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Automatic Modulation Classification for Emergency Radio Surveillance

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Abstract
Radio frequency (RF) surveillance is becoming more important to protect the right of primary users as well as various civilian and military applications. In case of disaster scenario precise and efficient estimation of the RF parameters with effective signal processing techniques are necessary to detect the presence of different rescue teams. Blindness of the receivers about the transmitted signals made the problem more challenging. This dissertation investigates the design and implementation of an RF surveillance system for emergency communications termed as wireless disaster area emergency network (W-DAEN). A real-time database created with the PHY parameters collected by localized clusters can provide the desired interference avoidance and platform for interoperability. Additionally the proposed system can allow more rescue teams on the scene by introducing localized spectrum allocation for mobile rescue teams. However, for an automatic system, direct application of most of the currently available RF parameters detection techniques is restricted due to the limitations on practicability. For instance, existing automatic modulation classification (AMC) algorithms are rather restricted in practice due to the lack of pre-processing like carrier frequency offset (CFO), SNR and symbol rate estimations. Motivated by this, a feature based AMC algorithm for eight basic analog and digital modulation schemes has been developed in this dissertation also. Presence of the signal is detected by energy detection while CFO estimation of the intermediate frequency (IF) signal has been performed by using an autocorrelation based technique. SNR and symbol rate estimation is made by empirical mode decomposition (emd) based algorithms. The received data are divided into several non-overlapping segments, and the classification is done on each segment simultaneously to make the final decision by voting over multiple segments. J48 decision tree algorithm is found to be most suitable for this purpose. As the threshold of the features are dependent on the SNR and symbol rates, the system is trained with data with varying SNR and symbol rates. SNR and symbol estimation employed in the pre-processing stage is used to select the proper decision tree for classification. This multi decision tree technique improved the classification performance significantly. Most of the literature performs badly in SNR=0dB. But the proposed algorithm shows more that 90% success rate at SNR=0dB. The classification performance reaches close to 100% at SNR=6dB and above. Proposed algorithm ensures the robustness of the classification system against the variation of SNR and symbol rates by using a machine learning algorithm. Finally, a test bed has also been developed for the proposed system by utilizing the software defined radio (SDR) tools and mostly open-source software.

Keywords
Emergency Network — Modulation Classification — Parameter Extraction

*This work is accomplished under the supervision of Professor Jun-ichi TAKADA at Takada Lab, IDE, Tokyo Institute of Technology, Japan

Contents

Introduction

Disasters like earthquakes, hurricanes, terrorist attacks etc. are major threat to the modern civilization nowadays. Collapse of the existing infrastructure takes down the public and commercial telecommunication services. This situation demands immediate response from the rescue teams. Low frequency (LF) narrow-band mobile radios with fixed physical specifications are commonly used by the rescue teams for intra-agency communications. Usually emergency frequencies are pre-allocated for the first responders for better management. But for a big disaster rescue teams come from all over the world and set-up their own wireless networks. In emergency situation, interferences occur when two or more networks try to use same carrier frequency for intra-agency communications in close proximity. This interference among the corresponding radios is a big hindrance to the rescue operations.

Cognitive radios [1] are developed to utilize the spectrum gaps and avoid interference in such cases. But in reality it is very difficult to replace all emergency radios with cognitive radios. National Institute of Justice of USA has identified five major reasons that hinder the inter-agency collaborations [2]. These reasons include incompatible and old communication equipments, inadequacy of funding for the emergency responders, limited and fragmented planning, lack of coordination and communication among the management personnel and limited and fragmented spectrum allocation for emergency communications. These problems are normally valid for almost all of the emergency communication systems in the world. Moreover, wireless radio vendors are also not much interested to invest in development of emergency communication systems because of limited number of users and revenues. Thus the focus should be given to ensure the proper utilization of existing radios in emergency situation and develop an automatic radio management system for Disaster Management Center (DMC).

Wireless disaster area emergency network (W-DAEN) is expected to be placed in the disaster area by the DMC to monitor and manage the emergency rescue teams. W-DAEN is expected to help in solving three basic problems mentioned in Table 1 that have been occurring in past emergency situations. For example, in Haiti earthquake emergency radios interfered with each other because of common PHY properties [3]. In London subway bombing, rescue teams lost their connection with the ground base stations after entering to the tunnel. Although different teams were working in close proximity, they could not communicate with each other [4]. In 9/11, firemen who entered into the twin tower did not hear the announcement of evacuation instructions transmitted by police because of interoperability issues[5]. Solutions of these problems will require both technical and non-technical collaboration among the rescue agencies. For technical issues, a database of all the active emergency radios inside the disaster area should be developed. Hence the main goal of the W-DAEN is collecting necessary information from the disaster area by building a spectrum sensor network. Sensors placed in the target area are expected to capture samples from occupied frequency channels to extract necessary parameters. Figure 1 is showing the basic organization of the spectrum sensing network. Spectrum sensors placed inside the disaster area are expected to detect the presence of emergency radios. These sensors can form a cooperative network to increase the detection accuracy. This system is comprised of spectrum sensing, PHY parameter extraction and database maintenance subsystems to address these issues. Figure 2 shows the data flowchart of these operations.

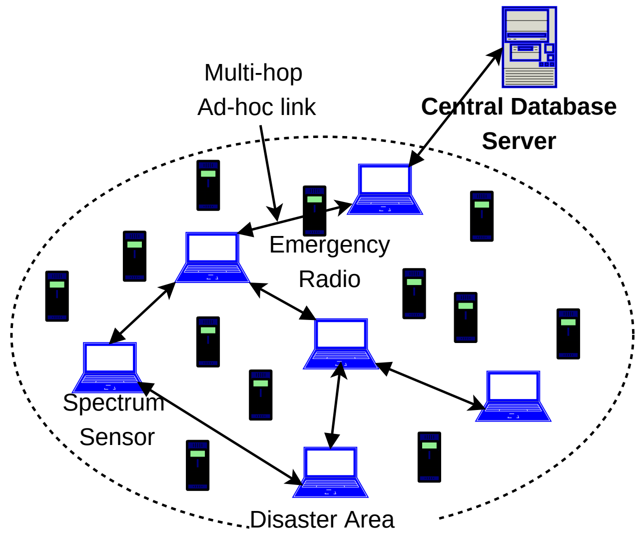


Figure 1. W-DAEN framework

Table 1. Issues for disaster communications systems

Issue	Description
Spectrum allocation	Disaster control center can allocate a specific frequency to one rescue agency for the whole area. For big area, channels can be reused by localized spectrum allocation.
Interference	Occurs when two or more rescue teams try to transmit on the same frequency in close proximity. So localized spectrum monitoring is necessary.
Interoperability	Currently not possible because of no knowledge of location and PHY parameters of inter-agency radios.

1. Background

Amateur radio (or ham) is often used as an option for emergency communication when wired communication networks, cellular wireless networks and other conventional means of communications fail. In the Indian Ocean earthquake and tsumani in 2004, expedition carrying VHF devices provided the only mode of coordination among the relief efforts [6].

