Signal Sensing and Modulation Classification Using Pervasive Sensor Networks

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Abstract— **This paper discusses the use of asynchronous low-cost sensors in distributed locations for sensing and classifying weak wireless signals. This weak signal may not be identified by using a single sensor alone, but can be detected and classified by fusing multiple weak signals collected by sensor networks. The asynchronous signal copies have unwanted offsets in time, frequency, and phase due to the diversities in local oscillators and unknown communication channels. This work proposes a post-synchronization method to estimate and compensate for offsets in the fusion process without adjusting the sensor parameters. The properly combined signal from the distributed sensors achieves a higher processing gain for reliable signal exploitation.**

Index Terms — Spectrum sensing, Automatic modulation classification, cognitive radios, distributed sensors, sensor network.

I. Introduction

With the rapid growth of wireless communication services and high performance electronic devices, modern wireless communications seek more intensive and efficient use of spectrum and higher data rates. New technology such as dynamic spectrum access, adaptive modulation, low-power transmission, and sensor networks have been investigated as desired capabilities of cognitive radios which can freely hop through available spectrum and nodes, modify transmission characteristics and waveforms, and exploit opportunities of using the spectrum and power effectively. This raises the great challenge of sensing the agile signal of interest (SOI) in a dynamic environment with unpredictable adaptations and low transmitting power. Currently, spectrum sensing and classification have largely been limited to use a single sensor/receiver with sophisticated signal processing. The performance of such techniques is significantly degraded by the location, channel quality, and the signal strength of the receiving sensor. In a non-cooperative communication environment (i.e., no handshaking between transmitters and receivers), the transmitting signal and communication channels are usually not favorable to an ad-hoc receiver or sensing unit and the received signal at the sensor could be weak and distorted so that signal sensing and classification becomes extremely difficult and unreliable. To address the sensing and classification bottleneck, the use of sensor network is studied. A network centric framework should not only build interfaces for connecting distributed devices, but also search for unknown dimensions for the new capabilities. Two major approaches have been investigated [1] which are the fusion of local signal decisions [2][3] and the central decision of the fused signals [4][5]. The former uses expensive distributed processors to make decisions locally and the latter combines the multiple signal copies from less-expensive sensors to make a central decision. However, the synchronization of time, frequency, and phase among sensors in making central decision is not only costly but also impractical in many operations. This paper focuses on the central decision of the fused signals approach by using the low-cost sensors or leverage the existing networked sensors distributed at all scales throughout everyday life without the accurate synchronization, The asynchronous signal copies are processed in the fusion center using post-synchronization before they are combined. Fast searching algorithms for parameter offsets are proposed. The copy of the optimally combined signals has been demonstrated to give more accurate description of the SOI than any one of the individual signal copies alone.

The rest of the paper is organized as follows. In Section II, the distributed sensing and classification concept is proposed. In Section III, the signal models at distributed locations are described. The post-synchronization approaches are formulated in Section IV. Automatic modulation classifiers are briefly introduced in Section V. Simulations are presented in Sections VI. Finally, conclusions and future work are provided in Section VII.

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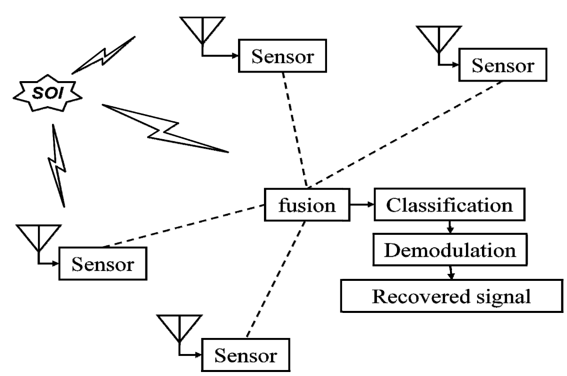

