# A MOBILE WIRELESS CHANNEL DISPERSION STATE MODEL

## *Enabling Cognitive Processing Situational Awareness*

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***Abstract*— Communication traffic is vulnerable to time-variant wireless channel conditions such as: fading, time dispersive, or frequency dispersive distortion which can render nonadaptive communication processing ineffective.**

***This paper surveys published wireless channel multistate hidden Markov models (HMM) revealing mature applications of HMMs and several approaches for modeling wireless channel parameters however none have been found that model channel dispersion and related conditions such as frequency selectivity and/or time selectivity. Therefore, a mobile wireless channel dispersion state model (DSM) is proposed to provide channel distortion awareness.***

***The authors introduce a mobile wireless channel DSM linking time-variant non-dispersive, single, or dual-dispersive channel states and signal to noise ratio (SNR) loss/distortion mitigation methods. If the DSM is coupled with a channel state recognition (CSR) process, channel distortion awareness is provided for cognitive processing. This enables near-real-time selections between appropriate SNR loss and inter-symbol interference (ISI)/inter-frequency interference (IFI) mitigation methods.***

***The effectiveness of the DSM coupled with a CSR algorithm is demonstrated by the application of reference waveform symbol streams to a recognition HMM. Simulation results agree with published standard HMM recognition accuracy in terms of sensitivity and specificity. The research results validate the utility of the DSM in time-variant mobile wireless channels and establishes a performance baseline for benchmarking future CSR algorithm research.***

**Keywords- Channel State Recognition; Cognitive Radio; Dispersion State Model; Distortion Mitigation; Mobile Wireless Channel State Model; Mobile Wireless Channel Dispersion State Model; Mobile Wireless Channel Environmental Awareness; Mobile Wireless Channel Situational Awareness; Mobile Wireless Channel State Recognition; Software Defined Radio.**

## I. INTRODUCTION

### *A. Background*

Reliability and quality of service (QoS) for communication network messages to/from distributed mobile users are vulnerable to unreliable mobile wireless channel conditions that exist within the resource disadvantaged mobile environment. 4G and beyond performance requirements drive needs for adaptive cognitive communication processing supporting exemplar commercial, defense, national infrastructure, homeland protection, and emergency response networks.

Research by the authors is enabling mobile wireless channel situational awareness; a critical function for cognitive communication processing. This paper contributes a novel DSM and a proof of concept (POC) demonstration confirming that blind recognition of distortion type and intensity is feasible with HMMs.

Wireless communication performance is dependent upon maintaining a match between transmitter and receiver processes with mobile wireless channel conditions, synchronization of time and frequency references, and efficient utilization of resources. Mobile wireless channel physical and environmental conditions challenge these relationships with time-variant losses, time, and frequency dispersion.

First, distributed mobile wireless users exist in a broad range of configurations supporting space, air, ground, marine, and subsurface environments. These environments introduce dynamic geometry and mobility between source and destination communication processes. Radio wave reflections from surfaces much larger than a wavelength such as ground, surrounding terrain, bodies of water, buildings, vehicles, foliage, and myriad other object types in the vicinity of the line of sight path produce a resultant received waveform subject to multipath delay and related signal frequency variations. Mobility between the transmitter and receiver produces Doppler frequency spreading and related signal time variations at the receiver.

Second, limitations exist with nonadaptive communication equipment with limited dynamic responses due to lack of: 1) environmental sensing, 2) adaptive and/or reconfigurable processing, and 3) dynamic management of resource consumption.

Third, many current mobile wireless channel estimation algorithms rely on channel transfer function (input/output) models that consume resources with required overhead in the form of training data or pilot waveforms.

Combinations of these characteristics limit performance, reliability, availability, capacity, and/or efficiency.

In contrast, cognitive communication equipment enabled by situational awareness, cognitive, and reconfigurable processing, improves these sets of limitations; producing situationally aware, autonomous, and adaptive responses to a range of dynamic wireless environmental conditions.

System behavioral state models characterize system relationships between system inputs, internal state, and output variables. System engineering analysis has been applied to the mobile wireless channel system to produce a functional cognitive processing architecture. A mobile wireless channel finite state Markov model (FSMM) is developed to relate mobile wireless channel inputs, internal dispersion, and output variables and further embedded for a CSR demonstration .

### *B. Impact, Significance, and Contribution*

Although offline training sequences are required for demonstrating channel state recognition with the DSM, no operational training sequences or pilot tones were required to generate the CSR results reported. Research contributions include design and proof of concept demonstration of the DSM.

### *C. System Engineering Models and HMMs*

*1) System Engineering Models:* Engineers often need to analyze problems associated with large complex systems to generate solutions. Systems models can be physical, mathematical, or logical representations of a complex system form, behavior, or process. See references [23][24] for detailed description of system engineering methods.

*2) Hidden Markov Models:* Mobile wireless channel internal behavior such as dispersion has been expressed with a dual statistical model formed with a HMM. See references [15][22][23] for an introduction to HMMs. When a system's internal behavior can be described with a finite set of states, a FSMM can be applied. Further, when these system states are not observable, the FSMM can be embedded in a HMM where the unobservable (i.e. hidden) states are represented as an internal statistical process and outputs are related with a secondary statistical relationship. Input signals can be discrete signal samples related to the hidden states. When the HMM is operating in a generative mode, and dwelling in a hidden state, time-invariant statistics are observed on the output based on an output probability distribution. However, when the HMM transitions to another hidden state, the statistics of the output change based on a different output probability distribution that relates the output to each hidden state, thus time-variant behavior can be modeled with a hidden state sequence. A transition probability matrix governs transitions among the unobservable hidden states. An output probability matrix relates the output to the hidden states; and thus, determines the observable output time-invariant statistics when dwelling in each hidden state. An initial probability matrix defines which state is most likely to occur at initialization. When the HMM is operating in training mode, off-line training sequences are required to estimate the transition and output probability matrices. The Viterbi or Baum-Welch forward/backward algorithms serve to estimate the HMM parameters. Once the HMM has been trained, they can operate in an evaluation mode where given an input data stream, the probability that the input sequence matches the trained model is estimated with a dynamic programming forward pass algorithm. An HMM can also operate in a decode mode with the Viterbi algorithm where given an input stream, an optimal hidden state sequence is estimated. HMMs have been successfully utilized for decades in mature structured pattern recognition applications such as automatic speech, image, facial, hand writing, gait, biological sequence, and network traffic recognition systems. HMMs have known limitations such as scaling with exponential complexity, requirements for offline training with significant amounts of relevant data, and recognition rate of convergence, and accuracy. On-going research by the authors will addresses these HMM limitations for CSR applications.

