

## TRANSMISSION OF COMPRESSED VIDEO SIGNALS THROUGH A SPREAD SPECTRUM CHANNEL

**Awad Kh. Al-Asmari**  
Dept. of Electrical Engineering  
King Saud University,  
Riyadh, 11421  
Saudi Arabia  
E-mail: akasmari@ksu.edu.sa

**C. Kwatra**  
Dept. of Elect. Eng. and Computer Science,  
The University of Toledo,  
Toledo, Ohio,  
USA

### ABSTRACT

This research studies the feasibility of devising a compression scheme for video sequences that is robust to fading errors in a spread spectrum environment. Schemes like subband coding and pyramid coding are inherently well suited for SS-CDMA environment and thus, pyramid coding is the chosen spatial decomposition scheme. Interframe coding using the two tap short symmetric filters reduces the complexity of motion adaptation techniques used in the MPEG standards. The various temporal low bands are vector quantized using the frequency sensitive competitive learning algorithm. For the temporal high bands, a simple method of geometric vector quantization is implemented. The coded bands are tested for robustness over a multi-path-fading channel at a vehicle speed of 65 mph. The simulation of channel is done according to the specifications of North American Digital Cellular Standard IS-95. The reconstruction of the coded bands results in image frames with average PSNR of 26 dB and average bit rate of 0.25 bpp. The subjective quality of these images is found to be satisfactory.

**KEY WORDS :** Video Sequences Coding, Pyramid Coding, Cellular Image Transmission

## 1. INTRODUCTION

The last decade has been a period of immense technological advancement, particularly in the areas of wireless and video communications. As the demand for multimedia communication services increases, mobility also becomes an important challenge for transmission of audio, data as well as visual information. As far as digital voice and data are concerned, there has been considerable progress in the past to identify major issues related to wireless and cellular radio environments. For instance, second-generation digital voice and data networks are developing rapidly and some are currently operational. However, despite its wide range of applications proven by a number of coding standards, video as a viable service for wireless multimedia communication has been relatively slow.

Currently a major challenge for video transmission is how to protect this sensitive signal against hostile radio environments. This is necessary because unlike the traditional error free media for which current coding standards have been designed, wireless channels do not offer guaranteed transmission. These channels can be corrupted by burst errors caused by environmental noise and, in the case of mobile communications, by multipath fading and shadowing.

The challenge of error-free transmission is further magnified because in order to comply with the low bit rate channel requirements, it is essential that video signal is compressed at very high compression ratio. Radio spectrum is a limited resource and is already congested due to existing wireless services. Compression methods can reduce the data rate in a digital video signal to a fraction of its original value by removing redundancy. But data compression makes the transmitted bit stream more vulnerable to channel errors. In an uncompressed digital video signal, an error in one bit might change the color or brightness of a pixel but there must be quite a few errors before they become noticeable to the eye. With compressed streams, however, a single bit error can cause much more noticeable image degradation since each bit encodes much more than a single point of the image.

Thus it is apparent that powerful techniques for digital compression are required while still maintaining an acceptable visual quality of the low bit rate video signals through noisy channels.

### Proposed Research

Recent works on digital image transmission over wireless channels have investigated image transmission in the IS-54 environment and achieved compression rates varying from 0.125 bpp to 0.35 bpp with image quality varying from a very good coarser approximation to a near original quality image [1]-[2]. In the DECT environment two studies have been investigated with a transmission rate in the range of 0.69 -to- 0.4 bpp [3]-[4]. But little work has been done so far for image transmission by employing the well-known antimultipath spread spectrum technique. Since the CDMA technique is gaining popularity with the cellular industry giants such as QUALCOMM and Motorola, it presented an obvious choice for this research work. A very short summary and a primary result for the proposed algorithm can be found in [5].

The exploitation of spread spectrum scheme elegantly resolves the two basic technical challenges of terrestrial digital cellular networks: multiple user interference and multipath propagation [6]. The first issue is resolved because each user's signal appears as benign white noise to all other users, which can be eliminated by digital demodulation and error-correcting decoding processes. The fading resulting from multipath propagation is mitigated due to the frequency diversity inherent in wide-band systems. The multipath reflections are received as replicas of original signal, with different delays. The delayed signals can be separated, individually demodulated, and recombined constructively using RAKE receiver's [7], so that multipath can actually be exploited to improve performance of the CDMA system.

Another advantage of IS-95 standard resulting from the code division multiple access (CDMA) technique is the universal reuse of the entire allocated frequency band by every user of every cell. This improves efficiency as well as increases capacity per cell. Significantly, it also avoids the burdensome requirement for frequency planning, even when new cells are added in response to additional traffic needs.