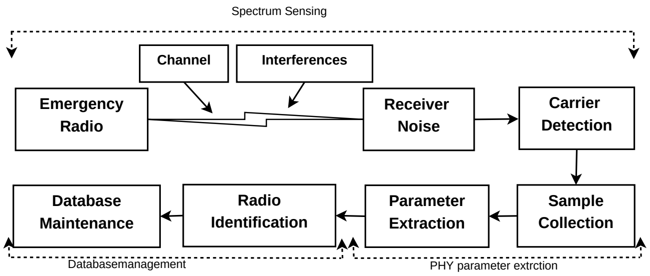


Figure 2. Data flowchart for W-DAEN

It is widely used by many rescue agencies throughout the world mainly because of easy to use feature. Professional mobile radio (PMR) [7] is also widely used by many first responders all over the world. PMR is composed of portable, mobile, base stations and console radios. Few standards have been developed for specifics usages: MPT1327, TETRA (the most developed) and APCO 25 [8]. Tetra uses the 400 MHz band. Project 25(P25) is a suite of standards for digital radio communications for use by federal, state/province and local public safety agencies in North America to enable them to communicate with other agencies and mutual aid response teams in emergencies. In this regard P25 fills the same role as the European Tetra protocol (although it is not compatible with Tetra). P25-compliant systems are being increasingly adopted and deployed. Radios can communicate in analog mode with legacy radios and in either digital or analog mode with other P25 radios. The protocol is secured with encryption. But, still most of the emergency radios uses basic analog and digital modulation schemes for communication.

1.1 Emergency System Limitations

All radio devices operate within the radio frequency spectrum, controlled by the Federal Communications Commission (FCC) or regional regulations. Devices used around the home, such as garage door openers, wi-fi networks, walkie-talkies, and many remote control devices, operate at such low power levels, licenses are not necessary and there is little chance of conflicting with other units. Once a device needs to communicate at a greater distance, it is necessary to operate at higher power levels, requiring FCC control. The number of radio frequencies available for public safety use is limited. While efforts are underway to reallocate more frequencies to expand capabilities, the reality in most areas are such that, first responders will continue to operate within a limited set of frequencies, for the foreseeable future. As such, radio spectrum is a limited commodity, in that there is a limit to the amount available for any given jurisdiction to use. Even where extra frequencies are available, the cost of hardware and infrastructure improvements provides practical financial limitation to many agencies.

Most of the countries have some fixed frequencies that are allocated for emergency situations. Developed countries have allocated the frequencies among the first responders in emergency situations. For example in Japan, emergency

Area	Department	Channels	Frequency (MHz.)	Modulation	Max. power (W)
Tokyo	Fire	A wave B wave Shared Shinagawa Oomori Kamata	151.69 152.79 466.3625 466.3500 466.3750 466.3875	Voice, FM Voice, FM Voice, FM Voice, FM Voice, FM Voice, FM	50 50 1 1 1 1
	Police	Shared Shinagawa Oomori Kamata	154.725 348.0625 348.0500 347.9125	Digital	50 1 1 1
	Disaster Prevention	Mobile Mobile	69.4500 466.2625 466.9375	Voice, FM Voice, FM Voice, FM	50 25 25
Kobe	Fire	1 to 9	148.29 - 158.35	Voice, FM	50
	Police	Shared	154.925 154.975	Digital	50
	Disaster Prevention	1 (whole city)	466.15	Voice, FM	25

Figure 3. Allocation of emergency frequencies in Japan

frequencies have been allocated for all the first responders for each state as shown in Figure ??. But in case of a big disaster rescue teams from different states/countries come to the scene. As same frequencies are allocated among the teams of different states, they may still interfere with each other.

One must not confuse the proposed network as an emergency network for communication among the rescue teams. Rather, the proposed system is expected to be able to detect and identify all emergency radios described above that may operate in a big disaster area. From the PHY point of view carrier frequency, bandwidth, SNR, symbol rate and modulation techniques used by individual systems should be estimated. Usually the bandwidth of narrow-band radios are quite similar and can be assumed from literature.

2. W-DAEN architecture

Establishment of network infrastructure for first responders after the disaster is the most important task. Sometimes the network collaboration is dependent on bureaucratic issues like policies/politics and regulations of the corresponding country or region which is beyond the scope of this discussion.In this work, discussion is limited on the implementation of a testbed to collect necessary information from the disaster environment. As mentioned earlier, emergency radios are not reconfigurable, so it's not possible to directly communicate with them. Moreover, each rescue agency may use secret coding for security purposes. For this reason, spectrum sensing is the only option to detect the presence of an emitter. Consequently blind signal processing should be performed to extract other PHY parameters for emitters. Thus the sole option to collect information is placing spectrum sensors in the disaster area. For ease of discussions, the whole system has been described as following four subsystems.

1. Network setup issues
2. Spectrum sensing
3. PHY parameter extraction
4. Database maintenance

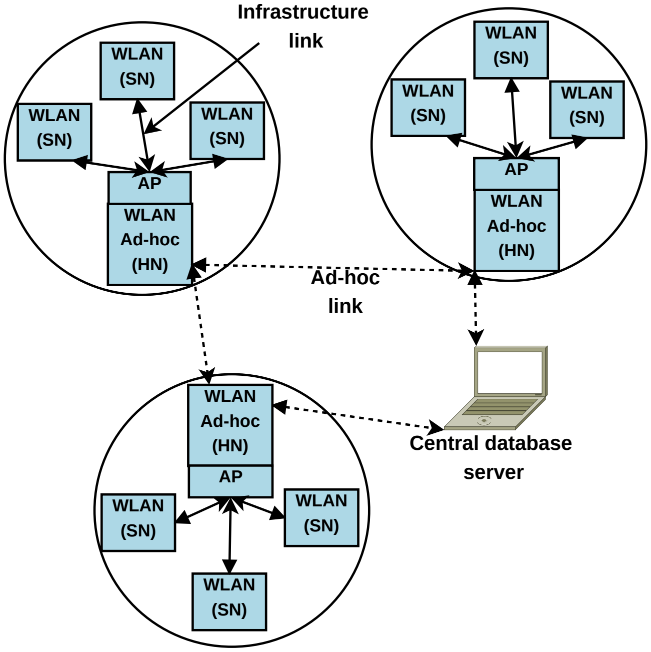


Figure 4. Cluster based spectrum sensing network

2.1 Network setup

Sensors placed in the disaster area can scan the spectrum to detect the presence of transmitting radios and forward the spectrum information toward the central database server. But, if the sensing network consists of a large number of sensing nodes, it will be very difficult to manage the network. The cluster based sensing network shown in figure 4 has been utilized in order to provide spectrum sensing coverage over a wide area by replication. Each cluster has a head which is responsible for final decision and routing the data toward the database server. After receiving data from the sensor, head nodes estimate the PHY parameters that are needed to be updated in the database. Activities for different nodes in the network should be assigned carefully to ensure reasonable processing time for a real-time system.

Cluster head estimates the modulation type, carrier, bandwidth and symbol rate that are needed to update the database. As the sensors in a cluster will be close to each other the IEEE 802.11 wireless LAN in infrastructure mode is used to transfer information from the sensor nodes to the head node with just a single hop. Maximum sensing coverage provided by a single cluster will depend mainly on the Wi-Fi range. Cluster size depends on sensitivity of each sensor and cooperative sensing scheme used. For real implementation a multi-hop mesh network can also be considered. IEEE 802.11 wireless LAN standard in Ad-Hoc mode and a multi-hop routing protocol Babel [9] is used to relay the extracted information toward the database. Babel is a proactive Ad-Hoc routing protocol with fast convergence properties, and is robust in mobile wireless ad-hoc networks. Communication among nodes uses the Transmission Control Protocol (TCP) to ensure reliable delivery of data. This is implemented on Python using the socket interface.