### *D. Published Multistate Mobile Wireless Channel HMMs*

Han et al. report that the earliest accounts of multistate mobile wireless channel models based on HMM was Gilbert and Elliott in a 1960 publication in [1]. Tan provided a historical overview of amplitude quantized FSMM in [2]. Lopez-Guerrero provides commentary on the development of error state models in [3]. Kundu asserts that n-state FSMM are required to achieve sufficient accuracy in [4]. Reidiger provides overview of information theoretic based FSMM in [5]. Kimwilaisak proposed variable length FSMM to better model dynamic channel conditions in [6]. Zhang proposed partitioned SNR defined not by amplitude but rather average dwell time in each state to deal with time-variant conditions in [7]. Pimental looks at high order FSMM to model error behavior with significant memory in [8]. Babich reaffirms the need for higher order FSMM for accuracy, however acknowledges the computational complexity and offers order reduction methods to reduce complexity to a 1st order model while maintaining accuracy in [9][10]. Xie asserts the need for higher order methods for accurate time-variant behavior and traced prior development of fading envelope distribution models and develops a general distribution model for all channel environments to overcome limitations of the Ricean distribution in [11]. General state variable models are provided in [12][13][14] which claim higher accuracy than convolutional channel models. Richter formulated state space models with Kalman filters to track the time varying parameters of the mobile channel from the Doppler power spectral density in [13]. Based on this literature search, the proposed DSM and application of HMMs to dispersion state recognition is novel and unique.

### *E. Paper Outline*

The rest of this paper is outlined as follows: section II presents a system model for wireless communication systems, cognitive radio systems, and channel state recognition; section III defines a DSM, section IV defines a CSR HMM, section V provides a proof of concept blind CSR demonstration, and section VI provides summary and conclusions.

## II. Mobile Wireless Channel System Model

In Fig. 1 a mobile wireless channel system block diagram highlights how waveforms propagate from a transmitter to a receiver and how the mobile wireless channel largely determines the nature of the waveform when it arrives at the receiver.

In Fig.2 the architecture elements of a cognitive radio are shown highlighting the processing elements of the transmitter and the receiver, the mobile wireless channel, and the role that environmental sensing provides to cognitive decision processes on both the transmitter and the receiver. The cognitive processes execute policy regarding configuration of the SDR functions.

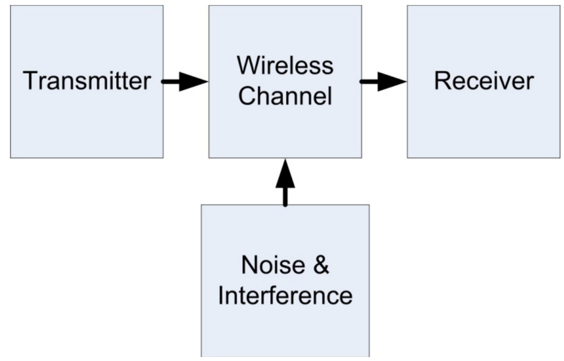


Figure 1-Mobile Wireless Channel System Architecture

Given environmental sensing provided by the DSM and the CSR algorithm, the transmitter and receiver become aware of time-variant mobile wireless channel dispersion. The result is a near-real-time adaptive transmitter and receiver that respond to current environmental distortion conditions. Given channel distortion awareness, cognitive transmitter and receiver processes are enabled to make selections regarding effective loss and/or distortion mitigation.

## III. Mobile Wireless Channel State Models

### *A. Mobile Wireless Channel DSM*

The state diagram in Fig. 3 illustrates each of the states in the mobile wireless channel DSM. When time dispersion exceeds ~10-20% of the symbol period, frequency selectivity becomes increasingly problematic and once it approaches and exceeds the bit period full ISI distortion produces frequency selective distortion. In a similar manner, when frequency dispersion exceeds ~10-20% of the symbol rate, time selectivity becomes increasingly problematic and once it approaches and exceeds the symbol rate, the mobile wireless channel becomes fully time