The research aim in this paper is to achieve bit rates of 0.25 bpp for video transmission, to be tested in the spread-spectrum environment. It has been shown that multiresolution techniques like sub-band coding and pyramid coding are well suited for SS-CDMA [8]. The quantized pyramid levels of the decomposed image form multiple parallel data streams, each of which is multiplied by its unique spreading code. All the product signals are then transmitted at the same time in the same radio channel. Each received signal is independently recovered at the decoder by

multiplying it with its spreading code and all the recovered subbands are then reassembled into a close reproduction of the original image. Thus, the proposed algorithm in this paper uses pyramid coding for spatial decomposition. Temporal decomposition is accomplished by the use of Short Symmetric-Kernel Filters [9], which offer the advantage of computational simplicity over the more complex methods, involved in any Motion-Compensation technique. The decomposed bands are coded using vector quantization (VQ). A neural network algorithm for vector quantization has been implemented. These algorithms are much faster than the classical ones as they process data in parallel. Another vector quantization scheme used is the geometric VQ [10], which is fast, simple and has a global codebook. The coded image sequence is tested in spread spectrum environment and analyzed for results. The wireless channel to be simulated for image transmission is chosen to be the CDMA-based North American digital cellular standard IS-95A.

The paper is organized as follows. We begin with a general overview of the 3-D decomposition of the image sequence in section two. Then, we describe the vector quantization design by using the neural network and its implementation for image coding in section 3. The vector quantization design for the low frequency bands and the high frequency bands are discussed in section four. The performance of the proposed algorithm is compared with the performance of MPEG standard algorithm in section five. The CDMA wireless channel is presented in section six. This simulation is conducted on Cadence's signal processing software SPW. In section seven, the overall compression algorithm is tested on video sequences with different activates. The simulation is done at 0.25 bpp at two vehicle speeds (0 mph and 65 mph). The conclusion of this work is presented in section eight.

## 2. 3-D DECOMPOSITION OF THE IMAGE SEQUENCE

Extending spatial filtering to three dimensions can make use of the temporal redundancy existing between the subsequent frames of a video sequence. Temporal filtering is achieved by applying the two-tap Haar filter, resulting in a temporal high band which contains sparse information, consisting of most of the high frequency motion components, and a highly correlated temporal low band.

The temporal low band is further filtered by applying the spatial 24-tap FIR filter given in [11]. Since this filter allows a decimation factor of four, greater compression ratio is possible here. But due to the sparse nature of information in the temporal high

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band, this filter does not work very well with it. The 5-tap Gaussian filter is used to decompose the temporal high band. The whole decomposition process is shown in Figure 1. In this decomposition process, most of the signal energy resides in the lower spatial frequency bands, namely bands 1 and 2. Subband 4, which corresponds to the high temporal/low spatial frequencies, carries most of the motion information and acts as a motion detector. Thus, by accurate coding of low spatio-temporal bands, the spatial details of the original image are conserved, and by careful encoding of band 3, most of the motion information will be preserved.

Once the original image has been decomposed and the redundancy in the data removed, next step in the image compression problem is to code the constituent bands. Vector quantization schemes have been found to be more effective here as compared to scalar quantization according to Shannon's rate distortion theory. In the next sections we discuss the two steps required during the quantization process: design of the codebook and matching the input vectors to the best possible code vector from the codebook.

### **3. VECTOR QUANTIZATION DESIGN USING NEURAL NETWORK**

Different techniques involving vector or scalar quantization can be used to encode the decomposed pyramid levels. From Shannon's rate distortion theory, it can be shown that vector quantization can achieve better compression performance than any other conventional coding technique which is based on encoding of scalar quantities. However, practical application of VQ techniques has been limited because of the prohibitive amount of computational complexity and time involved with the classical encoding algorithms such as the Linde-Buzo-Gray (LBG) algorithm [12].

Recently a number of studies have proposed the use of artificial neural network (ANNs) as a powerful technique for implementing VQ [13]-[15]. Neural network approaches appear to be more promising for intelligent information processing as a result of their massively parallel computing structures and self-organizing learning schemes. These algorithms are much faster than the classical ones as they process data in parallel. They have been found to be less sensitive to initial conditions, have fast convergence properties, and have the ability to produce a lower mean distortion codebook. Moreover, when the ANNs are implemented in hardware, vector

quantization can be done in real time since the networks have highly parallel structure [16].

