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Multisensor Modulation Classification (MMC)

Implementation considerations – USRP case study

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***Abstract*— This paper provides hardware implementation considerations for previously developed algorithms designed to improve the classification of the modulation of weak radio signals utilizing multiple sensors. The case study presented focuses on a likelihood-based approach in a centralized data fusion framework. Data sets from multiple sensors are fused to obtain a more accurate modulation classification as previously demonstrated in simulations. The algorithms are implemented on a hardware testbed that consists of the laboratory grade software defined radio platforms. The performance is examined in realistic environments and compared with results obtained via simulations. The testbed results indicate that the predicted performance improvements are difficult to achieve in practice and the algorithms need to be tailored to account for hardware features and signal propagation effects. Differences between results obtained in simulations and in hardware implementation are discussed and adjustments are made to achieve consistent improvement necessary for refinement of the solution toward military applications.**

Keywords—automatic modulation classification, multi-sensor systems, sensor fusion, USRPs, SDR

I. Introduction

A. Software defined radios and modulations

Recent advances in software-defined radio (SDR) and networking technology enable enhanced capabilities for radio frequency (RF) communication devices operating in difficult environments. Modulations in digital RF communication signals enable efficient usage of bandwidth and support transmission of information at an adjustable bit-rate for the same baud-rate. A transmitter can change the modulation of the signal based on the feedback from the cooperating receiver. An eavesdropping SDR receiver can self-reliantly recognize the modulation format from signal features. In the environments with degraded channel quality, such an SDR receiver loses its ability to self-reliantly recognize the modulation. In this case, several SDR receivers can cooperatively sense the signal and jointly classify the modulation.

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B. Automatic modulation classification

During the last decade a number of feature-based (FB) and likelihood-based (LB) techniques have been reported to advance receiver's automatic modulation classification (AMC) capability [1-4]. AMC is a difficult problem, even for the signals adhering to perfect mathematical models in low noise scenarios. The AMC is significantly more difficult on actual signals in hostile environments. Regardless of the algorithm employed, multiple receivers are expected to aid classification by exploiting signal diversity [5, 6, 8]. The features in a signal overwhelmed by noise may still be extracted if several receivers cooperatively observe the signal.

C. Objectives

Detection of RF signals encompasses extraction of appropriate spectrum content, appraisal of modulation, and triggering of an action (for example, decoding or jamming). The appraisal of modulation, or AMC, is often difficult due to signal degradation and lost features. Our objective is to develop and evaluate multi-sensor modulation classification (MMC) technology suitable for weak signals. The program aims to demonstrate that MMC can resolve modulation types in scenarios where single sensor AMC methods fail. In a noisy channel, an adaptive SDR will likely shift toward a low-bit rate modulation, which constrains the number of possible modulation formats to just a few. This paper addresses current implementation results and the performance of the AMC algorithm, both achieved in real-time on our SDR test bed.

D. Current state of practice

The likelihood-function-based methods for single sensor AMC are covered in [2]. The practice is limited because such AMC is only suitable for receivers operating in higher SNR region. During an engineering examination of modulated signals, it is common to plot the Constellation Diagram or I/Q scatter plot. For a modulated signal this Constellation Diagram exposes a pattern with clusters that reveal the modulation type (Q-PSK, 8-PSK, etc.). A better AMC is needed to reliably recognize modulations in a highly noisy non-cooperative environment. Fusion of data from multiple sensors could improve the clustering in a constellation diagram and unveil the modulation.

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II. Approach Overview

A. Multi-sensor approach

The multi-sensor approach exploits variants of the observed signal obtained from multiple coordinated receivers and classifies the modulation type based on a combined data set. This scenario is relevant for military applications that require RF signal sensing and classification. The sensing and classification tasks can be performed by a network of multiple low-cost receivers.

B. Synchronous and asynchronous cases

The theory and simulations for synchronous and asynchronous AMC using Expectation Maximization (EM) based algorithms are covered in [7-9]. The papers focus on the LB approach that requires computations of likelihood functions for each considered modulation format, and a knowledge of parameters associated with the observed model including channel gain, channel phase, noise variance and time offset at the receiver. When the parameters are not available, a conditional likelihood function is averaged over probability distribution of random *unknowns*. The resulting averaged function is maximized to estimate deterministic *unknowns*. The described variant of the LB approach is termed hybrid maximum likelihood (HML) approach. Finding *maximum likelihood* estimates of the *unknowns* can be computationally demanding, which can be circumvented using a numerical EM technique. The EM algorithm is performed in an iterative manner, starting with an initialization process for the *unknowns*. Similar to any other numerical algorithm, the initialization of the EM algorithm has a significant impact on the stationary point that the algorithm will converge to. Once the *unknowns* are estimated based on the EM algorithm, the *maximum likelihood* function for each modulation format is computed. Finally, the modulation corresponding to the *maximum log likelihood* value is selected.