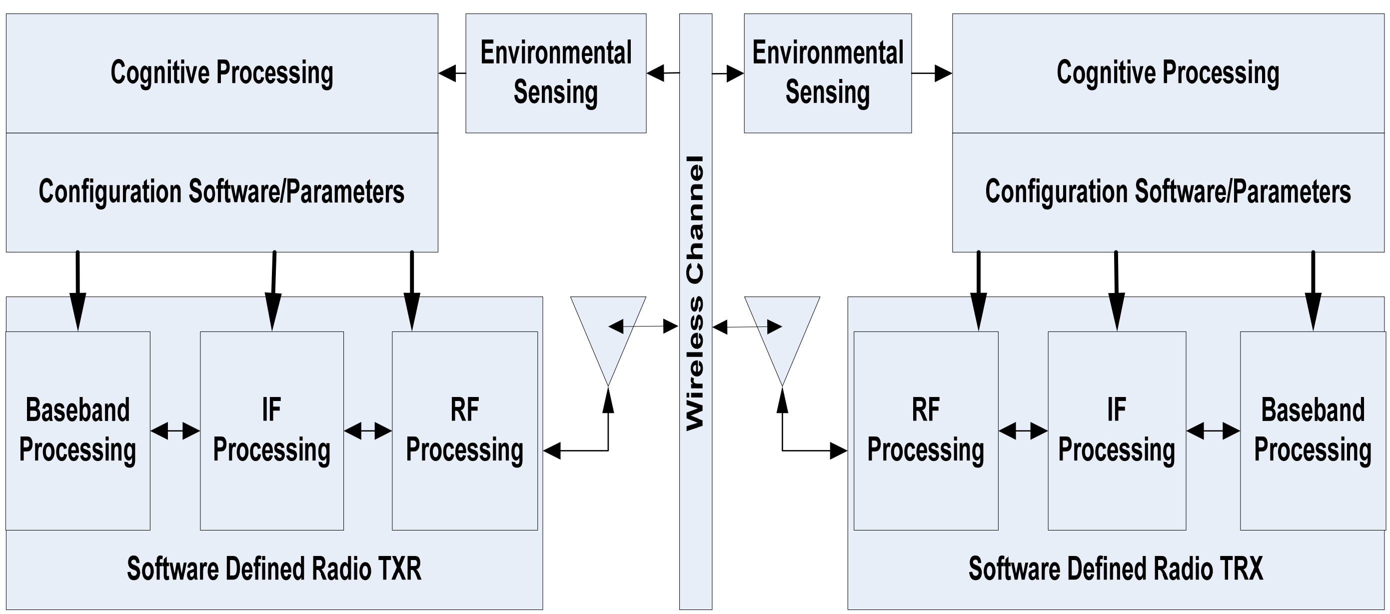


Figure 2-Cognitive Radio CSR Architecture Model

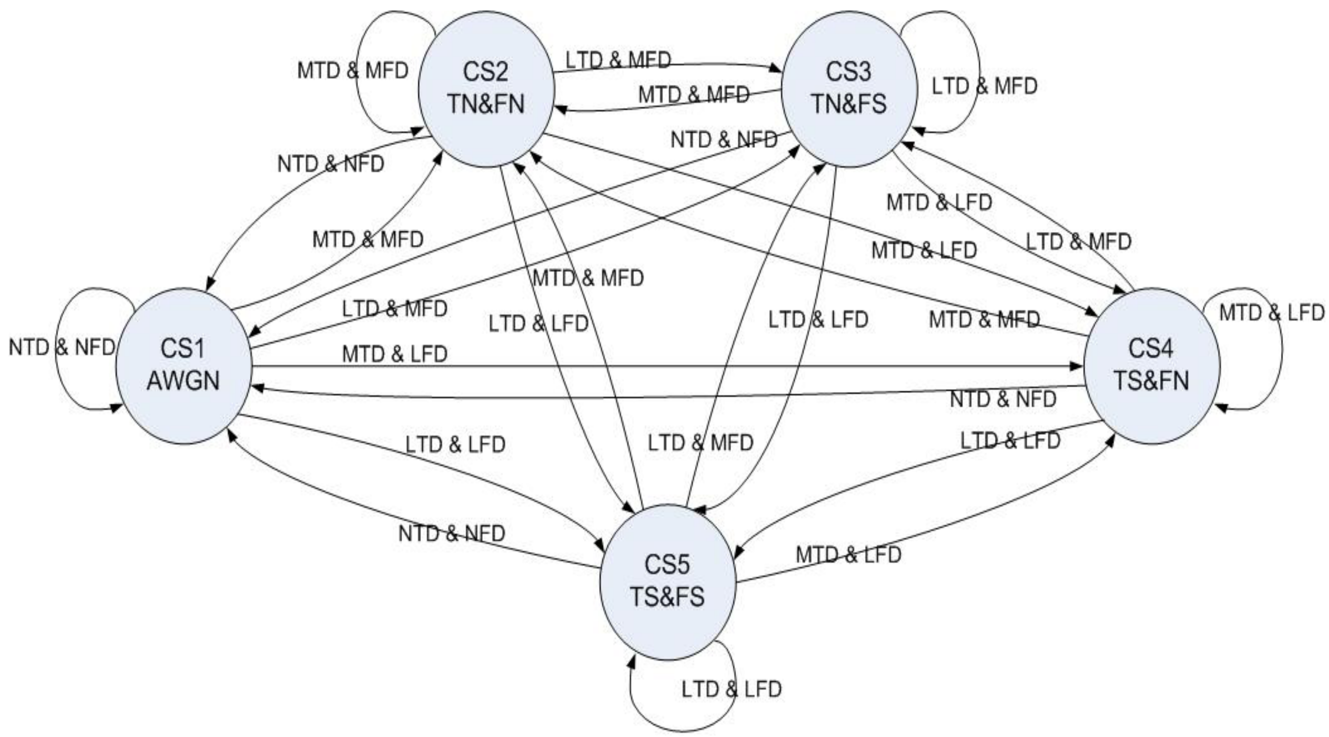


Figure 3-DSM State Diagram

selective.

Transitions between the states are defined in Table 1 in terms of dispersion magnitude relative to the bit period.

Table 1- DSM State Transition Definitions

| | |
|---|---|
| NTD&NFD | No Time Dispersion and No Frequency Dispersion |
| MTD & MFD | Minimal Time Dispersion and Minimal Frequency Dispersion |
| LTD & MFD | Large Time Dispersion and Minimal Frequency Dispersion |
| MTD & LFD | Minimal Time Dispersion and Large Frequency Dispersion |
| LTD & LFD | Large Time Dispersion and Large Frequency Dispersion |

Lack of time dispersion and frequency dispersion is representative of stationary links unaffected by multipath reflections. Minimal time dispersion and frequency dispersion is representative of mobile wireless channel conditions with very low relative velocities between the transmitter and the receiver and multipath components are present however their delay and magnitudes are such that they have minimal effects. Large time dispersion and frequency dispersion is representative of mobile wireless channel conditions when relative velocities between transmitter and receiver locations are moderate to high and multipath components arrive with significant delays and magnitude sufficient to significantly alter the phase and the frequency of the received signal. When mobile wireless channel conditions are dynamic, transitions between the states occur to represent current conditions. If mobile wireless channel conditions cease to change, the DSM settles into a single stable state.