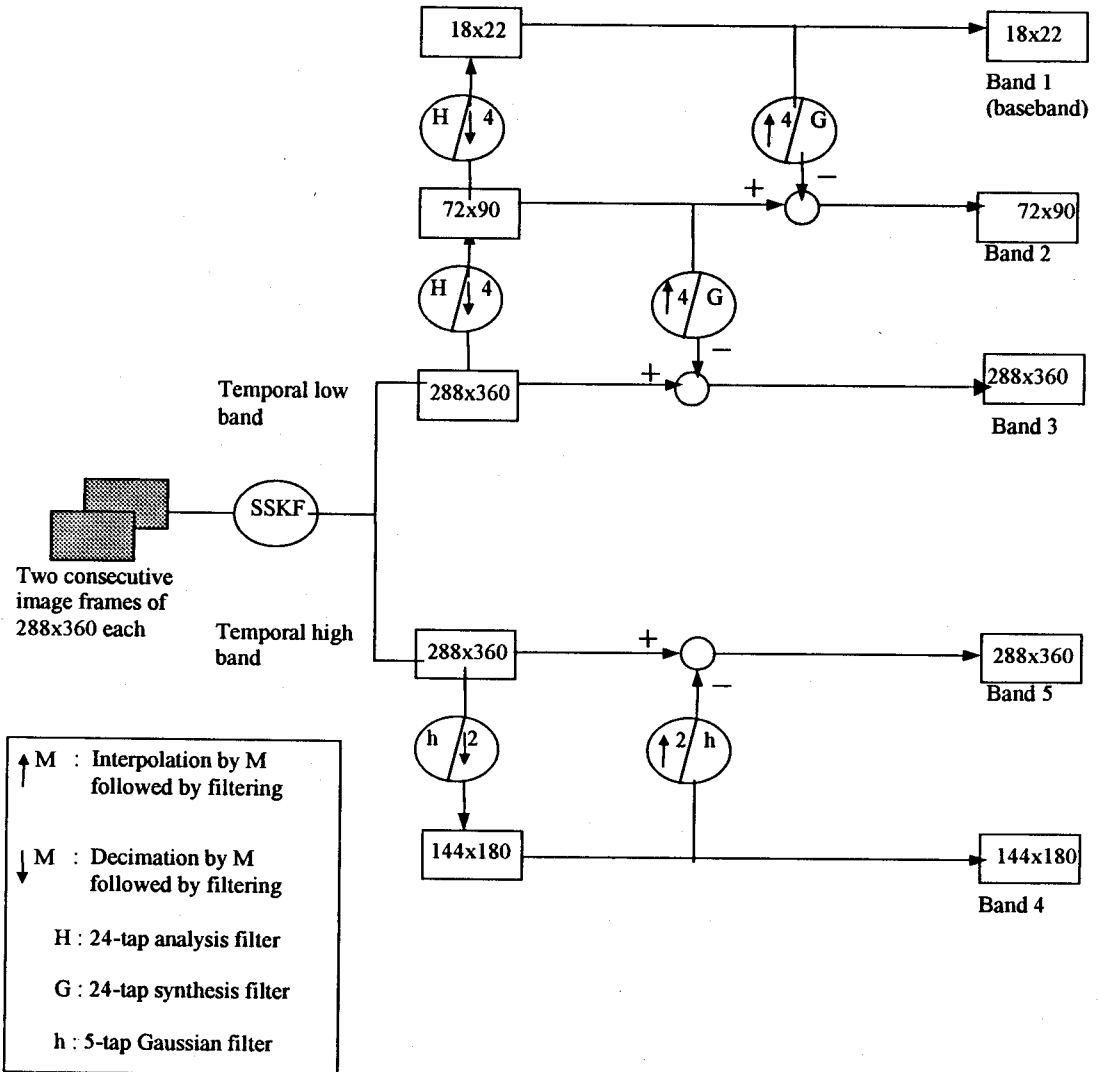


Fig. 1. Three dimensional decomposition of video sequence

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The architecture of ANNs basically consists of an input layer and an output layer. The layers are dense interconnections of simple processors, or neurons, which operate in parallel. Each interconnection is associated with a weight factor  $w_k$ . These weights are usually trained on one or more images so that they develop an internal representation corresponding, not to the image, but rather to the relevant features of a class of images.

One of the important purposes of neural VQ is to create an ordered mapping from a high-dimensional input space to a low-dimensional output space, and to extract meaningful features from the input data. Kohonen's self-organizing maps (SOFMs) have been regarded as one of the most powerful network in that sense. The work of Nasrabadi and Feng [13] has shown SOFM to give better results than the traditional LBG algorithm in the sense of the mean expected distortion. Kohonen's SOFM also addresses the problem of underutilized neural units faced by many other neural network algorithms. In many of the learning methods, the frequency of use of entries in the codebook can be quite uneven, leaving some codewords as underutilized. Kohonen's SOFM ensures that all codewords are doing their fair share in representing the input data by associating with each neural unit, a neighborhood of other neural units. During the training process, the winning neural unit as well as the neural units in the neighborhood of the winner are updated. Thus, by the use of neighborhoods, the SOFM network overcomes the problem of underutilized nodes, but at the expense of additional computation involved during training. This additional computation arises from both the calculation of the neighborhood of the winning unit, as well as from the updating of all members of the neighborhood.

### Implementation of the FSCL Neural Network

This research uses the frequency-sensitive competitive learning (FSCL) network [14]. One of the motivations for this is that it overcomes the limitations of underutilized networks while retaining the computational advantages of its neural structure. In the FSCL network, each neural unit incorporates a count of the number of times it has been the winner. This information is used to ensure that, during the course of the training process, all neural units are modified an approximately equal number of times. This is done by modifying the distortion measure used to determine the winner. The distortion measure is weighted by an increasing function of the number of wins for each unit. In this way, units that have had many wins, i.e. which are over utilized, are less likely to be chosen for modification, giving other units with a lower count value a chance to win the competition.

Specifically, let  $d(x, w_i(n))$  be the distortion measure that is to be minimized during the quantization process, and let  $u_i(n)$  be the total number of times that a neural unit  $i$  has been the winner during training. Then a modified distortion measure for the training process is defined as:

$$d^*(x, w_i) = d(x, w_i(n)) * u_i(n)$$

The winning unit at each step of the training process is the one with the minimum  $d^*$ . If a given neural unit wins the competition frequently, its count and consequently  $d^*$  increases. This reduces the likelihood that this unit will be the winner.