2.2 Spectrum sensing

In post-disaster scenario energy detector should be used for its suitability where many different emergency teams would be using various unknown systems. It is also suitable for quick scanning of a wide range of frequencies. In a disaster scenario, sensors do not have any information about the bandwidth of users signals. So it would be difficult to apply a filter matched to that bandwidth. The average periodogram approach has been used as the test statistic $\mathscr{T}_k$ for energy detection [10] in the target frequencies by equation (1).

$$\mathscr{T}_k = \frac{1}{M}\sum_{m=0}^{M-1}\frac{|Y_m(k)|^2}{L}. \tag{1}$$

where L is the FFT size, M is the total number of segments, and $k(=0,\dots,L-1)$ is the frequency bin index, and $Y_m(k)$ is the Fast Fourier Transform (FFT) of a windowed sample segment. As M sets of periodograms were used to calculate the test statistics, the number of samples used to calculate one FFT bin is also M.

Finally, the detection rule for determining the presence of a signal is as equation (2).

$$\begin{cases} \mathscr{T}_k \geq \gamma & \Rightarrow \quad \text{signal present} \\ \mathscr{T}_k < \gamma & \Rightarrow \quad \text{signal absent} \end{cases} . \tag{2}$$

where γ is a threshold value which is determined by given P_{fa}. Cooperative sensing is necessary to combat the adverse environment in a post-disaster scenario. In soft decision combining, data from each sensor are combined and then compared to a threshold to determine the presence of a signal [11]. Assuming that the noise variance in each sensor is the same and the signal received incoherently follows Gaussian process, the probability of detection for soft decision is approximately given by equation (3)

$$Q_{\mathrm{D,soft}} = \mathrm{Q}\left(\frac{\gamma - \sum_{j=0}^{J-1}(\sigma^2_{\mathrm{s},j}+\sigma^2_{\mathrm{n},j})}{\sqrt{\frac{1}{M}\sum_{j=0}^{J-1}(\sigma^2_{\mathrm{s},j}+\sigma^2_{\mathrm{n},j})}}\right), \tag{3}$$

$$\gamma = \mathrm{Q}^{-1}(P_{\mathrm{fa}})\sqrt{\frac{1}{M}\sum_{j=0}^{J-1}\sigma^4_{\mathrm{n},j}} + \sum_{j=0}^{J-1}\sigma^2_{\mathrm{n},j}. \tag{4}$$

where J is the number of cooperating users, $\sigma^2_{\mathrm{n},j}$ and $\sigma^2_{\mathrm{s},j}$ are the noise variance and signal variance at the j-th user respectively.

In hard decision combining, each sensor independently decides whether signal is present or not, and then sends their

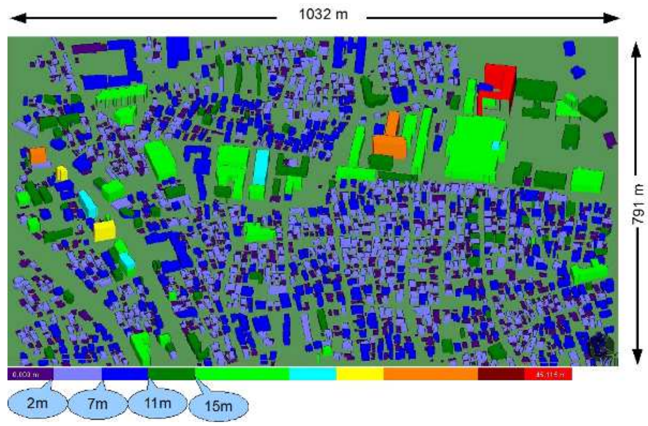


Figure 5. Top view of 3D model of target area

final 1-bit decision to the head node. The head node then uses the OR-rule [12]. The probability of detection for hard decision can be written as equation (5).

$$Q_{\mathrm{D,hard}} = 1-(1-P_{\mathrm{D}})^{n}. \tag{5}$$

where P_{D} is the probability of detection for each emergency radio.

2.2.1 Simulation performance of Spectrum Sensing

A ray-tracing simulation has also been carried out to check the performance of cooperative sensing in post disaster environment. The disaster affected area was modeled and the site specific propagation simulation was done by using a commercial simulator, "Wireless Insite" [13]. Effect of earthquake on Japanese houses were studied [14]. 3D model of an earthquake affected urban area (Ookayama, Tokyo, Japan) was developed as shown in Fig. 5. In accordance with the literature [15], 50% of wooden and 25% of concrete houses were destroyed/damaged for this simulation. A more realistic scenario where the channel model was generated by using ray tracing simulator was considered.

48 sensors and 520 emergency radios were uniformly distributed in the area for ray tracing simulation. Out of 48 sensors 12 were randomly selected and the average probability of detection (P_{d}) among 520 positions of emitters using energy detection method was calculated for specific false alarm probability P_{fa} [12] and averaged over 100 trials. The whole simulation was also conducted for the scenario before earthquake. Figure 6 compares P_{d} (before and after earthquake), and shows that after earthquake it was increased by 10% and within the range of 62.5% to 72% at 10% P_{fa}.

In this simulation hard collaboration (OR decision) was used. The cooperative probability of detection (Q_{d}) and false alarm (Q_{fa}) varying the number of cooperating sensors from 2 to 7 was also evaluated for both scenarios. The plot of Q_{d} versus Q_{fa} of an earthquake affected area is shown in Fig. 7. It is observed that cooperation between only 2 sensors can increase Q_{d} by 17% at 10% Q_{fa} compared to individual sensing. Q_{d} with increasing number of sensors in both scenarios (before and after earthquake) at 10% Q_{fa} was shown in Fig. 8. In both scenarios only 4 cooperating sensors are needed in this specific area to get Q_d above 95%.

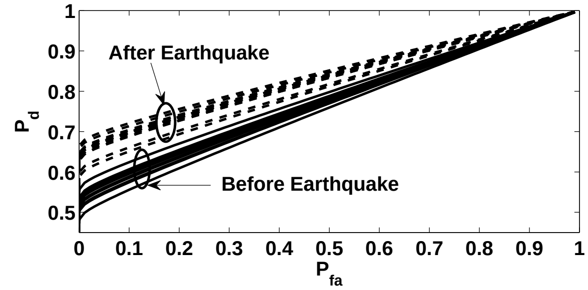


Figure 6. P_{d} of Individual sensors

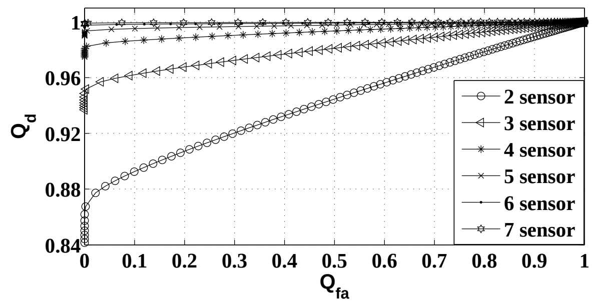


Figure 7. Q_{d} of cooperative sensing after earthquake

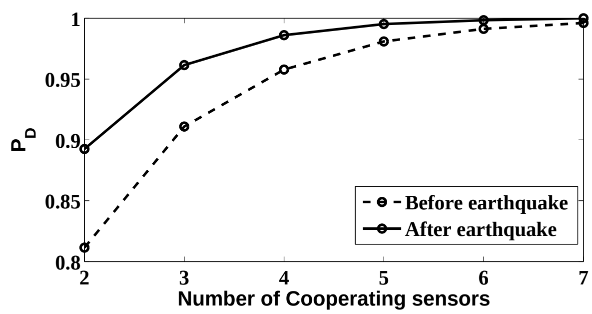


Figure 8. Q_{d} versus number of collaborating sensors

2.2.2 Experimental results for Spectrum Sensing

Experiment has been conducted to evaluate the performance of the proposed system setup based on the performance criteria for energy detectors. A signal generator was connected to an attenuator via coaxial cable to control the power of the input signal. One output of the power splitter was connected to a signal analyzer to observe the signal power, and the other output was connected to the daughterboard's (XCVR2450) [16] RF input of the universal software radio peripheral (USRP) which is assumed to be used as a sensor node. Experimental parameters are summarized in Table 2. For this specific exper-