*B. DSM State Definitions*

The paragraphs below describe waveform and mobile wireless channel parameters for each mobile wireless channel state. Each mobile wireless channel state has a unique statistical signature which provides discrimination by the CSR model.

State 1 (AWGN = Additive White Gaussian Noise). In this state virtually no multipath effects and virtually no Doppler shift exist. In Fig. 4 discrete-time samples from a 1 Mbps BPSK waveform generator were captured at the output of an AWGN 10 db SNR model cascaded with a Ricean channel model . The Ricean channel parameters are as follows: LOS Doppler shift = 0 Hz, diffuse Doppler shift = .01 Hz, Ricean K factor = 100, multipath delay vector = [0 .1e-6 .2e-6, .3e-6] seconds, and multipath gain vector = [0 -100 -100 -100] decibels. Similar time symbol sequences were captured for all five channel states described in the following paragraphs.

State 2 (FN&TN = Time Non Selective and Frequency Non-selective). In this state multipath component delay and gain are small such that time dispersion is less than 10% of the symbol period, and velocity is minimal such that frequency dispersion is less than 10% of the symbol rate. In this state frequency non-selective and time non-selective channel conditions exist. Discrete time samples from a 1 Mbps GMSK waveform generator are captured at the output of an AWGN 10 db SNR model cascaded with a Ricean channel model. The Ricean channel parameters are as follows: LOS

Doppler shift = 0 Hz, diffuse Doppler shift = .01 Hz, Ricean K factor = 1, multipath delay vector = [0 .1e-6 .2e-6, .3e-6] seconds, and multipath gain vector = [0 -3 -10 -20] decibels.

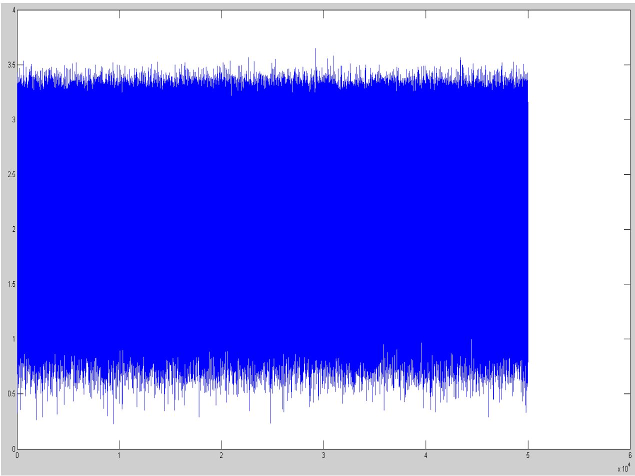

Figure 4- 1 Mbps BPSK at AWGN + Ricean Channel Output

State 3 (FS&TN = Frequency Selective and Time Non-selective). In this state multipath delay and gain are large enough such that time dispersion exceeds 20% of the symbol period, however velocity is small enough that Doppler spread is less than 10% of the symbol rate. In this state, frequency selective and time non-selective channel conditions exist. Discrete time samples from a 1 Mbps BPSK waveform generator are captured at the output of an AWGN 10 db SNR model cascaded with a Ricean channel model. The Ricean channel parameters are as follows: LOS Doppler shift = 0 Hz, diffuse Doppler shift = .01 Hz, Ricean K factor = 1, multipath delay vector = [0 1e-6 2e-6, 3e-6] seconds, and multipath gain vector = [0 -3 -10 -20] decibels.

State 4 (FN&TS = Frequency Non-selective and Time Selective). In this state multipath delay and gain are small enough such that time dispersion is less than 10% of the symbol period, however velocity is large enough such that Doppler spread is greater than 20% of the symbol rate. In this state, frequency non-selective and time selective channel conditions exist. Discrete time samples from a 1 Mbps BPSK waveform gene aptured at the output of an AWGN 10 db SNR model cascaded with a Ricean channel model. The Ricean channel parameters are as follows: LOS Doppler shift = 0 Hz, diffuse Doppler shift = 10 KHz, Ricean K factor = 1, multipath delay vector = [0 .1e-6 .2e-6, .3e-6] seconds, and multipath gain vector = [0 -3 -10 -20] decibels.

State 5 (FS&TS = Frequency Selective and Time Selective). In this state multipath delay and gain are large enough such that time dispersion is greater than 20% of the symbol period, and velocity is large enough such that Doppler spread is greater than 20% of the symbol rate. In this state, frequency selective and time selective channel conditions exist. Discrete time samples from a 10 Kbps BPSK waveform generator are captured at the output of an AWGN 10 db SNR model cascaded with a Ricean channel model. The Ricean channel parameters are as follows: LOS Doppler shift = 0 Hz, diffuse Doppler shift = 10 KHz, Ricean K factor = 1, multipath delay vector = [0 1e-3 2e-3, 3e-3] seconds, and multipath gain vector = [0 -3 -10 -20] decibels.

## IV. DSM Applied to CSR

### A. CSR Testbed

The DSM is embedded within a CSR model in a CSR testbed as shown in Fig. 5 which includes a wireless channel reference waveform generator (RWG), a training RWG, a waveform statistical quantizer, and a CSR HMM. The wireless channel RWG produces arbitrary sequences of waveform symbol streams with controlled waveform and channel parameters. The Training RWG produces similar sequences with correlated channel state sequences for estimating the hidden Markov Model (HMM) parameters. The statistical quantizer estimates the input waveform pdf and generates a bin index for each waveform sample. The CSR model is based on a HMM capable of operational maximum likelihood (ML) decoding the hidden state sequence of an operational input symbol stream.