A synchronous scheme assumes that the signal variants received by different sensors are sampled with a synchronized clock. An asynchronous scheme addresses the timing offset among sensors by considering it as one of the *unknowns*. Local sensor observations are fused with the assumption that they are independent. Flat block-fading that introduces coupling among the signal samples received by the same sensor over the duration of an observation period was ignored.

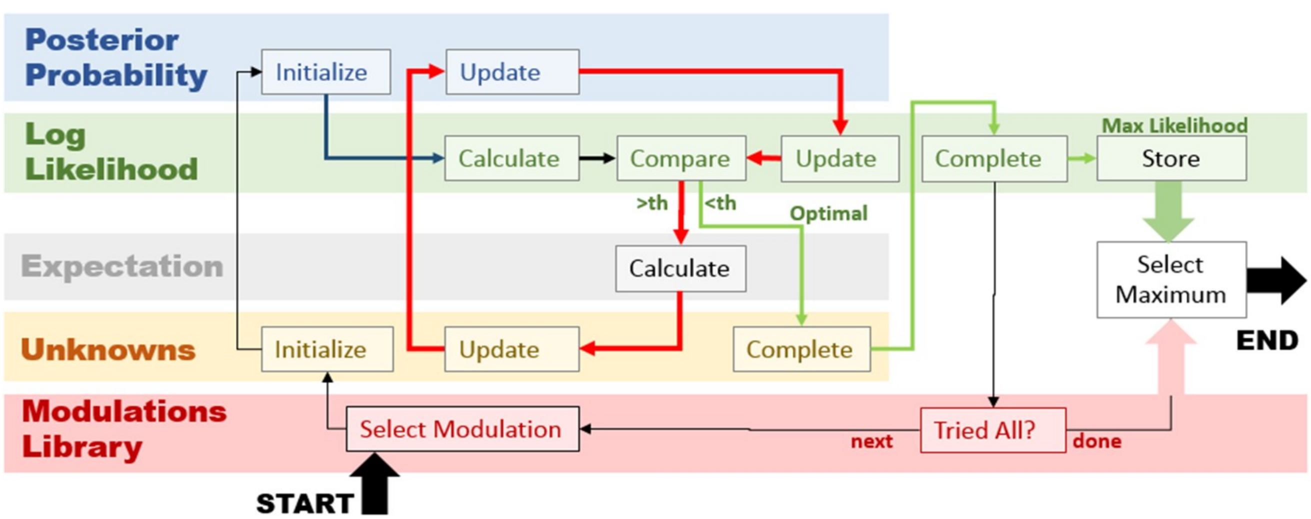
C. Implementation Considerations

A transmitting SDR can adjust its signal parameters (including signal strength, frequency and modulation) based on situational constraints (including channel conditions and priorities) and predefined patterns. Receiving SDRs will recognize the presence of a signal, coordinate sampling of the signal variants and jointly extract useful information from the combined sample.

Theory and simulation predict improvement in Probability of correct classification (P_c) for increasing number of sensors. For successful transition of this technology in military SDRs, in addition to demonstrating consistency of implementation with theoretical predictions and simulated results, we seek to adjust constraints so that these better reflect limitations of actual operational environments. The difficulties are examined to tie the unveiled limitations to the assumptions enacted during the theoretical development. The complexity of the involved algorithms, the execution time, and the amount of data shared among sensors all need to be reduced.

Fig. 1 shows the flow of the synchronous EM algorithm which starts with a selection of a modulation format from the library of modulations, estimation of the *unknowns* and initialization of the *posterior probability*. Variables are calculated and iteratively updated according to [8–9]. The time spent on the execution of the algorithm depends on the sample size and number of participating sensors, number of modulation formats, selected initialization procedure, and the exit criteria (loop indicated in red in Fig. 1). Initialization is the most time consuming procedure of the algorithm.

Fig. 1. Likelihood ratio based AMC via EM algorithm



The approach starts with assuming unknown parameters for the communication signal and assuming specific content for the library of modulations, and proceeds with an initialization process for the *unknowns*. These *unknowns* are updated using an iterative EM-based algorithm to find the *maximum log likelihood* values for each modulation in the dictionary. Finally the modulation corresponding to the maximum of *log likelihood* value is selected. Local sensor decisions or data are fused with the assumption that they are independent.