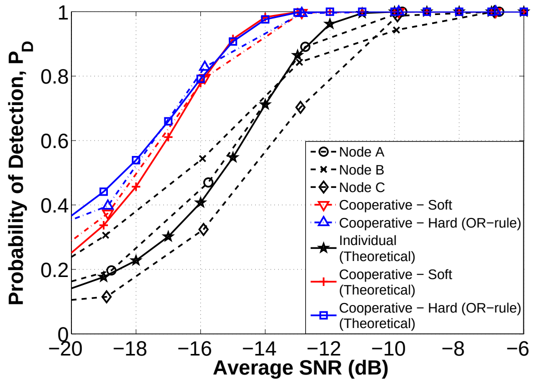


Figure 9. P_D for various SNRs for individual and cooperative sensing

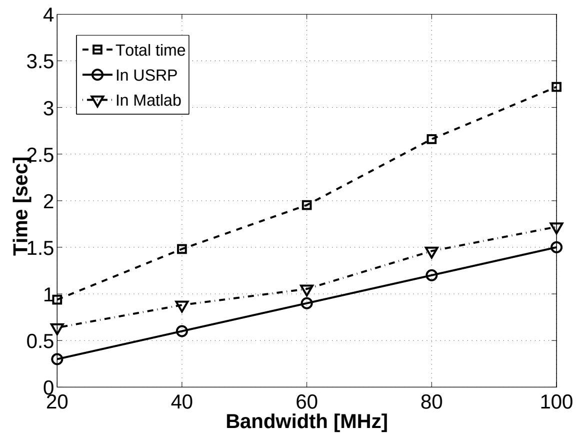


Figure 10. Time vs. Sensing Bandwidth (Tune Delay = 20ms, Sensing Time = 10ms)

iment frequency band 5 GHz has been chosen because of the availability of four daughter boards. However, experiments on 2.4 GHz. and 800 MHz. (with two sensor nodes) also showed similar performance.

Table 2. Experiment Parameters

Signal generator settings	
Center Frequency	5.003 GHz
Signal	Sinusoidal Wave
SNR Range	-20 dB $\sim$ 10 dB

USRP Settings	
Sampling Frequency	64 MHz
USRP Decimation	16
FFT Size	128
FFT Bin Resolution	31.25 kHz
Receiver Gain	60 dB
Tune Delay	20 ms
Sensing Time	100 ms
Samples per FFT Bin	3125
P_{FA}	5 %

Figure 9 shows the measured P_D and the theoretical P_D curve for SNRs ranging from -20 dB to -6 dB. In the fig., the curve of each node matches roughly with the theoretical curve. However, there were variations of performance among the three nodes of up to 2 dB. There are several possibilities for these variations, which come from the imperfection of the experimental configuration as well as the hardware limitations. Two different cooperative sensing schemes with three sensors are implemented to compare its performance to the theoretical curve as well as individual sensing. At $P_D = 0.9$, the cooperative sensing schemes managed to detect signals at $1 \sim 2$ dB lower than individual sensing. Increasing the number of sensor nodes would further increase the sensing performance. However, in a limited area, increasing the number of sensor nodes would also increase the shadowing correlation and this will limit the cooperation gain [12]. Also from Fig. 9, it can be seen that the hard decision scheme slightly outperforms the soft decision scheme for this particular SNR range and experiment setup.

However, the total sensing time is dependent on the maximum bandwidth that can be sensed at a time by the receiver hardware. For instance, in the experiments due to the limitations of USRP, a 2 MHz bandwidth can be sensed at a time. Therefore, more time is required to sense a larger bandwidth as the sensing is done sequentially. Through several tests, it was found that a tune delay of 20 ms would be enough for the USRP to tune to the proper center frequency and flush old data from its buffer. But this could be a bottleneck in sequential sensing. The processing time required in software also increases with the bandwidth. This is expected as a wider bandwidth would mean more data to process. This relatively long sensing time can be seen as a major limitation for the spectrum sensing system based on software defined radios (SDRs). Figure 10 shows the time required to sense a spectrum bandwidth of 80 MHz. This measurement was done on a Lenovo T400 notebook with an Intel Core2 Duo CPU with 2.26 GHz and 2 GB RAM. This total sensing time can be reduced by using receiver with more wide-band sensing capabilities.

3. Automatic Modulation Classification

Extraction of physical parameters is necessary to identify the emitters and share the information among stakeholders. Physical parameters that are necessary to be extracted includes carrier frequency, signal bandwidth, symbol rate, modulation scheme, signal power, location etc. Carrier frequency, signal bandwidth and signal power can be calculated by the energy detection based spectrum sensing. Automatic modulation classification (AMC) can be considered as the most challenging task in this step. Most of the other PHY parameters should be estimated for the implementation of AMC

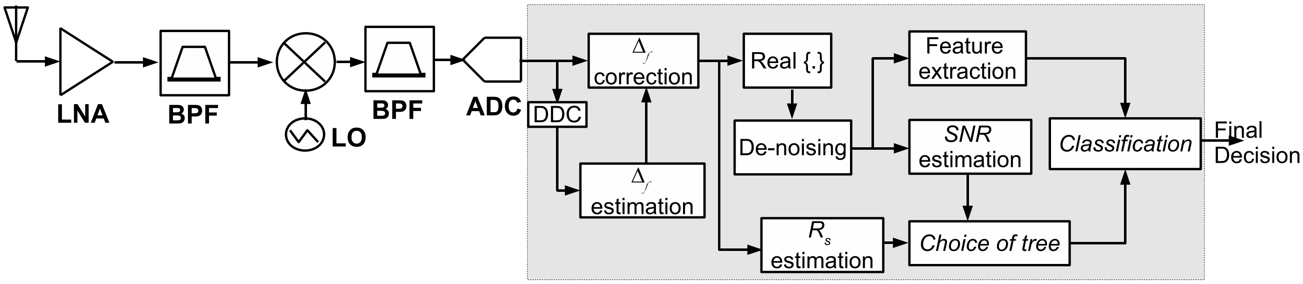


Figure 11. System model.

algorithm [17]. For example, carrier frequency offset (CFO) correction, signal-to-noise ratio (SNR) estimation, symbol rate estimation and so on. Hence, this section explains the AMC algorithm in detail. We assume the system model as shown in Fig.11. Main target of this processing is to extract meaningful features from the received waveforms. Certain features [18] that are also considered in this study is sensitive to the carrier frequencies. Thus this study considered processing at the intermediate frequency (IF) signal. A certain narrow-band signal with bandwidth B (symbol rate of R_s for digital schemes) appears within the system bandwidth W where a single signal is only considered. The signal within the system bandwidth is then down-converted into IF at f_{IF}. For the down conversion, the local oscillator is expected to regenerate the frequency exactly same as the RF frequency of the signal, which is practically impossible. Thus the down conversion introduces an offset called CFO denoted as (Δ_f). Then AMC classifies the modulation scheme of the input signal. In this system model, the target bandwidth is limited by $f_s/2$ where f_s denotes the sampling frequency. It is assumed that before AMC the spectrum sensing is performed by scanning the system bandwidth across whole target bandwidth with a tunable bandpass filter by varying oscillator frequencies.