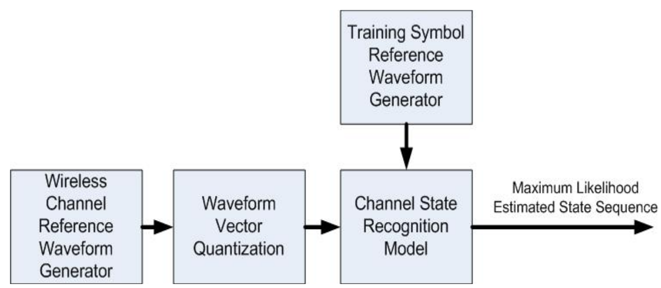


Figure 5- CSR Test System

### B. CSR Validation Approach

To demonstrate the effectiveness of the DSM and the feasibility of CSR, a CSR testbed was created as shown in Fig. 5. An example CSR model was trained with representative training sequences prior to ML decoding operational data sets. A set of training vectors were formed with 5 different combinations of hidden state sequences among 5 hidden states with output statistics within each state similar to the previously described DSM states. Correlated state vectors were also generated and submitted to the HMM to estimate internal parameters with the Viterbi and then refined by the Baum Welch algorithm. After training was completed, accuracy testing of the CSR model, was performed by submitting a single hidden state sequence to each of the 5 trained HMMs. Accuracy performance results from each ML decoding trial were recorded for evaluation. Accuracy performance metrics in terms of sensitivity and specificity coefficients are provided.

*C. Mobile Wireless Channel State Recognition Model*

*1) Waveform Statistical Quantization:* An example statistical quantized sequence for hidden state sequence 12345 is shown in Fig. 6. Each hidden state was formulated with controlled waveform and wireless channel properties consistent with the previously defined DSM channel states. These symbol sequences were applied to the statistical quantizer which estimated the waveform envelope probability distribution function (pdf) with a 200 bin [1] histogram[2] and outputs to the CSR model a bin index for each waveform sample.

*2) CSR HMM Training:* Refer to R. Durbin et al. [15] and Rabiner et al. [21][22] for details of HMM training algorithms such as Viterbi and Baum-Welch. Estimates for the transition and output probability matrices are formed by submitting a training symbol sequence statistically similar to the operational symbol sequences with an associated state sequence vector. As an example, a training statistically quantized sequence vector is shown in Fig. 6Figure with a hidden state sequence of 12345. This was input to the training algorithm with 50 000 symbols[3] for each hidden state. An associated known state vector was also generated with a correlated state variable for each symbol. For clarification, each state vector is formulated as in equation (1).

*3)* These vectors were input to the Viterbi training algorithm to formulate an initial rough order estimation of the transition and output parameters. Next these initial transition and output matrices were input into the Baum Welch training algorithm for fine-tuning. The Viterbi training algorithm is available in the MATLAB [20] function hmmestimate [17] and the BW algorithm is available in the MATLAB function hmmtrain [18].
This parameter estimation process produced estimates for the 5 state transition probability matrix (5x5) shown in Table 2 and the output probability matrix (5x200) shown in Fig. 7. This figure plots each of the rows of the output matrix similar to a pdf relating the HMM output to each of the hidden states.

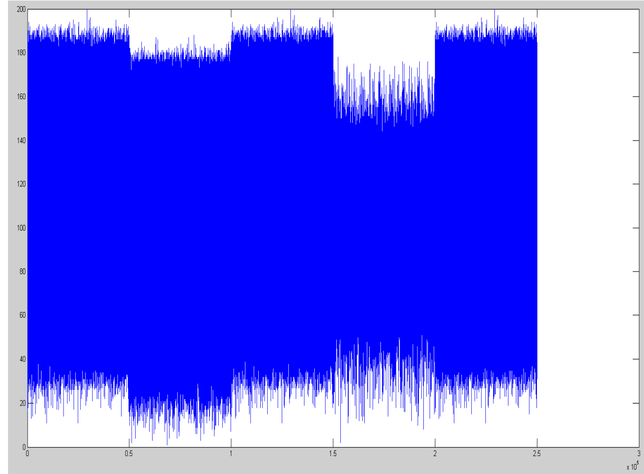

**Figure 6- State Sequence 12345 Histogram Bin Indices**

**Table 2- Dispersion CSR HMM Transition Probabilities**

| | | | | |
|---|---|---|---|---|
| 0.999920006399 | 1.9998400127e-05 | 1.9998400127e-05 | 1.9998400127e-05 | 1.9998400127e-05 |
| 1.9998400127e-05 | 0.999920006399 | 1.9998400127e-05 | 1.9998400127e-05 | 1.9998400127e-05 |
| 1.9998400127e-05 | 1.9998400127e-05 | 0.999920006399 | 1.9998400127e-05 | 1.9998400127e-05 |
| 1.9998400127e-05 | 1.9998400127e-05 | 1.9998400127e-05 | 0.999920006399 | 1.9998400127e-05 |
| 1.9998400127e-05 | 1.9998400127e-05 | 1.9998400127e-05 | 1.9998400127e-05 | 0.999920006399 |

Symbol sequences with varying combinations of hidden state sequences were concatenated to form a set of 250 000 element training vectors and after quantization each is similar in structure to the example shown in Fig. 4. The five training vectors are shown below.

1. State 1, State 2, State 3, State 4, State 5
2. State 2, State 3, State 4, State 5, State 1
3. State 3, State 4, State 5, State 1, State 2
4. State 4, State 5, State 1, State 2, State 3
5. State 5, State 1, State 2, State 3, State 4

Each training vector is applied to the HMM to form a statistically unique HMM for each case.

$$\boldsymbol{State\_vector} = [1_1 \cdots 1_{50000} 2_1 \cdots 2_{50000} 3_1 \cdots 3_{50000} 4_1 \cdots 4_{50000} 5_1 \cdots 5_{50000}] \quad (1)$$

[1] Less than 200 bins is inadequate to represent an accurate histogram function

[2] Mathworks, Inc.. MATLAB [20] function histogram(variable_name, bin_size) help pages.