The FSCL network architecture consists of three layers:

- an input layer that distributes the input vector from the training set to the second layer
- a second layer of units, where each unit computes the modified distortion  $d^*$  between its weight vector (code vector) and the input vector
- an output layer based on the minimum distance criteria that determines the winning neural unit from the distortions computed by the second layer units.

Thus there are  $N$  neural units in the input layer, and  $M$  units in the middle and output layers, where  $N$  is the dimension of the input vector, and  $M$  is the size of the codebook, i.e. the number of codevectors in the codebook.

The code vectors of the winning neuron are updated according to the one iteration learning rule described below:

- The codevectors  $W_i$  and the winning frequency associated with each codevector,  $F_i$  are all initialized for each distortion computing neuron in the second layer.

$$W_i(0) = R(i) \quad \text{and} \quad F_i(0) = 1, \quad i = 1, 2, \dots, M$$

Here  $R(i)$  are the initial codevectors, taken from a random vector-number generating function.



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- The distortion  $D_i(t)$  between an input vector  $X(t)$  and all the code vectors  $W_{ij}(t)$  is calculated as :

$$D_i(t) = \sum_{j=1}^N (X_j(t) - W_{ij}(t))^2$$

where  $t$  is the training iteration index

- The distortion computing neuron with the smallest distortion is designated as the winning neuron and its output is:  $W_i(t+1) = W_i(t) + C(t) * out_i(t) * [X(t) - W_i(t)]$  where  $C(t) = \frac{1}{F_i(t)}$ , if  $1 \leq F_i(t) \leq F_{thr}$  and 0, otherwise. Here,  $C(t)$  is the frequency sensitive learning rate and  $F_{thr}$  is the upper threshold frequency. In this research, an upper threshold of 250 is found to be adequate to allow training of the codebook.
- The above steps are repeated for all the training vectors  $X(t)$ . The final codebook obtained is an optimal codebook.

### 4. DESIGNING THE CODE BOOKS FOR VECTOR QUANTIZATION

The neural network algorithm FSCL (Frequency Selective Competitive Learning) discussed in the previous section is used for the design of the codebook for vector quantization. Our research involves design of two separate codebooks, one for the high frequency edge vector patterns, and one for the approximately stationary vector patterns. The reason for designing two separate code books is that while most of the vectors in the baseband (band 1) have low variance and are almost stationary, the vectors found in band 2 and 3 are mostly edge patterns and show high variances. So to have a good representation for both kind of input vectors, separate training sets have been used to simulate each codebook. Several different images are used for the purpose of the training set: the images are filtered into their low pass and high pass components and then used to simulate the neural network clustering technique. Once the codebooks are formed, the actual quantization occurs as follows.

### Vector Quantization of Bands 1, 2 and 3

Since most of the energy of the decomposed image is concentrated in the lowest spatio-temporal frequency band, also called the baseband (band 1), the dimension of the stationary codebook is kept quite small and is chosen as 4. Also, since the baseband contains only the slowly varying information content, its 4-dimension vectors do not exhibit widely varying geometric patterns. Thus, a small-sized codebook is sufficient to represent all the vectors in this band. A codebook of size 64 was chosen for this work.

The second level in the pyramid has the high-frequency content of the decomposed temporal low band and requires a separate codebook for its coding. This codebook has been trained on data that has a highly varying edge content so that it can faithfully code data of similar nature. The size of this codebook is 256 and dimension 4.

The first difference level (band 3) in the pyramid has the minimum information most of which is concentrated around the edges. This information can be coded by applying an edge detector to find the location of pixels that are perceptually important and then transmitting only these coded pixels. But this would also require the transmission of the position of these coded locations to the receiver in order to reconstruct this band. To avoid this, a scheme of predicting the edges of band 3 from band 1 and 2 is used. This is shown in Figure 2.

Before coding, the baseband is interpolated to the second level and added to band 2. This is further interpolated to the size of the original image. Edge-detection is applied to this up-sampled version and the corresponding pixels from the first difference level are formed into vectors and quantized. At the receiver, similar process is repeated by upsampling the quantized baseband, adding it to the quantized second level, and then upsampling it to the original image size. This partially reconstructed version of the original image is used for edge-detection which gives the location of the vectors of the band 3 that are coded. Once the locations are known, the coded vectors are suitably placed to form band 3. Thus, using this approach, no side information needs to be sent for the coded areas of the first difference image level and an average of only 4 % to 5% of this level needs to be coded. Thus, more compression is achieved by edge-detection instead of coding the band as it is.

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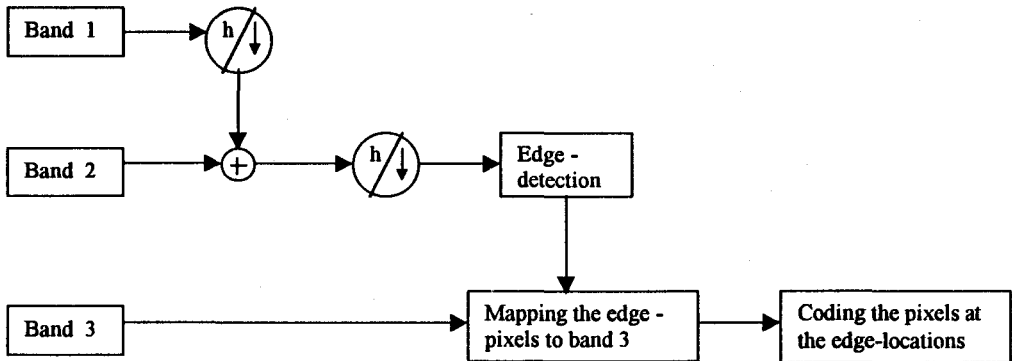


Fig. 2. Coding of edge location in band 3 using band 1 and 2.