Figure 1. Distributed signal exploitation

II. Description of the Method

The concept of the central decision based distributed signal sensing and modulation classification method, Fig. 1, is to utilize simple, inexpensive, low-maintenance, and heterogeneous sensors so massive sensing devices can be deployed to cover a wide-spread geographical area seamlessly and multiple narrow-band receivers can be collaborated to handle a wide frequency band effectively. The distributed sensors are optimally clustered and orchestrated by a fusion center with sufficient processing power. This dumb sensors and smart fusion center scenario has two extreme options: (i) deploying massive amounts of very low-cost and disposable sensors to cover remote, inaccessible, hostile and dangerous regions, and (ii) leveraging all existing infrastructure such as heterogeneous conventional or cognitive radios, Wi-Fi devices, phones, or mesh networks by contributing limited or partial operation for signal sensing (as a secondary function) under a service agreement without affecting their primary function. The latter is also considered to be an inexpensive and low-maintenance case since the assets are shared which are already established, managed and maintained by primary users. Under the framework of dumb sensors, the interfaces of the sensors are pushed towards the antennas. In other words, the burden of the extra signal processing is absorbed by the fusion center and the sensors only relay the raw data. All operational decisions are made and executed at the fusion center which not only avoids the requirements for demodulating signals at distributed locations and simplifies the security and operational requirements, but also makes the applications and future system upgrade independent to the distributed sensors. Each of these two options does not contradict the other and they can be used in the same platform or application.

The fusion center may be located at the same location as a sensor. The fusion center sends periodic requests to L distributed sensors, R_1, R_2, ..., and R_L to acquire the weak SOI. Upon the reception of the request, the distributed sensors take short time duration snapshots of the SOI. The distributed sensors are assumed to provide very limited signal processing capabilities such as RF reception and transmission, frequency tuning and down-conversion, filtering, and digitization. Thus, all sensors are asynchronous and non-cooperative to one another and are used only for communicating with, or relaying distributed snapshots to, the fusion center. It is important to indicate that the snapshots are very short and are taken periodically. Therefore there is ample time between any two snapshots for signal processing and analysis. The entire operation is conducted in real-time.

Earlier approaches for central decision signal sensing and classification were inspired by the success of the multiple-antenna based modulation classification [6]-[8] and require synchronous sensors for coherent signal combining. However, practically, the distributed signal copies will not be perfectly synchronous due to the unknown channels and Doppler effect between the SOI and the distributed sensors. In an asynchronous sensor scenario, magnitudes, phases, frequencies, and sampling clocks among sensors are all different. Consequently, the fusion center must estimate the relative phase offset (RPO) induced by different local oscillators (LOs), channels and filters, relative time offset (RTO) induced by different propagation paths and sampling clocks, the relative frequency offset (RFO) induced by different LOs and the Doppler effect, and the relative sampling frequency offset (RSO) caused by the jitter and aging of the sampling clocks before combining the signal copies coherently. The fusion center is designed to have adequate signal processing power and time to estimate, analyze, and process the data delivered by all sensors to generate an enhanced signal for detection, classification and blind demodulation.

III. SIGNAL MODEL

In the dumb sensor scenario, the sensors do not make local decisions but store the short snapshots, $r_i(t)$, $i=1, 2, ..., L$, as time-stamped data packets and forward them to the fusion center for processing. The packets can be transmitted to the fusion center using any communication method. Without loss of generality, R_1 is assumed to be the reference sensor, R_2, R_3, ..., and R_L are compared to R_1 for calculating all offsets. It is further assumed that the channels have no noticeable change within a very short collection time period. The signal packets received at the fusion center can be described as

$$r_i(t) = \Delta\alpha_i e^{-j(\Delta\omega_i t + \Delta\beta_i)} s(t + \Delta\tau_i) + n_i(t) \tag{1}$$

where $i=2, 3, ..., L$; $\Delta\omega_i$, $\Delta\beta_i$, and $\Delta\tau_i$ are RFO, RPO, and RTO, respectively, and $\Delta\alpha_i$ is the relative magnitude offset (RMO) which does not need to be known in the post-synchronization. All relative offsets are referring to

$$r_1(t) = s(t) + n_1(t) \tag{2}$$

where $s(t) = a_0 s_0(t) e^{-j(\omega_0 t + \beta_0)}$ is the frequency down-converted copy of the SOI observed at R_1, $s_0(t)$ is a sequence of pulse shaped information symbols, a_0, ω_0, and β_0 are gain, frequency, and phase offsets between the transmitter and R_1, respectively, and $n_i \sim \mathcal{N}(0, \sigma_i)$, $i=1, 2, ..., L$ is *i.i.d.* circularly symmetric complex additive white Gaussian noise (AWGN). If $\Delta\omega_i$ and $\Delta\tau_i$ can be estimated and eliminated, the signals can be combined to form

$$r^c(t) = \overline{\alpha} s(t) + \overline{n}(t) \approx \overline{\alpha} s(t)$$

where $\overline{a} = \sum_{i=1}^{L} \Delta\alpha_i \, e^{-j\Delta\beta_i}$ and $\overline{n}(t) = \sum_{i=1}^{L} n_i(t)$. If all signals have equal gains and all noises have equal variances, the SNR of the combined signal is L times the SNR of a single signal when $\Delta\beta_i = 0$. However, under the assumption of using only simple sensors, the offsets among sensors are not be able to be estimated locally and the sensors in the network will not be synchronous. The concept of post-synchronization method is to collect asynchronous signal copies first and compensates for them later in the fusion center.