[3] Statistical significance is a known HMM limitation, to avoid this problem a substantial number of samples were generated. Future research will investigate shorter training sequences.

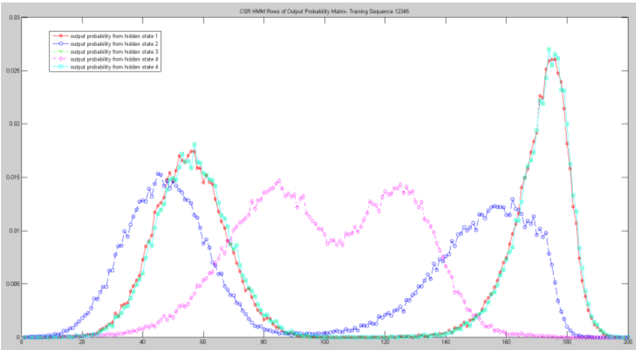

Figure 7- Dispersion CSR HMM Probability Matrix Rows

*2) CSR ML State Sequence Estimation*

Referring to R. Durbin et al. [15] and Rabiner et al. [21][22], there are many potential paths through a state space that can produce an observed symbol sequence. While some of these paths are not likely, there is perhaps a few or even a single path that is most likely. The Viterbi algorithm can be applied to the observed symbol sequence to estimate the most probable or the most likely state sequence given an HMM model. The maximum likelihood state sequence is described by equation (2):

$$\boldsymbol{\pi}^* = max_\pi \, P(x, \pi) \,, \qquad (2)$$

where $\boldsymbol{\pi}$ is the ML symbol sequence and $\pi_i$ is a specific symbol in the ML sequence. The Viterbi algorithm is initialized with the most probable state k known for all the states at position i and then backward iterates through to the beginning of the state space with equation (3) to identify the maximum likelihood path through the state space:

$$\boldsymbol{v_l}(i) = \, e_l(x_i) \, max_k(v_k(i) a_{kl}) \,, \qquad (3)$$

where $v_l(i)$ is the most probable path in the sequence through the state space at observation i, $e_l(x_i)$ is the associated output probability, $a_{kl}$ is the associated transition probability, and $v_k(i)$ is the highest probability state at observation i. The output is a state sequence $\boldsymbol{\pi}^*$ whose elements identify the most likely states associated with the symbol sequence x. The Viterbi decoding algorithm is implemented by the MATLAB hmmdecode function [16].

## D. DSM Recognition Accuracy

Decoded HMM output hidden state sequences are shown in Fig. 8. Statistical accuracy metrics sensitivity and specificity for the DSM CSR are summarized in Figs. 9-Fig. 12. For each test case, an operational hidden state sequence 12345 was submitted to each uniquely trained HMM. The HMM model utilized to recognize the sequence was varied as noted in each diagram. .

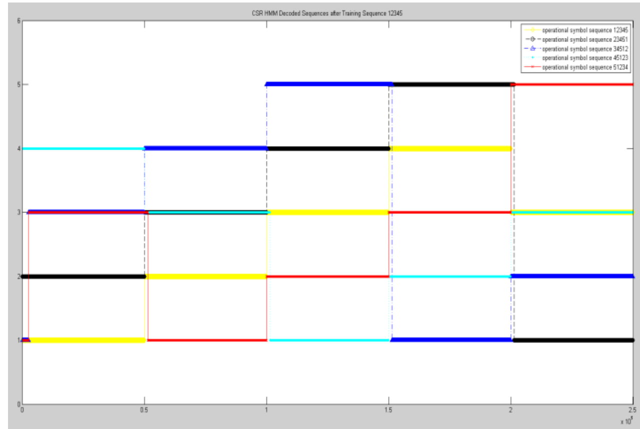

Figure 8- Dispersion CSR HMM- Decoded State Sequences

Accuracy is defined in terms of statistical tests for sensitivity and specificity as computed by equation (4) and (5).

Sensitivity is a statistical measure for a binary classification system which identifies the proportion of actual positive decisions that are correct, that is, the number of true positives (TP) as shown in equation (4):

$$Sensitivity = \frac{TP}{TP+FN} \,, \qquad (4)$$

where TP = true positives and FN = false negatives. With high sensitivity, a low type II error is expected, and a negative result would suggest a high probability of a negative result.

Specificity is a statistical measure for a binary classification system which identifies the proportion of actual negative decisions that are correct as shown in equation (5):

$$Specificity = \frac{TN}{TN+FP} \,, \qquad (5)$$

where TN = true negatives and FP = false positives.

The goal is 100% sensitivity (correctly predict all the positive outcomes) and 100% specificity (correctly predict all negative outcomes). With high specificity, a low type I error is expected, and a positive result would indicate a high probability of a positive result.

## E. Recognition Accuracy Results

Fig. 9 presents results for the CSR HMM operated with hidden state sequence 12345 and trained with a hidden state sequence 12345. Figs. 10, 11, 12, and 13 show similar results for an operational state sequence 12345 but the HMM was trained with the indicated state sequence.

The sensitivity results show how likely each HMM would correctly predict a positive outcome for each state while the specificity results show how likely each HMM would correctly predict a false outcome for each state.

Evaluating the results, several conclusions can be formed.

- None of the HMMs recognize dual dispersive state 5.
- All of the HMMs recognized the absence of dual dispersive state 5.