III. Implementation and Tests

A. Test Equipment

To perform testing and validation of the MMC performance with an increasing number of sensors, relevant scenarios were established and the algorithms were implemented in test-hardware consisting of the Universal Software Radio Peripheral N210 (USRP N210) and GNU radio platform. The power output of USRP is 15 dBm and the *noise figure* is 5 dB. The daughterboard performs mixing, amplification and low pass filtering of the signals. The on-board FPGA performs modulation, digital up/down conversion, interpolation and decimation before/after the dual DAC/ADC. Each USRP was paired with an omni-directional VERT2450 vertical antennas.

One USRP platform was designated as the transmitter. The remaining USRPs were used as receivers. In this paper we report experiments conducted with a varying number of receivers, ranging from two to four. Tests with four receivers demonstrated a sufficient increase in performance, reaching high probability of correct classification. Since four sensors provided high performance there was no motivation to consider a larger number of sensors. To assess the utility of the algorithms in a low SNR environment with a significantly larger number of receivers, the testbed would need to be expanded and enhanced with the means to provide efficient data sharing among sensors, as well as approaches to address increased computational complexity and decision timelines.

B. Test of synchronous MMC with two receivers

In the implementation of a synchronous MMC algorithm, the receiver was assumed to have no time offset. In this case, the modulation blocks in GNU radio were used to transmit signal modulated with 8-PSK. At the receiver, GNU radio blocks including *Costas loop* and *clock recovery* were used for frequency, phase and clock recovery of the carrier. In this setup, two sensors acquired variants of the transmitted signal modulated with 8-PSK. The dictionary was constrained to {8-PSK and 16-PSK}. The synchronous EM algorithm [8] was evaluated utilizing data from one sensor and from both sensors. During the tests, USRPs were equipped with RFX2400 daughterboards which did not have variable analog transmit gain. Instead, the receiver gain was varied in order to collect samples with different levels of distortion. Smaller gain led to a degraded constellation, representative of a low SNR scenario. One hundred Monte Carlo runs with consequent classification decisions were performed for each configuration. The probability of correct classification for each configuration was calculated by averaging recorded decisions and is presented in Table 1. The values of the probability of correct classification show that at low receiver gains, probabilities are low for one sensor but significantly higher with two sensors. This indicates that the addition of a second sensor improves the performance for weak signals. For visual clarity, color shading in Tables I–VI is used to highlight performance. Successful performance is indicated using light green shade. Yellow shade highlights mediocre performance. Unacceptable performance is indicated using light red shading.

TABLE I. P_C FOR SYNCHRONOUS TEST CASE

Number of sensors	Receiver Gain		
	5 dB	***10 dB***	***15 dB***
L=1	0.06	0.33	0.88
L=2	0.72	0.9	0.96

Dictionary: {8-PSK, 16-PSK}

C. Test of asynchronous MMC with two receivers

The asynchronous EM algorithm [9] was tested utilizing data from one sensor and from two sensors jointly. The dictionary was constrained to {QPSK, 8-PSK, and 16-PSK}. In this setup, a custom *root-raised-cosine* (RRC) pulse shaping filter was used at the transmitter (instead of the GNU radio block for RRC filter) for an increased degree of control over the pulse parameters. At the receiver, an identical pulse was used to estimate time offset. The modulated signals were transmitted sequentially and the probability of correct classification for each signal was calculated by averaging the results from 80 decisions. Unlike the synchronous algorithm, the asynchronous algorithm structure does not have a routine for estimating the noise variance. Thus, for the first set of tests, the SNR was assumed to be 10 dB, and later estimated to vary between 25 and 30 dB using a GNU radio *FFT block* at the receiver. Both, the assumed and estimated values were used with the same algorithm and configurations. From Table II, it is evident that the performance of the algorithm depends on the provided SNR. This indicates the need for accurate real time SNR estimation that should be performed in parallel with the data collection. As expected, the performance using two sensors was better compared to that of a single sensor for QPSK and 8-PSK. The performance decreased as the number of symbols in the constellation increased.