IV. POST-SYNCRONIZATION METHOD

Two categories of offsets in the network are the magnitude, time, frequency and phase offsets between the transmitter and receiving sensors and the relative offset among distributed sensors as shown in Fig. 2. The goal of post-synchronization is to compensate for the RTO, RFO, RPO, and RSO so that the distributed signal copies can be combined constructively without adjusting the parameters of the networked sensors or broadcasting reference signals. The post-synchronization consists of several steps including clustering, coarse and fine offset estimations. The clustering step sorts the signal copies and excludes the unreliable ones based on the signal power strength, channel conditions, and transmitter locations to form an optimized sensor cluster. The coarse offset estimation reduces the offset searching to a smaller searching domain, and the fine estimation conducts the final tuning to polish the offset estimation and optimize the compensation results. With time-varying channels, adaptive mechanism may be used to compensate the parameter variations. Finally, the distributed signal copies are combined to yield a centralized decision as show in Fig. 3.

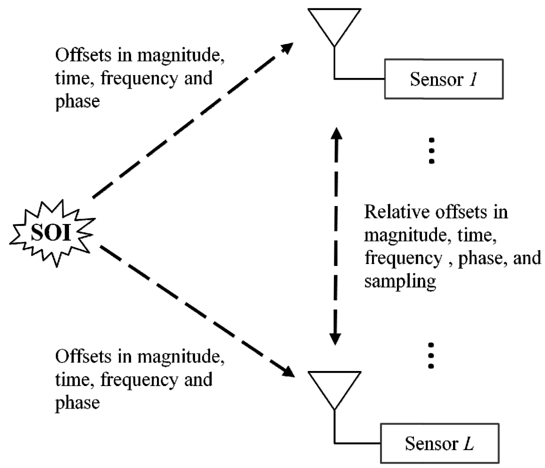

Figure 2. Time, frequency and phase Offsets

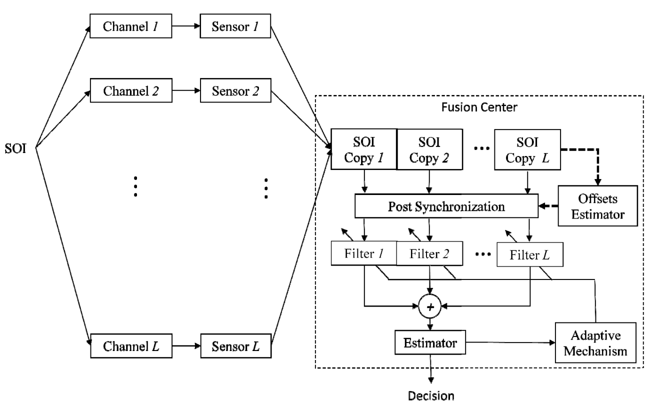

Figure 3. Post-synchronization and signal combining

Defining

$$q_i(\Delta a_i, \Delta\beta_i, \Delta\omega_i, \Delta\tau_i, t) = r_1^*(t) r_i(t)$$
$$= \Delta a_i e^{-j(\Delta\omega t + \Delta\beta_i)} s^*(t) s(t+\Delta\tau_i) + v_i(t), \quad (3)$$

where * denotes the complex conjugate, j is the imaginary unit, and $v_i(t)$ includes all the uncorrelated terms, the correlation function over the observation time period $T_0 >> \Delta\tau_i$ is

$$\chi(\Delta a_i, \Delta\beta_i, \chi_1) = \int_{t \in T_0} q_i(\Delta a_i, \Delta\beta_i, \Delta\omega_i, \Delta\tau_i, t) dt$$
$$\approx \Delta a_i e^{-j\Delta\beta_i} \chi_1(\Delta\omega_i, \Delta\tau_i). \quad (4)$$

