slightly lower percentage of decrease in the standard deviation of video output rate using the two Neuro-Fuzzy schemes for low-level noise, medium-level noise and high-level noise, which results in more burstiness and data loss for the ‘007 Die Another Day’ video clip. The percentage of data loss using the open loop VBR system for Table 6 ‘007 Die Another Day’ is much higher than the one for Table 4 ‘Chicago’. Moreover, for ‘007 Die Another Day’ the percentage of decrease in data loss using the two Neuro-Fuzzy schemes for low-level noise, medium-level noise and high-level noise are 85.79%, 73.22% and 46.19% respectively, which are much lower reduction than ‘Chicago’ in each case. Comparing the two video clips demonstrates that more intense motion picture scenes such as ‘007 Die Another Day’ generates higher burstiness and hence more data loss. The arrival-rate $R_a$, the departure-rate $R_d$ and the actual data-rate $R_{bandwidth}$ for all the three noise levels are plotted in Fig. 9. The graphs shows that the two Neuro-Fuzzy schemes decrease the burstiness of the departure-rate $R_d$ substantially for low-level noise, medium-level noise and high-level noise. However, the two Neuro-Fuzzy schemes are able to address various MPEG-4 video data sources and reduce the burstiness of the departure-rate $R_d$ to make sure that the data confirms to the traffic condition. The density histogram graph in Fig. 10 demonstrates that the video density of ‘007 Die Another Day’ is slightly greater and GOP size is more with a larger number of bits for the two Neuro-Fuzzy schemes than the traditional VBR system. Therefore, there is more data available for transmission using the two Neuro-Fuzzy schemes, which results in reduction in data loss and improvement in image quality. Comparing Figs. 8 and 10 shows that the overall density gain is greater for ‘Chicago’ than ‘007 Die Another Day’. Figs. 8 and 10 results are consistent with

![Fig. 10. 007 Die Another Day—probability density comparison of GOP size for VBR system and two Neuro-Fuzzy schemes.](image-url)
the overall findings of the paper, that is, the intense motion pictures such as ‘007 Die Another Day’ produces more data loss than video clip like ‘Chicago’ with relatively less motion complexity.

5. Conclusion

This paper presents two novel Neuro-Fuzzy schemes monitoring the input and the output of a traffic-regulating buffer in order to decrease the burstiness of output rate from the traffic regulator to make sure that MPEG-4 VBR video data confirms to the traffic condition before entering the ZigBee wireless. Two neural networks monitor and change the parameters of the membership functions of the two rule-based fuzzy logic controllers to readjust the video data values during the transmissions, taking into account the various noise levels experienced from both the IEEE 802.15.4 ZigBee and the surrounding area.

The proposed two Neuro-Fuzzy schemes are designed to monitor the traffic condition and reduce the standard deviation at various noise levels representing real scenario interferences, such as noise in the ZigBee channel, noise from the neighboring devices operating at 2.4 GHz ISM frequency band, and noise from a microwave device. The two Neuro-Fuzzy schemes are highly capable of reducing the burstiness and data loss of MPEG-4 VBR video for various noise levels by a considerable amount proving that the presented methodology is suitable for real-time applications as results of feedback obtained from the traffic during the transmission. The reduction in burstiness and data loss of MPEG-4 VBR video results in more data transmission and consequently a better and a stable image quality.

Acknowledgment

This work was part funded by the Emerald Grant UK. The work was carried out at London Metropolitan University, UK.

References

[20] IEEE 802.15.4, Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low Rate Wireless Personal Area Networks (WPANs), September 2009.