TABLE II. P_C FOR ASYNCHRONOUS TEST CASE

Number of sensors	Modulation of transmitted signal			SNR
	QPSK	***8-PSK***	***16-PSK***	
L=1	0.267	0.429	0.259	10 dB
L=2	1	0.681	0.4	
L=1	0.867	0.25	0.3	25-30 dB
L=2	0.917	0.5	0.22	

Dictionary: {QPSK, 8PSK, 16PSK}

D. Test of synchronous MMC with four receivers

The USRP's SBX and CBX daughterboards have a feature to vary the analog transmit gain. This feature enabled a set up in which the receive gain was kept constant while the transmit gain was varied to emulate scenarios with different levels of SNR. For example, Fig. 2 shows instantaneous power of an example signal depicted with three power levels:

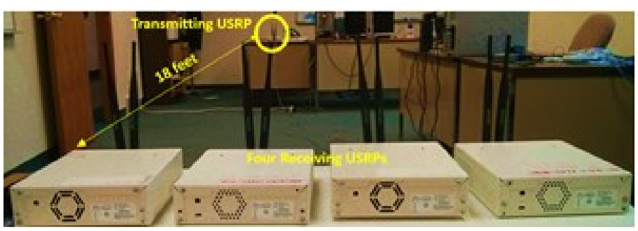
- High with SNR ranging between 25 dB and 30 dB,
- Medium with 10-15 dB SNR, and
- Low with 0-5 dB SNR.

The Low signal level is of primary interest. A range of SNR values is indicated rather than a single value, because the noise floor continuously fluctuates, while the portion of the signal containing information maintains its primary characteristics.

Fig. 2. Example of a modulated signal with three different power levels

Fig. 3 depicts the test set up consisting of one transmitting USRP and four receiving USRP nodes located 18 feet away from the transmitter. In this configuration, closely spaced receivers can be wired for complete data sharing. The SBX and CBX daughterboards with variable transmit gain allow for laboratory testing with gain control which affects signal quality.

Fig. 3. Experimental set up



The probabilities of correct classification for transmitted QPSK and 8-PSK signals are presented in Table III and IV, respectively. The results for QPSK in Table III are clearly excellent. The results for 8-PSK in Table IV are conflicting.

Tests of the synchronous MMC with four receivers were carried out with a similar configuration to that described in Section II.B-C with one difference. The signal strength was altered by an application of variable transmit gain. The receive gain was set to a constant 30 dB. The results for classifying 8-PSK modulation show improvement when two sensors are used. However additional sensors lead to a degradation of performance. This degradation was expected only for high SNR scenarios due to an inaccurate initialization process, in agreement with simulations of such conditions. For low SNR conditions, the expected monotonically increasing performance with a higher number of sensors was not evident in the results. The degradation is due to the phase error encountered when data from different sensors are combined.

If two sensors can provide improvement in a low SNR case, the multi-sensor concept can be adjusted to include distributed pairs of sensors. Hence, the 8-PSK MMC in low SNR case was evaluated using pairs of sensors. The experiments were conducted using a synchronized EM based algorithm with various pairwise sensors combinations to assess potential hardware problems or trends. Table V shows the probability of correct classification using different combinations of USRPs labeled as A, B, C and D. The performance showed high degree of variance from one pair to the next. This induced the need to investigate the received data for possible anomalies. The anomalous data could be potentially tagged and excluded from analyses.

TABLE III. P_C WHEN TRANSMITTED QPSK

Average SNR	**Number of sensors**			
	L=1	***L=2***	***L=3***	***L=4***
2 dB	0.15	0.94	0.90	0.95
12 dB	0.24	0.90	0.96	0.91
27 dB	0.39	0.93	0.93	0.92

Dictionary: {QPSK, 8PSK}

TABLE IV. P_C WHEN TRANSMITTED 8-PSK

Average SNR	**Number of sensors**			
	L=1	***L=2***	***L=3***	***L=4***
2 dB	0.69	0.88	0.64	0.58
12 dB	0.76	0.91	0.54	0.58
27 dB	0.82	0.93	0.72	0.56

Dictionary: {8PSK, 16PSK}

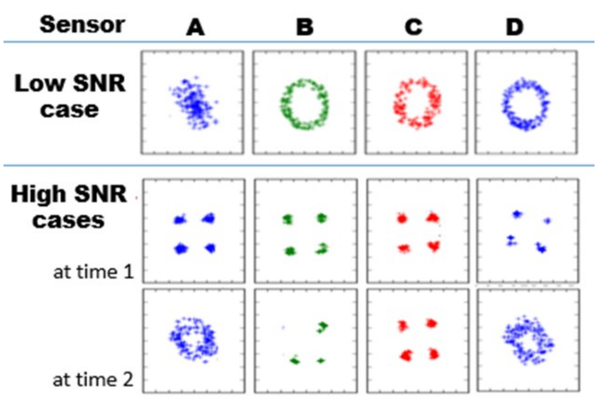
TABLE V. P_C WHEN TRANSMITTED 8-PSK IN LOW SNR WITHOUT VERIFYING DATA INTEGRYTY

Sensor	***A***	***B***	***C***	***D***
A		0.84	0.71	0.68
B	0.84		0.66	0.51
C	0.71	0.66		0.63
D	0.68	0.51	0.63	