Information signal $m(t)$ is modulated with a carrier signal. The effect of the environment i.e fading, path-loss etc. degrades the received signal power. For the narrow-band signal it is not always necessary to consider the frequency selective fading (delay spread) of the channel. Moreover, for a quasi-static environment where the movement of the transmitters or receivers during the reception are not that significant, the channel can be regarded as time invariant AWGN channel for the duration of measurement. So the SNR is the sufficient parameter to check the classification performance.

The received signal in the front of the receiver for common analog and digital modulation schemes can be represented by equation (6).

$$r_{RF}(t) = h(t) \cdot s(t) + w(t), \tag{6}$$

where $h(t)$ denotes the impulse response of narrow-band fading, $s(t)$ is the band-passed modulated signal and $w(t)$ is additive white Gaussian noise (AWGN). The received signal after down-conversion into IF is represented by assuming time-invariant AWGN channel as equation (7).

$$r_{\mathrm{IF}}(t) = \mathrm{Re}\left[h \cdot s(t) e^{\mathrm{j}2\pi(f_{\mathrm{IF}}+\Delta_f)t}\right] + w(t). \tag{7}$$

3.1 Proposed AMC algorithm

At first the AMC system has been trained with multiple training signals. SNR and symbol rates of the data are varied to generate multiple decision trees. A feature based AMC algorithm has been developed to classify eight modulation (AM, FM, BASK, BFSK, BPSK, QPSK, $\pi/4$-QPSK, and MSK)widely used by emergency radios. Extracted features can be compared with the thresholds calculated from the training data. Accuracy of these features depends mainly on the availability of number of samples of the received signal. As mentioned in earlier sections, robustness of these features against the CFO, symbol rate estimation error, SNR etc. are important factor for classification. CFO should be estimated and corrected before extracting the unique features from the received signals. Multiple decision trees for different combinations of SNR and symbol rates during the training phase ensures robustness in the classification phase. Figure 12 shows the operation sequences that are carried out in the training phase.

Block diagram of the proposed classification algorithm is also shown in Fig. 13. The pre-processing block is introduced to improve the quality of input signal. SNR and symbol rate estimations in the pre-processing stage is used to select the appropriate decision tree generated in the training phase. This selection ensures the robustness of the algorithm against these two physical factors.

Processing a long sequence of data requires longer time with more computations. To overcome this problem the received sequence is divided into a number of short blocks with limited number of samples. The channel can be assumed as quasi static for the duration of a block hence the consideration of AWGN should be sufficient. For pre-processing the feature extraction as shown in Fig. 13 has performed for each block. Finally, a majority rule is applied to decide the overall classification of the received signal. So it is quite evident from here that the number of blocks is an important parameter for the performance measure (classification accuracy) of the AMC.

The classification problem is to identify the corresponding

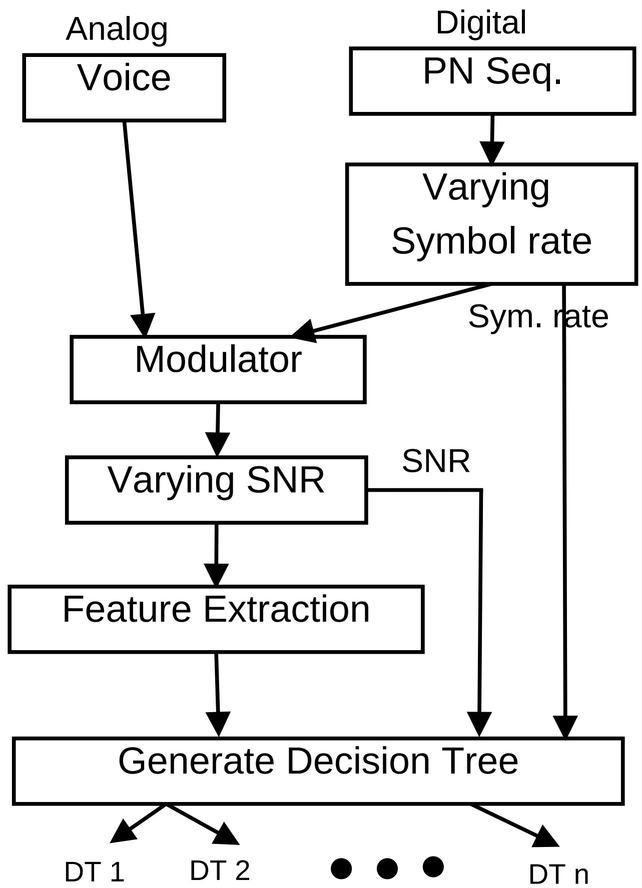


Figure 12. Training phase operations

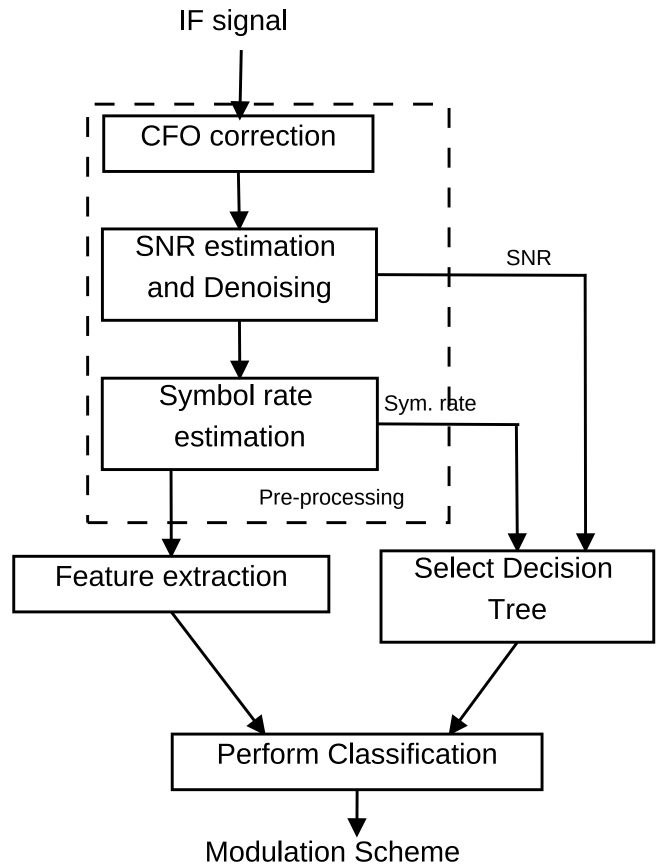


Figure 13. Proposed classification block diagram

class from the set of eight modulation schemes. As the modulation classes are finite, a supervised learning based decision tree classification algorithm can be used here. If the parameters can hold their uniqueness under varying SNR, using any standard machine learning classification techniques should provide similar performance. In this study decision tree algorithm based on C4.5 [19] is used for training set generation and classification purposes. The algorithm is developed in JAVA environment called J48 and included in WEKA [20].