### Coding the decomposed temporal high band

Bands 4 and 5 form the pyramid levels of the decomposed temporal high band. The subbands whose energy falls below an empirically derived threshold value are discarded without causing severe degradation to the reconstructed image. Band 5 has extremely low energy content and the sparse information carried in it is not significant in the final image reconstruction, thus it can be safely discarded. The coding process for band 4 is discussed below.

This is the nondominant subband that contains a small amount of the total signal energy yet data that is perceptually very significant as it contains most of the sharp edge and contour information as well as the fast motion aspects. The neural vector quantization approach used for the decomposed temporal low band does not work very well for this. Instead, a perceptually efficient image coding scheme is required that can preserve the underlying edge geometries in the high frequency signals at low coding rates. A geometric vector quantization (GVQ) scheme proposed in [10] is adapted in this paper where the codevectors are derived from a small set of local geometric patterns found in the high-frequency subbands. This method takes advantage of the human eye's sensitivity to sustained intensity changes as found in an edge.

In general, the GVQ method provides an optimum  $l$ -level scalar quantizer for each data vector for a given error metric. In this paper, a two level GVQ based on the minimum mean square error (MMSE) criterion is used. Unlike traditional VQ, GVQ does not require a training set for its codebook design. Instead, it makes use of the fact that the high-frequency bands have a lot of edges that can be represented by typical geometric shapes. Thus a codebook of simple geometric shapes like strips or strip combinations of various orientations and thickness is sufficient to represent this data. The codevectors for two-level GVQ are binary valued blocks reflecting these basic shapes. Each coded block is accompanied by two locally adapted intensity values, representing the binary values of the block. The dimension of the codevectors is chosen to be  $3 \times 3$  blocks, so an exhaustive binary codebook of all possible shapes can be formed by  $2^{9-1} = 256$  code vectors. The other 256 code vectors are just the complements of the first 256 code vectors. The latter codebook gives better results as compared to a codebook of elementary shapes.

The image is divided into  $3 \times 3$  non-overlapping subblocks of input vectors. For a given input vector, an adaptive procedure modulates the two intensities of each code vector, and the code vector with the best match is used to reproduce the input image block. The transmitted information includes the index  $k_{best}$  of the chosen code vector as well as its chosen intensity levels  $L_1$  and  $L_2$ . The index  $k_{best}$  is given by 8 bits and each of the intensity values  $L_1$  and  $L_2$  is represented by a uniform 5-bit scalar quantizer.

## 5. PERFORMANCE EVALUATION OF THE COMPRESSION ALGORITHM

The performance of the proposed algorithm is compared with the performance of MPEG standard algorithm. The MPEG standard does not give detailed rules of how a sequence should be coded. The standard is like a protocol for the decoding procedure. The broad guidelines for achieving good compression are mentioned but many choices are left for the user to decide. Thus the comparison made here with MPEG is more analytical than experimental.

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### **Qualitative Evaluation**

The visual quality of the reconstructed sequence is excellent in both algorithms. The reconstructed sequence is almost indiscernible from the original sequence.

### **Quantitative evaluation**

The performance of the two algorithms is compared based on the signal to noise ratio, and the bit rate (bpp) requirements. The average PSNR of the reconstructed Miss America sequence using MPEG is approximately similar to the PSNR that can be achieved with the algorithm presented in this paper. The algorithm introduced presents a major advantage over MPEG here, by supporting the possibility of progressive transmission of the video signal. The bits per pixel (bpp) requirements for both algorithms are very similar.

## **6. SIMULATING THE WIRELESS CHANNEL**

The transmission and reception of the compressed bands through a CDMA wireless channel is depicted below in Figure 3. The actual simulation has been done using Cadence's signal processing software SPW. The simulation files used have been shown in Appendix A. Although CDMA technology allows transmission of all the coded bands at the same time unlike the TDMA technique, to avoid complexity of diagram, the transmission of only one band is shown in the Figure 3. But in the actual simulation of the channel, two coded bands have been transmitted simultaneously. Walsh codes 1 to 4 have been used to separate data of one band from the other band.

Once the image has been compressed by the image coder, it is error-protected by using a convolutional code  $(2, 1, 5)$ ,  $n = 2$ ;  $k = 1$ ;  $m = 5$ . Further, to combat the burst errors associated with a fading channel, the error-protected data is interleaved. Interleaving spreads out the data in time so that burst errors are spread out to appear independently making a bursty channel similar to an AWGN channel. The interleaved data is modulated using a QPSK modulator and the in-phase and quadrature components of the output are spread by PN sequences. The I-channel PN generator function is '0121641' and the Q-channel PN generator function is '0116171'. The spreading factor is 128 as specified by the IS-95A standard with a bit rate of 9600 bps and chip rate of 1.2288 Mcps. Walsh functions from 1 to 4 are used for the four bands. A square root raised cosine filter with a roll-off factor of 0.35 is used for pulse shaping

and the data is fed through a frequency selective multipath fading channel. White noise corresponding to 18 dB channel SNR is added to the output of the fading channel. At the receiver end, the data is again filtered by the same filter used for pulse shaping. Despreading takes place and the despread data is demodulated. The deinterleaver is used to record the data back to its original sequence. After passing through a convolutional decoder, the data is sent to the image decoder for reconstruction of an approximation of the original frames.