Dictionary: {8PSK, QPSK}

Investigation of the varying classification performance evident in Table V revealed that not all of the USRPs were receiving the constellation correctly at all times. Fig. 4 provides examples of received signal constellation diagrams, modulated with QPSK. The example depicts two SNR cases: Low SNR and High SNR. The High SNR examples are provided for visual clarity and to highlight the artifact. The constellation diagrams were examined continuously in real-time for all four sensors. It was discovered that each constellation became corrupt due to a frequency offset which would appear from time to time. No obvious pattern to such occurrences was observed. The corrupt constellation eventually cleared up on its own. The time varying nature of signal artifact was difficult to observe in the constellation diagram of a low SNR scenario (one snapshot of which is presented in the top row of Fig. 4). We increased the signal' SNR by properly adjusting the gains and were able to observe the artifact. The High SNR data snapshot is shown in the second row of Fig. 4. This is a good example of reliable data. Another High SNR data snapshot is shown in the bottom row of Fig.4. This is a representative example depicting the presence of the artifact. Even signals with higher SNR exhibited inconsistencies in their constellation due to the frequency offset. These inconsistencies appearing as random phase rotations occurred during the observation period on all of the sensors.

Fig. 4. Example constellation diagrams for sensors A, B, C and D.



Since our objective was to verify the effectiveness of algorithms under low SNR conditions, reliable data sets at low SNR were required for an accurate assessment of the algorithms' utility. When an integrity check was used to flag or discard degraded data, the algorithms performance was adequate, and the classification improved consistent with the reported simulation results [8-9].

E. MMC by individual estimation of unknowns

A rigorous scrutiny of the implementation results exposed that the values of the *maximum likelihood ratios* for different modulation formats in the dictionary were extremely close. This effect was speculated to be caused by the joint estimation of the *unknowns* based on a marginalized joint likelihood function. When the *unknowns* were estimated individually, and the sum of the *maximum likelihood ratios* was used to make the final decision, the performance was expected to improve with addition of sensors. Table VI depicts the results for a setup in which the *unknowns* were estimated individually. A lower SNR scenario was emulated by setting the transmit gain and the receive gain to 1 dB. The classification was carried out in configurations involving a varying number of receivers: each sensor performed classification, four pairs of sensors were randomly chosen, and all four SDRs were utilized for a joint decision. In each configuration, one hundred Monte Carlo runs were used to make decisions and determine the probability of correct classification. This procedure was performed twice, once for signals modulated with 8-PSK and again for QPSK modulation.

TABLE VI. P_C USING INDIVIDUAL ESTIMATION OF UNKNOWNS

Tx Gain=1 Rx Gain=1	Probability of correct classification (Pc) from indicated ***Number of sensor L and sensor identification***					
Tx Modulation	***L=1***	***USRP ID***	***L=2***	***USRP ID***	***L=4***	***USRP ID***
8-PSK	0.32	A	0.86	A, B	0.92	A, B, C, and D
	0.88	B	0.45	A, C		
	0.20	C	0.88	C, B		
	0.19	D	0.88	C, D		
QPSK	0.86	A	0.86	A, B	0.96	A, B, C, and D
	0.56	B	0.77	A, C		
	0.86	C	0.86	C, B		
	0.83	D	0.86	C, D		

Dictionary: {8PSK, QPSK}

Table VI shows that the performance of multiple sensors was much better compared to that of single sensor. It is also evident that, when using the method of individual estimation, the performance increase depicts a monotonic trend and eliminates any kind of degradation that was observed when using joint estimation of the *unknowns*. This was a very positive aspect of these results - the performance improved as the number of sensors was increased consistent with simulations predictions.