3.2 Feature extraction for AMC

A total of six unique features are extracted to classify eight modulation schemes. Four of the features are extracted from the extrema of the received waveforms by using SSC techniques, and the remaining two are calculated from time-frequency distributions of the signal. SSC parameters can be calculated by [21]:

$$A_{\mathrm{M}} = \frac{1}{N_{\mathrm{S}}}\sum_{i=1}^{N_{\mathrm{S}}} A_i, \quad A_{\mathrm{D}} = \frac{1}{N_{\mathrm{S}}}\sum_{i=1}^{N_{\mathrm{S}}} |A_i - A_{\mathrm{M}}|,$$
$$T_{\mathrm{M}} = \frac{1}{N_{\mathrm{S}}}\sum_{i=1}^{N_{\mathrm{S}}} T_i, \quad T_{\mathrm{D}} = \frac{1}{N_{\mathrm{S}}}\sum_{i=1}^{N_{\mathrm{S}}} |T_i - T_{\mathrm{M}}|. \tag{8}$$

where A_{M}, T_{M}, A_{D} and T_{D} are amplitude mean, period mean, amplitude deviation and period deviation respectively, N_{S} is number of SSC segments and A_i and T_i are amplitude and time respectively for the corresponding SSC segment. One SSC segment is defined by the area surrounded by consecutive maxima and minima. The fifth feature the mean absolute deviation of the $f_{\mathrm{m}}(t)$, obtained by [22]

$$M_{\mathrm{f}} = \frac{1}{N}\sum_{i=1}^{N}\left| f_{\mathrm{m}}(i) - \frac{1}{N}\sum_{j=1}^{N} f_{\mathrm{m}}(j)\right|, \tag{9}$$

Here, $f_{\mathrm{m}}(t)$ is the first moment of Wigner-Vill Distribution (WVD). Sixth feature is calculated by [22][23]

$$M_{\mathrm{p}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} p_{\mathrm{m}}^2(i) - \left(\frac{1}{N} p_{\mathrm{m}}(i)\right)^2}. \tag{10}$$

Here, p_m is the maximum value of $p(n)$ among all the received symbols calculated from the Cross Margenau-Hill Distribution(CMHD) . Extracted six features can be used in four steps for classification.

1. Separate signals with fixed and variable amplitude (using A_{M} and A_{D})
2. Separate signals with single and multilevel frequencies (using T_{M}, T_{D} and M_{f}).

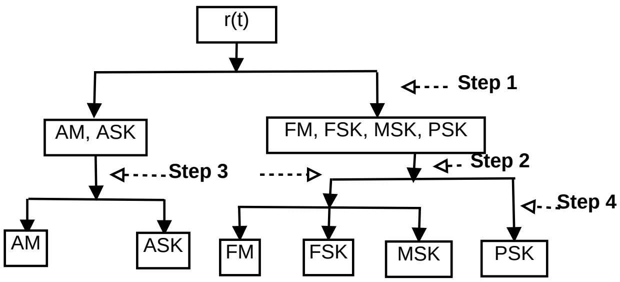


Figure 14. Decision tree steps

3. Check the amplitude and frequency levels to distinguish among analog and digital schemes (A_{M}, A_{D}, T_{M}, T_{D})
4. Separate the PSK schemes by checking phase levels (using M_{p})

These steps are presented in Fig. 14. Thus these six parameters are sufficient to classify the eight modulation schemes widely used by emergency radios.

3.3 Preprocessing for Parameter Extraction

The CFO has been estimated by using a classical correlation based technique. If we consider receiving a PSK signal in the receiver, the received signal becomes

$$r(t) = \sum_i d_i g(t - iT)e^{-2j\pi\Delta ft} + w(t) \tag{11}$$

Where, d_i is the complex symbol and $g(t)$ is the convolution of the raised filter and the channel impulse response with the AWGN $w(t)$. The non-conjugate autocorrelation of the squared received signal $R\{r(t)^2\}$ can be written as

$$R\{r(t)^2\} = R\{d_i^M\}\sum_i (g(t - iT))^2 e^{-4i\pi\Delta ft} \tag{12}$$

Here, M is the modulation level. This function can be represented by the Fourier series with the fundamental frequency $2\Delta_f$. Frequency offset can be calculated by finding the spectral peak from the Fourier transform of the $R\{r(t)^2\}$. To increase the accuracy of CFO estimation, the offset is calculated for each block. Mean of these values are taken as the final CFO.

$$\widehat{\Delta_f} = \frac{1}{N_{\mathrm{b}}}\sum_{i=1}^{N_{\mathrm{b}}} \Delta_{f_i}. \tag{13}$$

here N_{b} is the number of blocks. In this simulation 100 blocks are used for the carrier estimation. The signal $r_{\mathrm{IF}}(t)$ is then corrected by again modulating with a signal of $\widehat{\Delta_f}$ frequency. The bandwidth of the IF filter can be set as per the emitter specifications. For instance, in case of emergency radios typically a 25KHz bandwidth is used.

Denoising is performed by following the adaptive thresholding based empirical mode decomposition called iterative EMD interval-thresholding (EMD-IIT) technique described on [24]. To estimate the total noise power of the signal, we calculated the noise power from first few noisy IMFs and added together. Rest of the signal is regarded as the original signal. Then the ratio of these two powers are taken as the SNR of the received signal. This denoising technique gives a passive improvement on the feature quality. As the signal is transferred to a more reliable high SNR region the variance of the extracted features decrease. This EMD based techniques can upshift a 0dB SNR signal upto 10dB SNR signal [24]. Hence, the probability of right classification improves significantly.

Koh et. al. [25] described a classical (square) symbol rate estimation algorithm. In this algorithm the spectrum of the squared envelop signal r_{e}^2 has the form [26]. This classical method has been implemented in an iterative EMD algorithm to estimate the symbol rate.Proposed algorithm to calculate the symbol rate estimation is as follows.

- Take the square of the received signal $r^2(t)$.
- Apply the sifting process to calculate the IMF of $r^2(t)$. The last IMF is the estimate of the signal envelop ($r_{\mathrm{e}}^2(t)$).
- Subtract the $r_{\mathrm{e}}^2(t)$ from the $r^2(t)$ to get $s_{\mathrm{e}}^2(t) = r^2(t) - r_{\mathrm{e}}^2(t)$.
- Take the Fourier transform of $s_{\mathrm{e}}^2(t)$ and find the maximum peak except few bins near the carrier frequency. The frequency associated with the maximum bin is the symbol rate of the signal.

This symbol rate estimator effects the classification performance in two ways. First of all the number of samples for each block can be determined by the symbol rate depending on the IF and corresponding sampling rate. If the number of symbols in a block is too small the extracted features will not have sufficient statical information. Secondly, threshold value for each feature is also heavily dependent on the symbol rate of the signal. Hence, the symbol rate estimation will help in determining the appropriate threshold for the signal under consideration. That means the corresponding decision tree from the estimated symbol rate can be used in the classification step. This ensures the robustness of the classification algorithm against the different symbol rates of the received signal. Detail description and the related simulation performance of the AMC is available in the manuscript published by the same authors [17].

3.4 Simulation performance for AMC

A recorded continuous voice signal modulated by AM and FM schemes has been generated as the input signal for the analog modulation. For the digital modulation, PN sequence modulated with BASK, BFSK, BPSK, QPSK, $\pi/4$-QPSK and MSK scheme have been used as the input signal. One important performance criterion for the proposed AMC is determining the number and necessary samples. Figure 15 shows the average classification performance for digital modulations against the number of blocks for varying segment size for 20 ksps symbol rate and SNR of 3 dB. However, for