where $\Delta a_i e^{-j\Delta\beta_i}$ is a complex number representing the linear offsets, and

$$\chi_1(\Delta\omega_i, \Delta\tau_i) = \int_{t \in T_0} e^{-j\Delta\omega t} s_1^*(t) s_i(t+\Delta\tau_i) dt \quad (5)$$

is a function for nonlinear offsets with a maximum magnitude of

$$\chi_1(0,0) = \int_{t \in T_0} s^*(t) s(t) dt \quad (6)$$

Equation (5) is widely used for detecting cyclostationarity [9] and Doppler shift [10], where $\Delta\omega_i$ and $\Delta\tau_i$ are estimated by maximizing $|\chi_1(\Delta\omega_i, \Delta\tau_i)|$. $\Delta\beta_i$ can be calculated by calculating the phase of $\chi(\Delta\alpha_i, \Delta\beta_i, \chi_1(0,0))$.

The corresponding frequency domain correlation can be obtained by using the Fourier transfer of r_i and r_1 as below:

$$R_i(\omega) = \Delta\alpha_i e^{-j(\Delta\tau_i\omega + \Delta\beta_i)} S_i(\omega + \Delta\omega_i) + N_i(\omega) \quad (7)$$
$$i = 2, 3, \ldots, L, \text{ and } R_1(\omega) = S(\omega + \Delta\omega_i) + N_1(\omega),$$

wherec $R_i(\omega)$, $R_1(\omega)$, $S(\omega)$, $N_i(\omega)$, and $N_1(\omega)$ are the Fourier transform of $r_i(t)$, $r_1(t)$, $s(t)$, $n_i(t)$, and $n_1(t)$, respectively. Defining

$$Q_i(\Delta a_i, \Delta\beta_i, \Delta\omega_i, \Delta\tau_i, \omega) = R_1^*(\omega) R_i(\omega)$$
$$= \Delta a_i e^{-j(\Delta\tau_i\omega + \Delta\beta_i)} S^*(\omega) S(\omega + \Delta\omega_i) + V_i(\omega) \quad (8)$$

where $V_i(\omega)$ is the uncorrelated terms. The frequency correlation over the observation frequency domain $W_0 >> \Delta\omega_i$ is

$$\Omega(\Delta a_i, \Delta\beta_i, \Omega_1) = \int_{\omega \in W_0} Q_i(\Delta a_i, \Delta\beta_i, \Delta\omega_i, \Delta\tau_i, \omega) d\omega$$
$$\approx \Delta a_i e^{-j\Delta\beta_i} \Omega_1(\Delta\omega_i, \Delta\tau_i) \quad (9)$$

where

$$\Omega_1(\Delta\omega_i, \Delta\tau_i) = \int_{\omega \in W_0} e^{-j\Delta\tau_i\omega} S^*(\omega) S(\omega + \Delta\omega_i) d\omega \quad (10)$$

is used for estimating the nonlinear offsets $\Delta\omega_i$ and $\Delta\tau_i$ with a maximum magnitude of

$$\Omega_1(0,0) = \int_{\omega \in W_0} S^*(\omega) S(\omega) d\omega \quad (11)$$

Unfortunately, the two-dimensional searching of $\Delta\omega_i$ and $\Delta\tau_i$ for $i=2, 3, \ldots, L$ is a tedious and computationally-intensive process. This paper proposes a one-dimensional search method known as Magnitude Correlation Function (MCF) for estimating RFO and RTO. The RTO can be estimated by finding the best estimate $\Delta\hat{\tau}_i$ such that the time-domain MCF

$$\rho(\Delta a_i, \Delta\hat{\tau}_i) = \int_{t \in T_0} \|r_1(t)\| \, \|r_i(t - \Delta\hat{\tau}_i)\| dt \approx \Delta a_i \rho_1(\Delta\tau_i) \quad (12)$$

is maximized. Where,

$$\rho_1(\Delta\hat{\tau}_i) = \int_{t \in T_0} \|s(t)\| \, \|s(t+\Delta\tau_i-\Delta\hat{\tau}_i)\| dt \tag{13}$$

If the signal is digitized, the values between two samples may be interpreted for the better time resolution in correlation. Applying the estimated RTO to compensate $\Delta\tau_i$ in either (4) or (9), the two-dimensional searching is reduced to the one-dimensional one for estimating RFO alone. Thus, both RTO and RFO are estimated promptly.