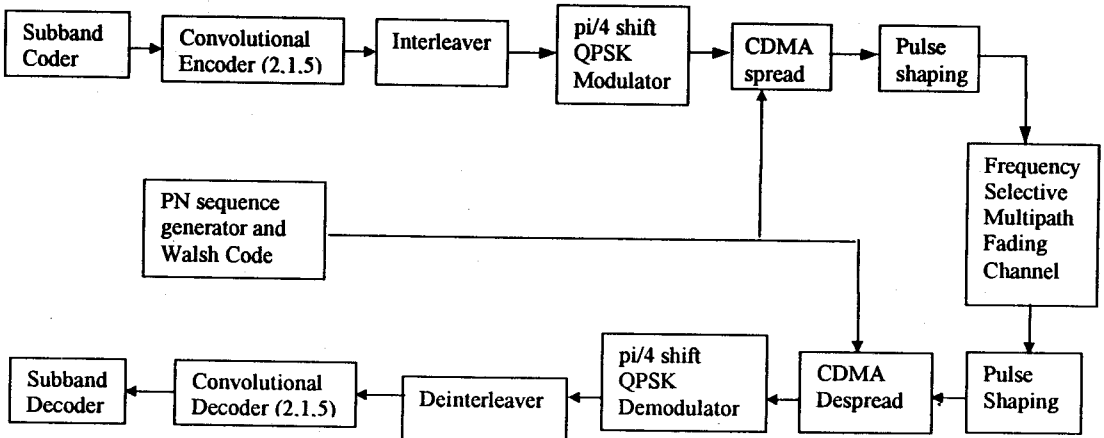
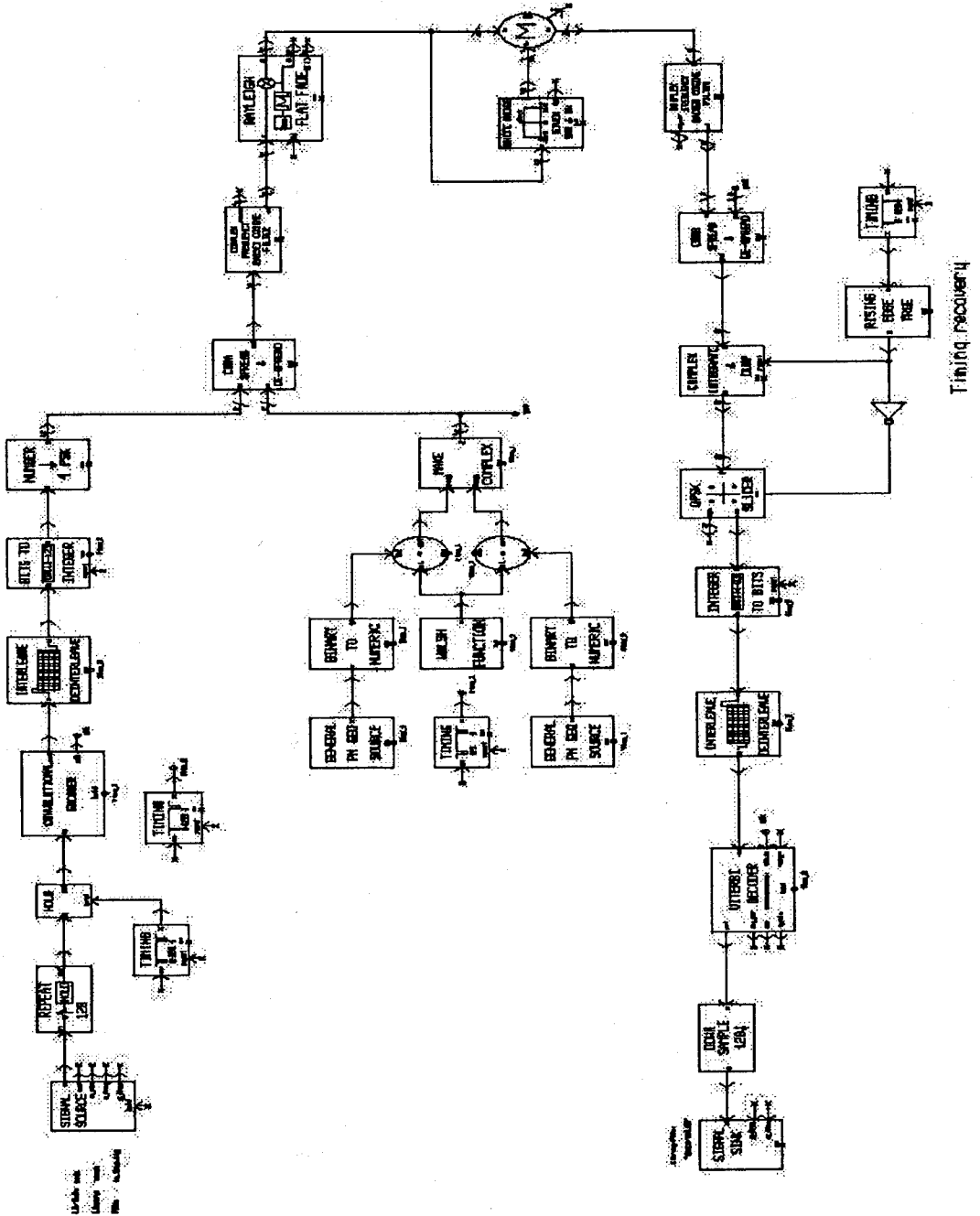