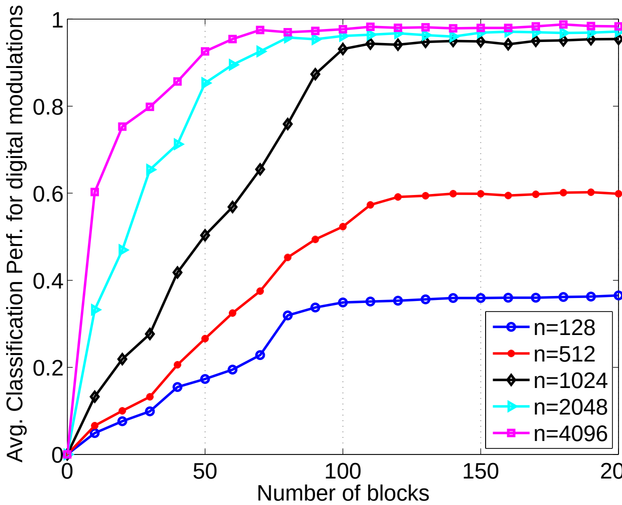


Figure 15. Effect of Samples

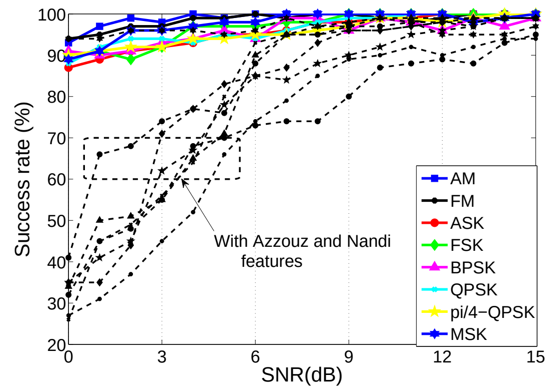


Figure 16. Classification performance after the pre-processing

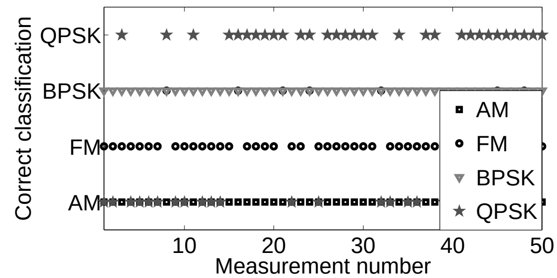


Figure 17. Classification performance in the developed prototype

analog modulations average classification performance is not much influenced by the block size. In digital modulations for smaller number of samples, the block can not get adequate number of symbols. In that case, increasing the number of samples does not show significant improvement in the classification performance. Here, AMC achieves 90% success rate with 50, 70 and 100 segments for 4096, 2048 and 1024 samples per segment respectively. Therefore for this specific example, minimum number of samples to achieve more than 90% success rate is 100 segments with 1024 samples. This combination has been chosen for the final simulation for the AMC system.

For this simulation IF is chosen as 50kHz. If the frequency of the training and testing data are similar, this does not effect the classification performance. A number of simulation are carried out for 50kHz., 60kHz. and 70kHz. The results are obtained for 100 segments with 1024 samples each. IF signals has no significant effect on classification performances. However, the sampling rate and block size should also be varied with the change of IF. As we can control these parameters in our system, selection of IF is dependent on the availability of the hardware. The value for SSC parameters is also heavily dependent on the over sampling rate of the signal. In this case the sampling rate is selected as 4 times as recommended by [21].

In the simulation estimated SNR and symbol rates are rounded toward to the closest value to select the corresponding decision tree. Figure 16 shows the classification performance for simulation of eight modulation schemes with the pre-processing blocks. It has been found through simulation that the pre-processing has improved the overall performance by about 15% in lower SNR cases. The proposed system outperformed most of the existing AMC algorithms specially the most popular [27] by a big margin in the low SNR region.

3.5 Experimental results for AMC

Experiments have been conducted for four basic modulation schemes (AM, FM, BPSK and QPSK) signals inside laboratory. Figure 17 shows the performance for fifty measurement samples at around 15dB SNR. Classification performance for some measurement samples for QPSK are below the expectations, because of the instability of the USRP data. Reasons of this instability includes the memory buffer problem as well as the impairments due to USRP hardware. However, the overall success rate for the prototype is quite satisfactory.

4. Testbed Development

For the identification of the emitter, some prior information about the possible emergency emitters are assumed to be stored beforehand. The PHP script compares the extracted information with the existing database. If it finds a match for frequency, bandwidth, modulation scheme, predicted transmitting power for any emitters in the data, the emitter is identified as a node of that specific network. The database has the following classes and fields:

- Emitter {em_location∗, em_network∗, em_freq∗, em_mod, em_pow, em_sen∗, em_date, em_time}
- Network {net_id∗, net_name∗, net_freq, net_mod, net_wave,

net_maxpow, net_coun∗}

- Modulation{mod_id, mod_name∗}
- Frequency{freq_id, freq_name∗, freq_bw}
- Sensor{sen_id∗, sen_location∗, sen_emi_id∗}
- Country {coun_id, coun_area∗, coun_name∗}

'∗' denotes the primary keys of each table. Table "Emitter" contains the extracted information received from the sensors. The 'date' and 'time' fields are used to check activity duration of sensors. The extracted information are used to extract the network identity from the "Network" table that already has some previously collected information. "Frequency" and "Modulation" tables are maintained to check the conflicts or the interference among the emitters. "Sensor" table holds the information about the active sensors on-site and the "Country" table is used to distinguish different systems from different countries.

Text files sent by the head nodes are saved to a directory of the database server. The developed PHP script checks for new text files received by the server. Whenever a new file is received, it reads the received contents from the file. The file consists of the following information:

1. Center frequency
2. Bandwidth
3. Received power
4. Modulation scheme
5. Geolocation
6. Cluster number
7. Sensor ID

First four parameters are compared with the existing database by a MySQL query to detect the association with which the emitter belongs to. If no prior information is found, an entry is made to the corresponding tables in the database. After finishing the identification process the corresponding tables are updated accordingly. Apache web server in Xampp [28] is also configured to make the data available over the Internet.

The testbed of the proposed sensor network has been implemented inside the laboratory. Modulation classification system for basic analog and digital modulation schemes has also been integrated with the system. Python scripts were used to transfer the sensed data from sensors to the head node of each cluster. Figure 18 shows a photograph of the experimental set-up. Two sensor nodes in conjunction with a cluster head and database server have been set-up for the experimental setup. Two emitters (A signal generator and an USRP) are used to transmit the AM, FM, BPSK and QPSK signals. Signal analyser was used to observe the carrier frequency and for verification.

Average periodogram of the received signal is directly fed to the Matlab module. A graphical user interface (GUI) was also created in Matlab, and a screen-shot of this GUI can be seen in figure 19. Basic parameters of the USRP as well as