Furthermore, RFO can be expressed using

$$\varphi(\Delta\beta_i, \Delta\omega_i, t) = \angle [r_1^*(t) r_i(t)] \tag{14}$$

with a noiseless form of

$$-\varphi(\Delta\beta_i, \Delta\omega_i, t) = \Delta\beta_i + \Delta\omega_i t \tag{15}$$

The slope (RFO) and the intercept (RPO) are described by a linear regression equation. RFO can also be discussed by the average, E, of phase differences, that is

$$\Delta\hat{\omega}_i = -E\left(\frac{d\varphi_i(\Delta\beta_i, \Delta\omega_i, t)}{dt}\right) \tag{16}$$

Unlike χ, ρ does not suppress the additive noises. However, it provides a faster and effective one-dimensional search for RTO and the parallel processing can be used for correlating multiple signal copies.

After estimation, the correlation in (5) can be compensated to have

$$\chi_1(\varepsilon_i, \delta_i) = \int_{t \in T_0} e^{-j\varepsilon_i t} s^*(t) s(t+\delta_i) dt \tag{17}$$

where $\varepsilon_i = \Delta\omega_i - \Delta\hat{\omega}_i$ and $\delta_i = \Delta\tau_i - \Delta\hat{\tau}_i$ are residual RFO and RTO, respectively. Experiment shows that those residuals are negligible in most of applications. If the further correction of RFO and RTO is necessary, optimization can be conducted by fine tuning ε_i and δ_i in the vicinity (a smaller searching area) of the optimal estimates to obtain $\Delta\tilde{\omega}_i$ and $\Delta\tilde{\tau}_i$. $\Delta\tilde{\beta}_i$ can be calculated using the phase of χ in (4) after estimating RFO and RTO. Note that (i) the RMO will not affect the post-synchronization result. (ii) A small RPO will not significantly complicate the signal processing. It can be shown that if RPOs are uniformly distributed in a domain less than 2π, the combined signal with existing RPOs has a higher SNR compared to the single one if L is sufficiently large (iii) the smaller the RPO, the higher the SNR of the combined signal. (iv) The post-synchronization largely depends on the estimation of the nonlinear offsets: RTOs and RFOs. (v) $r_1(t)$ and $r_i(t)$ are correlated but $n_1(t)$ and $n_i(t)$ are not which provides the noise insensitive estimation.

The equivalent one-dimensional faster search for RFO can be obtained by modifying (9) to yield a frequency-domain MCF

$$\upsilon_1(\Delta\hat{\omega}_i) \approx \int_{\omega \in W_0} \|S(\omega)\| \, \|S(\omega+\Delta\omega_i-\Delta\hat{\omega}_i)\| dt \tag{18}$$

and RTO can be estimated with the one-dimensional search by using the estimated RFO to compensate $\Delta\omega_i$ in either (4) or (9). Zero-padding may be needed for the better frequency resolution for correlation.

For the simulation with synthetic signals, RSO is not an issue. But with field-collected signal copies, if the sampling clocks at the distributed locations are not synchronized, the samples of r_i won't be lined up with the samples of r_1 and must be re-sampled with interpretation, in the fusion center, after RSO estimation.

After estimating all offsets, the signal copies from L sensors are combined to

$$r^c(t) = \sum_{i=1}^{L} g_i(t)\Theta[r_i(t-\Delta\tilde{\tau}_i)e^{j(\Delta\tilde{\omega}_i t - \Delta\tilde{\omega}_i\Delta\tilde{\tau}_i + \Delta\tilde{\beta}_i)}] \tag{19}$$

where $g_i(t)$ is an adaptive filter applied to the i^{th} signal copy to compensate for the channel variation and Θ is the convolution operator. Adaptive mechanisms, as shown in Fig. 3, such as maximum ratio combining and beam forming can be used to adjust the filter weights to maximize the SNR and minimize the interference and fading.

The fusion center converts the SIMO signal to SISO one, $r^c(t)$, in a form which can be further processed by applications such as automatic or blind signal classifiers[6][7]. Since $r^c(t)$ has higher SNR compared to $r_i(t)$, the former achieves a more reliable classification result.