Fig. 3. IS-95A Standard specification for transmission and reception across a wireless channel.

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## Appendix A Simulation file



## 7. SIMULATION RESULTS

The compression algorithm is tested on two sequences, one with slow motion and static background, the Miss America sequence, and the other with faster motion and noisier background, the Salesman sequence. Both are gray-scale sequences having  $288 \times 360$  pixels per frame at the rate of 30 frames /s.

This research is aimed at compressing video sequences at 0.25 bpp at vehicle speed of 65 mph. The bit rate calculations of 0.25 bpp or less for the Miss America sequence is shown in Table 1 for two frames, frame 5 and frame 6. Simulation results have been obtained for two frames each from both these sequences. Quantitative evaluation involving the calculation of the peak-signal-to-noise ratio (PSNR) as well as qualitative analysis is performed to judge the quality of the image sequences.

**Table 1 Bit rates and PSNR for miss america sequence.**

Band	Bit rate	PSNR	Average Bit rate
Band 4	1.01	33.97	$1.01/4 = 0.25$ bpp
Band 3	0.08	32.31	0.08 bpp
Band 2	2.0	34.56	$2/16 = 0.125$ bpp
Band 1	1.5	38.64	$1.5/256 = 0.03$ bpp
			0.245 bpp

The first tests were performed on the Miss America sequence. Two frames with distinct motion in the eyes and lips area are chosen as data for channel simulation. The original frames, frame 4 and frame 5, are shown in Figure 4 for comparison. Figure 5 shows the reconstructed frames in the absence of channel errors; the only information loss is due to the compression involved. It is seen that the coding scheme produces results comparable to the original data with very slight deterioration around the edges and in the motion information. The PSNR of these frames are 36.51 dB and 36.52 dB respectively.



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**Frame 4**



**Frame 5**

**Fig. 4. Two original consecutive frames of miss america sequence.**



**Frame 4**



**Frame 5**

**Fig. 5. Reconstructed frames of miss america sequence at 0.25 bpp.**

Figure 6 shows the reconstructed frames after passing through the IS-95 channel at a vehicle speed of 0.1 mph and a channel SNR of 18 dB. The PSNR of these frames are 34.65 dB and 34.68 dB respectively. It can be seen that the coding scheme is very robust to channel noise in the absence of fading. Fading errors are introduced in the channel by increasing the vehicle speed to 65 mph, which is a typical highway speed, and with a channel SNR of 18 dB. The corrupted frames are reconstructed and shown in Figure 7. The PSNR after introduction of fading errors reduces to 27.26 dB and 27.21 dB. The major contributor to the overall degradation in the reconstructed frames is the baseband. Any burst errors in the lower levels of the pyramid have less effect on the picture quality.



Frame 4



Frame 5

Fig. 6. Reconstructed frames at 0.1 mph and channel snr 18 db.



Frame 4

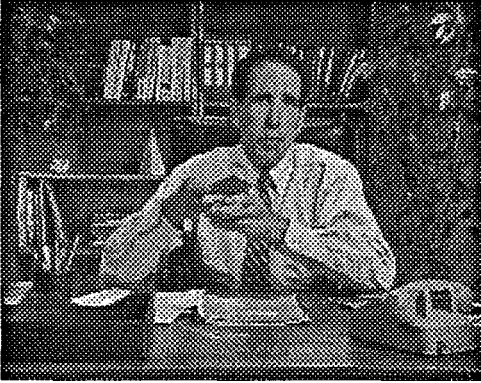


Frame 5

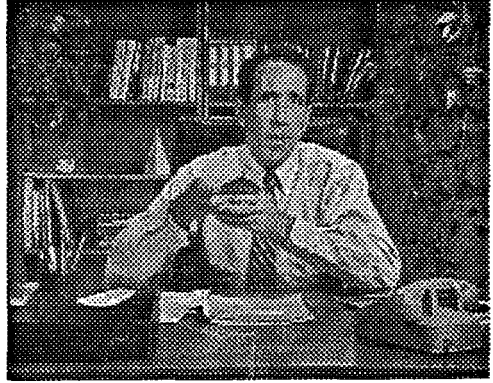
Fig. 7. Reconstructed Frames At 65 Mph And Channel Snr 18 db.

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Similar results for the Salesman sequence (frame 16 and frame 17) are shown in Figures 8 through 11. The Salesman sequence has faster motion and has noisier background and foreground as compared to the Miss America sequence. Despite the increase in activity, the compression scheme produces near original results in the absence of channel errors at a bit rate of 0.25 bpp. Table 2 compiles channel simulation results for both sequences for comparison.