- All of the HMMs would accurately predict the presence or the absence of dual non-selective state 2 or singly frequency dispersive state 4.
- All of the HMMs would recognize the presence of AWGN State 1 with greater than 85% accuracy and would recognize the absence of AWGN S state 1 greater than 80% of the time.
- Two the HMMs would recognize the presence of singly time dispersive state 3 with greater than 80% accuracy while all of the HMMs would recognize the absence of singly time dispersive state 3 with greater than 70% accuracy.
- Preliminary results suggest that the approach is insensitive to waveform parameters such as modulation or data rate. This will be a topic for further CSR research.
- If these HMMs were arranged in parallel and their outputs were logically combined, states 1, 2, and 4 could be recognized with 100% accuracy and state 3 could be recognized with greater than 90% accuracy.
- As suggested by this observation, HMM structures for CSR will be a subject for further research.
- It is clear that the dual dispersive state 5 training sequence is not representative of the operational data.
- State transitions in a few of the cases were not consistent with the operational data consistent with known rate of convergence issues with HMM approaches.
- The results suggest that the dual dispersive state 5 training sequence is inadequate and training would need to be repeated with data that is more representative of the operational data to improve performance. Accuracy and convergence are less than preferred, however, it is clearly feasible to recognize internal mobile wireless channel state parameters such as dispersion with the HMM. Improving performance will be the subject of future CSR research.

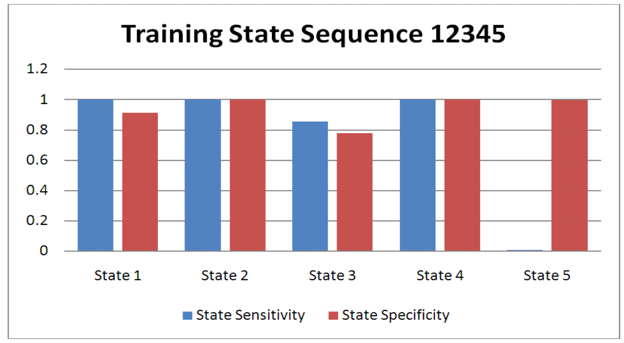


**Figure 9- Training State Sequence 12345 Results**

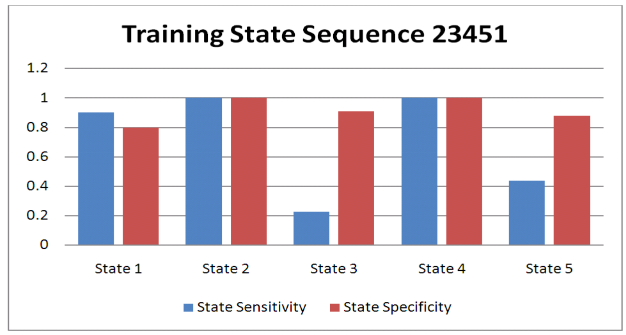


**Figure 10- Training State Sequence 23451 Results**

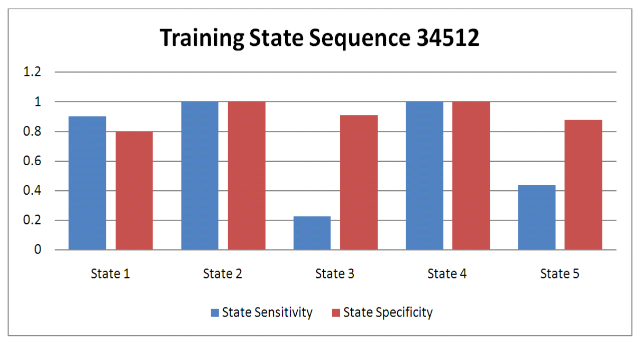


**Figure 11- Training State Sequence 34512 Results**

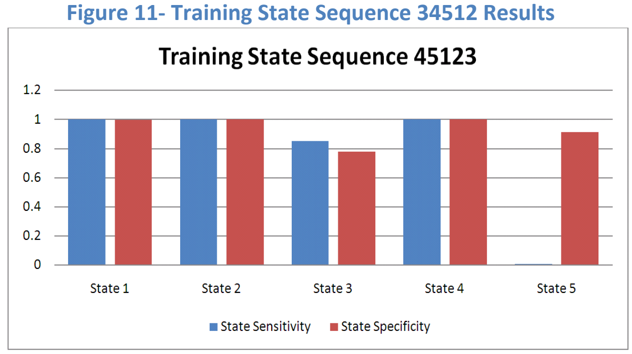


**Figure 1-Training State Sequence 45123 Results**

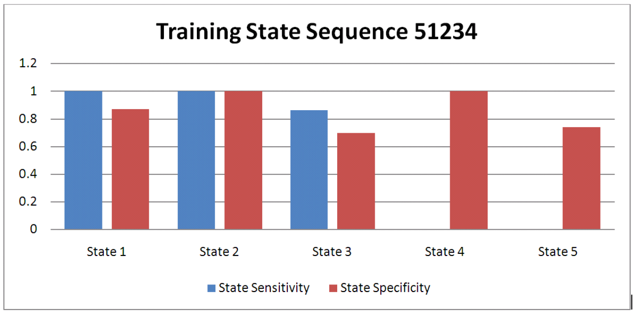


**Figure 13-Training State Sequence 51234 Results**

## V. DSM Situational Awareness Conclusion

As introduced, this research was motivated to define and demonstrate the uniqueness, benefits, and operational utility of the DSM and the feasibility of recognizing mobile wireless distortion. Mobile wireless channel dispersion was described as a behavioral FSMM and embedded within a HMM. The DSM has been defined through system architecture and state diagrams. A conceptual CR system architecture has been proposed which would enable the DSM to provide environmental sensing enabling cognitive processing channel distortion awareness. Finally the DSM was demonstrated in a CSR model whose sensitivity and specificity was quantified. The results were comparable to published results from biological sequence recognition systems shown in [15]. These results suggest that with proper training, the DSM HMM would be better than 80% accurate at properly identifying the mobile wireless channel states associated with non-dispersive, time dispersive, frequency dispersive conditions. The results were negative with regard to the dual dispersive case necessitating further investigation into this case.