It is remarkable that $r^c(t)$ is not in general coherent to the SOI transmitter since it adopts the non-coherency from the distributed sensors. In other words, there are unknown magnitude, timing, carrier frequency and phase offsets between the SOI and $r^c(t)$ although RTO, RFO, and RPO are eliminated after fusion., The non-coherence between the unknown transmitter and the combined signal is not an obstacle to signal sensing and modulation classification since the practical automatic modulation classifier has been designed to address the offset problem for SISO RF/IF signals, although most of publications only discuss baseband signal classification.

V. AUTOMATIC MODULATION CLASSIFICATION

Distributed signal exploitation benefits many research areas and applications such as RF power detection, emitter geolocation and identification, spectrum survey and monitoring, etc. This paper uses automatic modulation classification as an example which has applications in both military and commercial systems [11]. AMC is a tool to identify the modulation scheme of a transmitted signal with a high probability of success within a short observation time period. In general, the software operates with wideband signal sensing or detection hardware. The signal sensing equipment scans the specified wideband for an SOI defined by certain criteria such as carrier frequency, spectrum power, preamble, bandwidth, etc. Signal sensing methods have been extensively discussed in open literature and spectrum power search with a given threshold or template is a very popular signal sensing method used by signal exploitation equipments. The fusion of multiple asynchronous signal copies provides a higher probability of successful signal detection and classification.

Modulation classification starts with the band-limited, digitized, and unknown IF signal intercepted by the sensing unit as an input and ends with an estimated modulation scheme as an output. It can be described as a statistical process for estimating the modulation scheme of an unknown signal based on multiple matching templates or hypotheses. Figure 4 shows the brief layout of a modulation classifier for digital linear signals. This process may consist of IF signal conditioning, modulation scheme estimation, and confidence measurement. The IF signal conditioning may include multiple stages of signal bandwidth estimation and band pass filtering, frequency estimation and down conversion, signal and noise power estimations, symbol rate detection and estimation, pulse shape estimation, timing and frequency synchronization between the transmitter and fusion receiver, modulation phase estimation and correction, and blind transmission channel compensation. If the system cannot perform the signal conditioning properly, modulation estimation will not be possible and a "failure" status will be reported. Modulation estimation usually includes the modulation feature extraction, statistical feature processing or transformation, and decision making based on the templates or hypotheses of chosen modulation schemes. Confidence measurements are used to rate the estimation results and control the quality of the modulation recognition decision. With high-confidence estimation, the decision of the modulation scheme will be reported as "success", and with low-confidence estimation, the decision of the modulation scheme will be reported as "unknown".

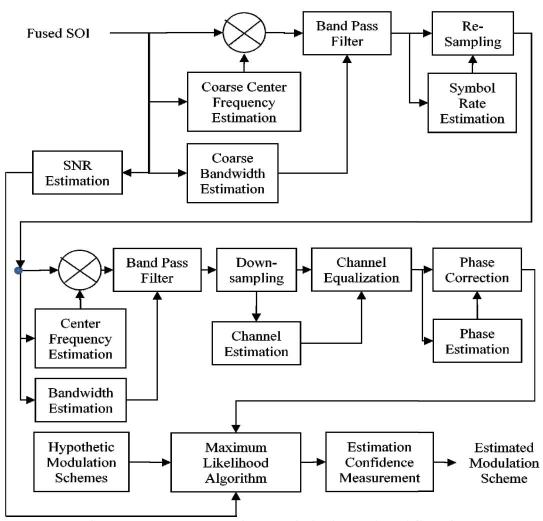

Figure 4. Automatic modulation classification

For modern communication waveforms, extra processing may be needed between the spectrum power sensing and modulation classification by identifying antenna dimension and coding, extracting downlink/uplink bursts, separating multiple users, removing unwanted headers and the cyclic-prefix, etc. After signal sensing and modulation classification, the resulting decision is used for post-processing with further signal analysis or message decoding.

The fused signal $r^c(t)$ can be an input to the automatic modulation classifier for signal sensing and classification. Depending on the application, the recognized outcome may be used to activate a demodulation unit, a specific modem in the universal demodulation library, with the classified signal modulation parameters and the appropriate modulation scheme for signal demodulation. A modulation classifier has been successfully developed to recover most analog and digital signal types [9] [11]-[16]. Recently, the real-time approach has been discussed [17][18] and MIMO/OFDM modulation schemes have also been investigated [19]-[21].

VI. Simulation

Computer simulations are conducted to demonstrate the effectiveness of RTO and RFO estimations.