IV. PRACTICAL CONSIDERATIONS

A. Algorithms tunining

The inconsistencies seen between simulations and implementation in our evaluation and tests may be attributed to a combination of factors including lack of independence in signal variants observed by closely spaced receivers, multi-path fading, instability in frequency-selective time-varying channels, and minor changes in carrier frequency. Generally there is a stated need for the preprocessing of a signal for noise reduction, and estimation of various parameters, including carrier frequency, symbol period, and signal power. When several variants of the same signal are expected, there is a need for equalization and synchronization. When multiple sensors provide data for the same signal of interest, discarding data that is a suspect of being corrupted is easier and faster. In the context of an operational system, real-time interception and processing are vital for actionable response and decision making. Our preliminary analyses of achievable processing time indicate a trade-off between prediction quality and real-time operations.

Depending on the nuances of a classification algorithm, different preprocessing tasks may be required. Multi-sensor classifiers are developed assuming spatial diversity and independent channels and often require a large number of samples. The implementation challenges correlate to the quality of hardware under consideration. Different SDR hardware may present various challenges and limitations in terms of sensitivity to noise and ability to recover carrier phase and frequency. In a case study with USRPs, the time varying random distortion in the received signal was evident. This distortion may have been the cause of degraded performance manifesting itself in larger signal variation over that predicted through simulations. Thus, the algorithms needed to be tuned to suit the hardware under consideration to ensure the consistent and reliable performance.

B. Relevancy and Impact

Those responsible for communications integrity should use the results in this paper to help them understand the difference between theoretically predicted possibilities, and the capabilities that are actually achievable in the battlefield.

The impact of our success is an improved capability to classify modulations of weak signals using a handful of low-cost sensors, sharing data in a coordinated manner.

V. Conclusion

An overview of the technology aspects encompassing utilization of multiple low-cost sensors for automatic modulation classification of weak signals was presented in this paper with a focus on a case study using USRPs. The implementation of synchronous and asynchronous EM algorithms on a testbed consisting of several SDRs was presented and discussed in light of refining achieved solutions for relevant military applications.

The initial implementation showed evident improvement in performance when two sensors were used for classification compared to a single sensor scenario. However, due to initialization errors and joint estimation of the *unknowns*, the performance of the algorithm declined as the number of sensors increased. This was a counterintuitive and disturbing finding. However, there was an evident improvement in the USRP case study when the procedure for estimation of the *unknowns* was adjusted. Once the algorithm was modified to estimate the *unknowns* individually and make the final decision from the sum of the individual *maximum likelihood ratios* of each sensor, a performance improvement became evident for an increasing number of sensors.

References

[1] O. A. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, “Survey of automatic modulation classification techniques: classical approaches and new trends,” *IET Communications*, vol. 1, no. 2, pp. 137–159, Apr. 2007.

[2] J. L. Xu, W. Su, and M. Zhou, “Likelihood-ratio approaches to automatic modulation classification,” *IEEE Trans. Systems, Man, and Cybernetics - Part C: Applications and Reviews*, vol. 41, no. 4, pp. 455–469, Jul, 2011.

[3] F. Hameed, O. A. Dobre, and D. C. Popescu, “On the likelihood-based approach to modulation classification,” IEEE Trans. Wireless Comm., vol. 8, no. 12, pp. 5884–5892, Dec. 2009.

[4] W. Wei and J. M. Mendel, “Maximum-likelihood classification for digital amplitude-phase modulations,” IEEE Trans. Commun., vol. 48, no. 2, pp. 189–193, Feb. 2000

[5] A. Abdi, O. A. Dobre, R. Chauchy, Y. Bar-Ness, and W. Su, “Modulation classification in fading channels using antenna arrays,” in *Proc. IEEE MILCOM*, Monterey, CA, Nov. 2004, pp. 211–217.

[6] B. Dulek, O. Ozdemir, P. K. Varshney, and W. Su, "Modulation discovery over arbitrary additive noise channels based on the Richardson-Lucy algorithm," *IEEE Signal Processing Letters*, vol. 21, no. 6, pp. 756-760, June, 2014

[7] A. P. Dempster, N. M. Laird, and D. B. Rubin, “Maximum likelihood from incomplete data via the EM algorithm,” Journal Roy. Stat. Soc. (Series B), vol. 39, no. 1, pp. 1–38, 1977.

[8] O. Ozdemir, R. Li, and P. K. Varshney, "Hybrid maximum likelihood modulation classification using multiple radios," *IEEE Communications Letters*, vol. 17, no. 10, pp. 1889-1892, Oct. 2013

[9] O. Ozdemir, P. K. Varshney, and W. Su "Asynchronous hybrid maximum likelihood classification of linear modulations," IEEE Global Communications Conf. (GLOBECOM), Atlanta, GA, Dec. 2013.