There are known accuracy limitations with HMM approaches and next steps in CSR research will include optimized HMM estimation processes, adaptive HMM parameter tracking, CSR architecture, and/or hybrid HMM/neural network CSR systems.

## References


[1] *"Estimated Measurement-Based Markov Models: Towards Flexible and Accurate Modeling of Wireless Channels,".* **Han, SeonYeong and Abu-Ghazaleh.** s.l. : " Wireless and Mobile Computing, Networking and Communications, 2009. WIMOB 2009. IEEE International Conference on , 12-14 Oct. 2009. vol., no., pp.331-337.

[2] *"On first-order Markov modeling for the Rayleigh fading channel,".* **Tan, C.C. and Beaulieu, N.C.** s.l. : Communications, IEEE Transactions on , vol.48, no.12, pp.2032-2040, Dec 2000.

[3] **Lopez-Guerrero, M. and Gomez, J.** *"A mobility-based channel model for wireless systems with adaptive modulation,".* s.l. : Electrical and Computer Engineering, 2009. CCECE '09. Canadian Conference on , vol., no., pp.750-755, 3-6 May 2009.

[4] **Kundu, S.R., Basu, K. and Das, S.K.** *"Finite state Markov model for effective bandwidth calculation in wireless packet networks,".* s.l. : Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks, 2005. WIOPT 2005. Third International Symposium on , vol., no., pp. 351- 357, 3-7, April 2005.

[5] **Riediger, M. and Shwedyk, E.** *"Communication receivers based on Markov models of the fading channel,"* . s.l. : Communications, IEE Proceedings- , vol.150, no.4, pp. 275- 279, 12 Aug. 2003.

[6] **Kumwilaisak, W. and Kuo, C.-C.J.** *"Adaptive variable length Markov chain for non-stationary fading channel modeling,".* s.l. : Global Telecommunications Conference, 2002. GLOBECOM '02. IEEE , vol.3, no., pp. 2046- 2050 vol.3, 17-21 Nov. 2002.

[7] **Zhang, Qinqing and Kassam, S.A.** *"Finite-state Markov model for Rayleigh fading channels,".* s.l. : Communications, IEEE Transactions on , vol.47, no.11, pp.1688-1692, Nov 1999.

[8] **Pimentel, C., Falk, T.H. and Lisboa, L.** *"Finite-state Markov modeling of correlated Rician-fading channels,".* s.l. : Vehicular Technology, IEEE Transactions on , vol.53, no.5, pp. 1491- 1501, Sept. 2004.

[9] **Babich, F., Kelly, O.E. and Lombardi, G.** *"Generalized Markov modeling for flat fading,".* s.l. : Communications, IEEE Transactions on , vol.48, no.4, pp.547-551, Apr 2000.

[10] *"A Markov model for the mobile propagation channel,".* **Babich, F. and Lombardi, G.** no.1, s.l. : Vehicular Technology, IEEE Transactions on , Jan 2000, Vol. vol.49. pp.63-73.

[11] **Xie, Yongjun and Fang, Yuguang.** *"A general statistical channel model for mobile satellite systems ,".* s.l. : Vehicular Technology, IEEE Transactions on , vol.49, no.3, pp.744-752, May 2000.

[12] *MIMO Wiener Model Identification for Large Scale Fading of Wireless Mobile Communications Links.* **Galvao, R. K. H., et al.** June 2007, s.l. : IEEE Communication Letters, 2007, Vol. 11 no. 6.

[13] *An Algorithm for Estimation and Tracking of Distributed Diffuse Scattering in Mobile Radio Channels.* **Richter, A., Salmi, J. and Koivunen, V.** Cannes : Signal Processing Advances in Wireless Communications, 2006. SPAWC '06. IEEE 7th Workshop on , 2006. 2-5 July 2006 ; pp. 1 - 5 .

[14] *Time varying channel modeling for ad-hoc mobile wireless networks.* **Olama, M.M., Djouadi, S.M. and Charalambous, C.D.** Las Vegas, NV : Wireless Communications and Networking Conference, 2006. WCNC 2006. IEEE , 2006. 1525-3511 .

[15] Durbin, R., Eddy, S., Krogh, A., & Mitchison, G. (1998). *Biological Sequence Analysis.* New York: Cambridge University Press.

[16] Mathworks. (2011, 03). *hmmdecode function*. Retrieved from MATLAB®:Statistics toolbox technical documentation: http://www.mathworks.com/help/techdoc/stats/hmmdecode.html

[17] Mathworks. (2011 03). *hmmestimate function*. Retrieved from MATLAB ® :Statistics toolbox technical documentation: http://www.mathworks.com/help/techdo/stats/hmmestimate.html

[18] Mathworks. (2011 03). *hmmtrain function*. Retrieved from MATLAB ® :Statistics toolbox technical documentation: http://www.mathworks.com/help/techdoc/stats/hmmtrain.html

[19] Mathworks. (2011 03). *hmmviterbi function*. Retrieved from MATLAB ® :Statistical toolbox technical documentation: http://www.mathworks.com/help/techdoc/stats/hmmviterbi.html

[20] MATLAB ®. (2011 03). Registered Trademark. Natick, MA, U.S.A.: Mathworks Inc.

[21] An Introduction to Hidden Markov Models. Rabiner, L.R. and Juang, B. H. January,1986 : IEEE ASSP Magazine.

[22] A tutorial on Hidden Markov Models and Selected Applications in Speech Recognition. Rabiner, L. R. No 2, s.l. : IEEE, 1989, Vol. 77. 8825949.

[23] Maier, Mark W. and Rechtin, Eberhardt. The Art of Systems Architecting, 2nd Edition. s.l. : CRC Press, 2000.

[24] Kossiakoff, Alexander and Smart, William N.Sweet. Systems Engineering: Principles and Practice. s.l. : John Wiley and Sons, 2003.