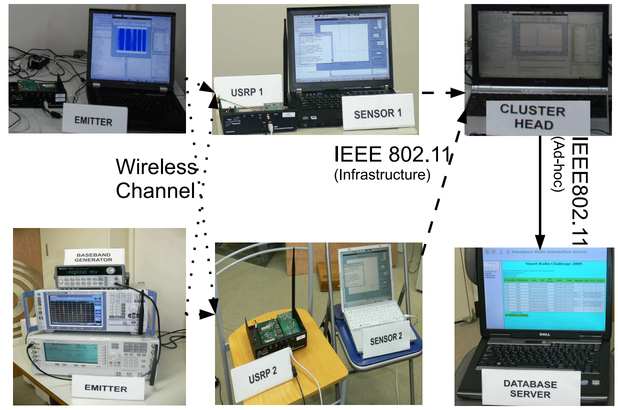


Figure 18. Experimental setup

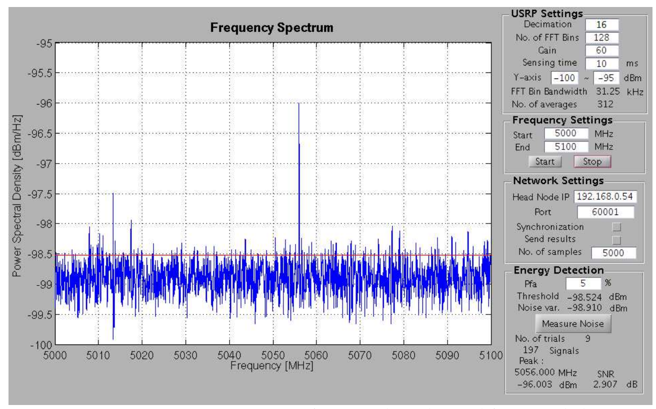
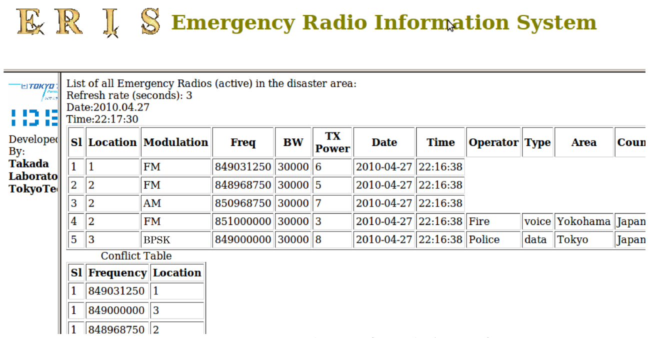


Figure 19. Spectrum viewer developed in Matlab

the network can be set by this interface. The interface can show the frequency spectrum with the noise threshold. The sensing bandwidth is limited by the USB 2.0 data transfer interface between the USRP and the GNU Radio [29]installed on personal computers. Sensing bandwidth above 4 MHz suffered from data loss in the USB interface.

One of the most important challenges for cooperative sensing in this environment is synchronization. There are several methods to achieve synchronization among nodes. One method is to utilize the Global Positioning System (GPS), but this would require the installation of GPS receiver hardware on each node. From an implementation point of view, a simpler method would be network-based clock synchronization, and one example is the Network Time Protocol (NTP), which is widely used in computers nowadays [30]. NTP typically provides accuracy of less than a millisecond on LANs and up to a few milliseconds on WANs. For the proposed system, the target is to detect the presence of emergency radio around the sensor node. In emergency situation, the emitters are expected to transmit signal more frequently. So, for the proposed system the time delay of NTP is quite acceptable. Figure 20 shows the snapshot of the final view of the web-interface for the interested groups. First table shows the active emitter information detected by the sensors. For some emitters the ex-


ERIS Emergency Radio Information System

Developed By: Takada Laborato TokyoTe

List of all Emergency Radios (active) in the disaster area:
Refresh rate (seconds): 3
Date:2010.04.27
Time:22:17:30

Sl	Location	Modulation	Freq	BW	TX Power	Date	Time	Operator	Type	Area	Coun
1	1	FM	849031250	30000	6	2010-04-27	22:16:38				
2	2	FM	848968750	30000	5	2010-04-27	22:16:38				
3	2	AM	850968750	30000	7	2010-04-27	22:16:38				
4	2	FM	851000000	30000	3	2010-04-27	22:16:38	Fire	voice	Yokohama	Japan
5	3	BPSK	849000000	30000	8	2010-04-27	22:16:38	Police	data	Tokyo	Japan

Conflict Table

Sl	Frequency	Location
1	849031250	1
1	849000000	3
1	848968750	2

Figure 20. Snapshot of web interface

tracted information matched with prior information. So their name and country can also be seen from the table. Second table shows the conflicting frequencies.

5. Conclusions

This dissertation designed a wireless disaster area emergency network (W-DAEN) to collect the information of emergency radio after disaster. In a post disaster scenario, emergency teams come from different countries to perform rescue operations. Wireless radios used by these mobile teams may interfere with each other to hinder the rescue operations. Moreover, interoperability is not possible due to the lack of information sharing.

W-DAEN proposed here, requires placement of some cheap spectrum sensors in the disaster area. The sensors work cooperatively to built-up a database of active emitters in the area. Data will be forwarded to a cluster head, where all the processing are done on a software radio platform. Finally the information can be broadcasted among the emergency teams. A web-page is also developed to show the information on the Internet.

Hard combining sensing has been employed to detect the presence of radio transmitter. One of the most important challenges for cooperative sensing in this environment is synchronization. There are several methods to achieve synchronization among nodes. One method is to utilize the Global Positioning System (GPS), but this would require the installation of GPS receiver hardware on each node. But to avoid complexity Network Time Protocol (NTP) is used. NTP typically provides accuracy of less than a millisecond on LANs and up to a few milliseconds on WANs. For the proposed system, the target is to detect the presence of emergency radio around the sensor node. In emergency situation, the emitters are expected to transmit signal more frequently. So, for the proposed system the time delay of NTP is quite acceptable.

Data sent by the head nodes are saved in a directory of the database server. The developed PHP script checks for new text files received by the server. Whenever a new file is received, it reads the contents from the file and updates the database if necessary. The file consists of center frequency, bandwidth, received power, modulation scheme, symbol rate, geolocation, cluster number and sensor ID.

To perform the emitter identification, captured signals from the detected emitters should be analyzed further. To perform this, at first we need to identify the modulation schemes used by the emergency rescue teams. Thus an automatic modulation classification (AMC) has been developed in this study. In literature survey, works of Azzous and Nandi are found to be pioneer and popular for AMC. A thorough evaluation on the well-known features proposed by Azzouz and Nandi has been conducted in the beginning stage of this dissertation research in order to examine their performance and capability in automatic modulation classification. The computer simulation results have demonstrated that the applications of these features are restricted in practice. The causes leading to the restrictions are discussed.

A feature based practical AMC algorithm is proposed to improve the classification performance. Features are extracted from four statistical signal characterization (SSC) parameters 1) amplitude mean, 2) amplitude deviation, 3) period mean and 4) period deviations. These features can directly identify the amplitude and frequency variations of the received waveform. Hence, the operation is very quick and suitable for real-time implementation. One problem with this SSC parameters is that, they cannot calculate the phase variations of the signal. For that time-frequency based features should be used. Two features based on Wigner-Vill distribution (WVD) and Cross Margenaeu-Hill distribution (CMHD) has been utilized for this purpose. These six parameters were able to successfully classify eight analog and digital modulation schemes used by emergency radios. To further quicken and improve the accuracy of classification the received waveform is divided into segments and classification is done on each segment simultaneously. Finally, a majority rule is applied to determine the modulation scheme.

For practical systems, carrier frequency offset (CFO), SNR and symbol rates determines the quality of the extracted features. CFO introduces phase rotation on the received signal. Thus it becomes difficult to identify the PSK schemes correctly. An autocorrelation based carrier estimation technique is used to calculate the CFO and corrected with remodulation with the offset frequency. To combat with the SNR, an empirical mode decomposition (EMD) based algorithm is used for De-noising. This de-noising can improve the signal quality from 9dB to 15dB. Adequate number of samples per segment are required to improve the reliability of the extracted features. To decide about the size of segment, symbol rates must me estimated. Again an EMD based algorithm is developed for this purpose.

Finally, a decision tree is used to perform the classification in each segment. J48 decision tree algorithm is found to be most suitable for this purpose. J48 is a java implementation of well known C45 machine learning algorithm. The software is available in WEKA tools. As the threshold of the features are dependent on the SNR and symbol rates, the system is trained with data with varying SNR and symbol rates. SNR and symbol estimation employed in the pre-processing stage is used to select the proper decision tree for classification. This multi decision tree technique improved the classification performance significantly. Most of the literature performs badly in SNR=0dB. But the proposed algorithm shows more that 90% success rate at SNR=0dB. The classification performance reaches close to 100% at SNR=6dB and above.

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