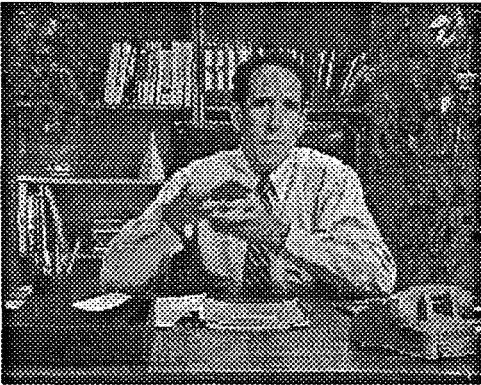


**Frame 16**

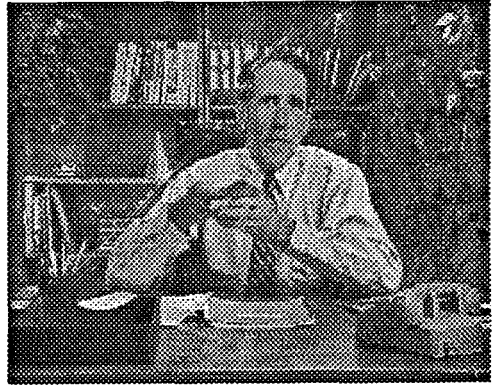


**Frame 17**

**Fig. 8. Two original consecutive frames of salesman sequence.**



**Frame 16**

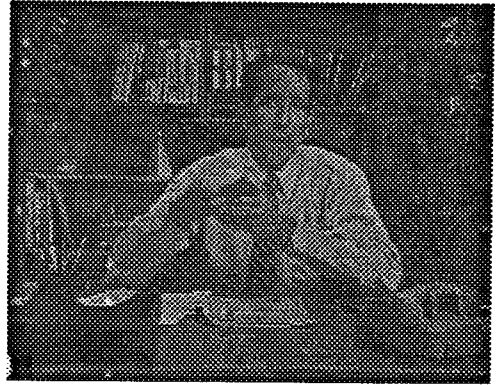


**Frame 17**

**Fig. 9. Reconstructed frames of salesman sequence at 0.25 bpp.**



Frame 16



Frame 17

Fig. 10. Reconstructed frames at 0.1 mph and channel snr 18 db.



Frame 16



Frame 17

Fig. 11. Reconstructed frames at 65 mph and channel snr 18 db.

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**Table 2. Simulation results for miss America sequence and salesman sequence.**

Reconstructed Frames	PSNR for Miss America sequence at 0.25 bpp		PSNR for Salesman sequence at 0.25 bpp	
	frame 5 (dB)	frame 2 (dB)	frame 16 (dB)	frame 17 (dB)
No fading errors, no channel errors	36.51	36.51	33.43	33.41
0.1 mph vehicle speed, 18 dB channel SNR	35.15	35.18	31.83	31.89
65 mph vehicle speed, 18 dB channel SNR	27.26	27.21	25.07	25.10

For a more subjective evaluation of the results presented above, the mean opinion score (MOS) is used as a basis to reflect the quality of the image. A number of viewer rate the image according to how appealing it is visually, and the mean of these ratings gives the MOS. The results presented before were compared side by side with the original images by ten viewers. The MOS scales for the two test frames of Miss America sequence and the Salesman sequence are given in Table 3 (a) and (b).

**Table 3a. MOS Results for the miss America sequence.**

Channel SNR and Vehicle Speed	MOS
0 dB SNR, 0 mph	4.75
18 dB SNR, 0.1 mph	4.50
18 dB SNR, 65 mph	3.25

**Table 3b. MOS Results for the salesman sequence.**

Channel SNR and Vehicle Speed	MOS
0 dB SNR, 0 mph	4.60
18 dB SNR, 0.1 mph	4.25
18 dB SNR, 65 mph	3.50

## 8. CONCLUSION

In this paper, a novel compression scheme for video sequences that is robust for fading error in a spread spectrum environment is presented. A 3-D coder has been designed in which the sequence is decomposed into spatio-temporal sub-bands. The proposed algorithm involves the design of two separate code books, one for the high frequency edge vector patterns and one for the approximately stationary vector patterns.

The encoded bands are sent through a channel based on IS-95A (North American digital cellular standard) specifications and the bands are later combined to recover the original sequence at the image decoder.

The Miss America compressed sequence can be transmitted at a rate of 715 Kbps and the Salesman sequence requires 793 Kbps. Vehicle speeds of 0.01 mph and 65

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mph are considered which represent two extreme channel conditions: stationary and rapidly time-varying, at channel SNR 18 dB. The PSNR of the frames in the presence of fading errors was found to vary between 25 dB to 28 dB. Most of the degradation in performance is attributed to errors in the baseband. Errors in the lower levels do not significantly affect the image quality. Performance can be improved by increasing the channel SNR to be more than 18 dB (22 dB for example). Moreover, the baseband can be transmitted without any compression. This would augment the bit rate by 0.03 bpp but will make the transmitted images more robust to channel errors.

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