A QAM 16 signal is generated with 5,000 symbols which are random integers processed by a square-root raised cosine filter with a roll-off factor of 0.35 and SNR = 3dB. The symbol is sampled at 40 MHz with 4 samples per symbol. $\Delta\omega_2/2\pi$= 4 Hz, $\Delta\tau_2$ = 50 μsec, Δa_2 = 1, and $\Delta\beta_2$ = 0. The RTO is estimated using (12) and the result is shown in Fig. 5, the RFO is estimated using (18) as shown in Fig. 6, and the RSO is not considered. Accurate estimation of RTO and RFO is obtained by applying the MCF method.

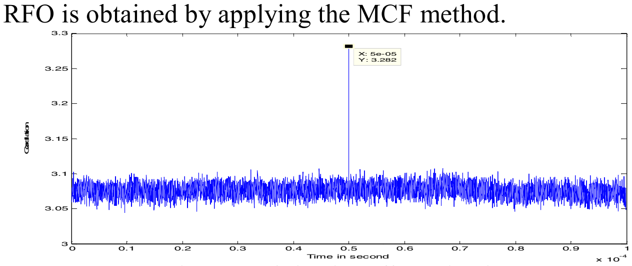

Figure 5. Relative time offset estimation

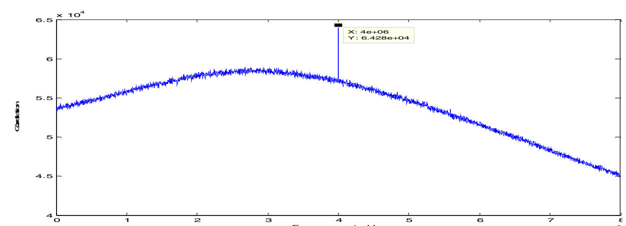

Figure 6. Relative frequency offset estimation

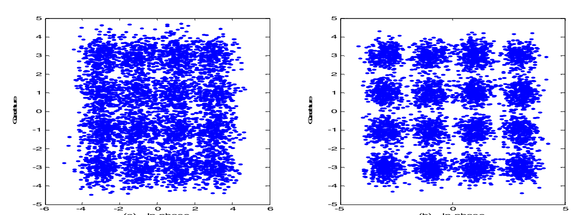

Figure 7. Demodulated QAM16 symbols: (a) signal sensor, (b) two sensors

After estimating offsets, multiple signals can be combined coherently to improve the signal quality. Fig. 7(a) and 7(b) show the demodulated symbols of r_1 and r^c (fused r_1 and r_2), respectively. It is obviously the latter has the much lower bit-error rate (BER) than the former. Roughly speaking, the more sensors you use, the lower the BER will be. It is remarkable that the demodulated symbols are not required in post-synchronization and the perfect post-synchronization provides an upper-bound performance of the signal combining. In practical environment, the performance will be degraded due to the estimation and processing errors, unexpected signal distortion, and unpredictable channel conditions. The simulation of the automatic modulation classification of distributed signal copies and the probabilities of correct classification of various modulation schemes have been discussed and compared in [2][3] using both the maximum-likelihood and cumulants tests.

VII. Conclusion

Distributed signal sensing is an important subject with a lot of interest in recent years. The advantage to using asynchronous and heterogonous sensors is to leverage the low-cost or existing communication devices and network without significant investment.

The nonlinear offsets RTO and RFO can be estimated independently with the fast search using MCFs, and the linear offsets RMO and RPO can be calculated directly after RTO and RFO estimation. The offset estimation does not need the knowledge of the based band signal information. That is, the symbol rate, carrier frequency, carrier phase, pulse-shaping filter, over-sampling rate, etc. are not known. The estimation is robust in the low SNR. The asynchronous signal copies with RMO, RTO, RFO, RPO, and RSO can be combined coherently after post-synchronization. The properly combined signal has been demonstrated to achieve the better performance in signal sensing and modulation classification.

Since distributed signal sensing and classification is an emerging technology, more efficient non-pairwise post-synchronization methods should be exploited for fusing signals in an extremely large sensor network within a short time period, sensor interfaces and operation scenarios should be studied by identifying a current or future platform covering a wide frequency range, simulation should be conducted to evaluate the post-synchronization based AMC methods, theoretical upper and lower bounds may be calculated based on the number of sensors in the network, and the time-varying channel parameter must be investigated for optimal signal combining. Asynchronous signal sensing and classification is a new and challenging subject which presents many opportunities for future research and potential advancements.

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