CLASSIFICATION OF MULTIPLE SIGNALS USING 2D MATCHING OF MAGNITUDE-FREQUENCY DENSITY FEATURES

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ABSTRACT

Signal classification is an important function of modern communication systems in Software Defined Radio (SDR) applications. The ability to quickly recognize the type of received signals allows a system to automatically adapt the processor to properly decode the signals. Many classification techniques assume that the received signal space is occupied by only one signal, and that the frequency of operation is known. However, in some systems, the receiver may be completely blind to the number and characteristics of signals within the bandwidth of interest. The technique introduced in this paper proposes the collapsing of localized magnitude peaks from consecutive short time Discrete Fourier Transform (DFT) bins into magnitude histograms to create a two dimensional image of the frequency-magnitude density of the received signal space. This image can be a useful visualization tool in the characterization of the signal space in user assisted modes of classification. Alternatively, the process could be automated by utilizing pattern recognition and image processing algorithms.

1. INTRODUCTION

Modulation detection is one of the most important aspects of signal classification. Information bearing signals will usually employ carrier modulation. The first order characteristics in detecting and thus classifying an information bearing signal include carrier frequency and modulation type. If a given slice of arbitrary bandwidth is selected for signal search, the number of signals may be unknown in that bandwidth. If there are multiple signals in the selected bandwidth, the frequency of operation for each of the multiple signals as well as modulation type may be unknown. When multiple signals of unknown characteristics are present in the band, the use of a single signal classifier such as a constellation detector is impractical. What is required for these conditions is a classifier by which these characteristics can be determined jointly across multiple signals.

As pointed out in [1], most of the research in the area of signal classification is related to the recognition of a single signal in space. Little research has been done to classify multiple signals simultaneously in a given bandwidth. Within the realm of single signal classification techniques, a broad summary has been provided by [2], in which the methods are divided into two main categories: 1) likelihood based (LB), and 2) feature based (FB). The metric proposed in this paper falls into the category of feature based methods. The proposal herein is to create a two dimensional image of the localized peak frequency and magnitude statistics within the bandwidth of interest. This image will hereafter be referred to as a Peak Frequency-Magnitude (PFM) histogram. The classification can occur in a pipeline fashion, partitioned logically into two main steps. The first step is to create the 2D image. The second step is to employ pattern matching techniques on the generated image to classify the signals. The use of signal spectrum in the task of signal classification is a frequently employed technique. Although some techniques have utilized statistical spectrum features and even proposed the use of 2D images to facilitate classification [3] - [5], 2D spectrogram images, which are frequency-time plots, vary constantly with time and thus do not lend themselves to image pattern matching techniques. [3] extends the use of spectrograms by creating a histogram of the single highest peak from each spectrum column to generate a 1D histogram. The key difference in this proposal is the collapsing of all localized maximums from each spectrum capture into a 2D image for pattern matching, thereby simultaneously including other signals that may be present in the band, even those of lower power than the strongest signal.

The focus of this paper is on the construction of the PFM histogram. Areas for further research include selecting optimal pattern matching techniques and predicting performance of an automatic pattern matching classifier. Without an automatic classification algorithm, the PFM histogram image that is proposed herein is still useful in user assisted methods of classification.

2. SIGNAL CONSTRUCTION AND ASSUMPTIONS

For the purpose of this paper, we assume that an analog signal has been band limited and sampled with sufficient performance to neglect any aliasing effects. We also assume that the sampling amplitude range is large enough to include all potential signals for classification, and the input range will be normalized. Another assumption is that the ratio of the sample rate to block size (samples) is larger than the bandwidth of the signals being analyzed. Essentially, this means that generally the signals in the analyzed band are narrow relative to the sample rate. If this were not true, then the wideband signal would consume the band nearly exclusively. It is from this sampled signal that we obtain the input to the signal classifier. So the signal classifier input will be a composite signal containing up to M independent signals of varying characteristics with non-overlapping spectrum. The signal to noise ratio of the composite signal in the simulations conducted in this paper is assumed to be 10 dB or greater. This composite signal, which will be referred to as $x(n)$, is therefore a discrete, time invariant stream of samples of bounded amplitude represented by

$$x(n) = N(n) + \sum_{m=1}^{M} S_m(n) A_m e^{j(2\pi n f c_m + \varphi_m)}$$

where $S_m(n)$ are the baseband signals of unknown modulation format, amplitude, etc. and $N(n)$ is the post sampled noise of the composite signal (assumed to be AWGN). The values fc_m, φ_m are the center frequency and phase offsets for each sub-signal.

3. PFM HISTOGRAM CONSTRUCTION

The streaming input signal $x(n)$ will be partitioned into blocks of length L samples for processing. The signal classifier will employ a Discrete Fourier Transform (DFT) of length K, and the block length L will be chosen to be less than or equal to the DFT length K.

Though it is not required for the PFM histogram construction, we will assume in this paper that a finite number of blocks I are analyzed in the classifier (each of length L). These I blocks will be given index i = (0, 1, … I-1) and each containing L samples, so:

$$x_i(n) = \langle x(iL+1), x(iL+2) \cdots x(iL+L) \rangle$$

Each block will be processed through a window function $w(n)$. The window function is not bound by this method and the use of different window functions and the resulting image patterns generated is the topic of further research. This paper will assume the use of a Hanning window function. Signal $s(n)$ is thus created as:

$$s_i(n) = x_i(n) \cdot w(n)$$

Each windowed block will be processed by the DFT of length K. If the DFT length K is larger than the block size L, then the block will be zero padded between the windowing and DFT operation. The magnitude of the DFT operation will be represented as $s_i(\omega)$:

$$s_i(\omega) = |DFT\{s_i(n)\}|$$

where ω in this case contains discrete frequency bin values. The frequency domain data is processed to extract the localized peaks above a given threshold of the blocked spectrum. In order to obtain the values of the localized peaks, the frequency index of the localized peaks which are higher than the threshold must first be determined. To do this, a sparse impulse train that contains a value of 1 at each positive inflection and zero everywhere else is created. This signal will be referred to as $D_i(\omega)$:

$$D_i(\omega) = \sum_{j=1}^{J} \delta_k(\omega - \omega_j)$$

where ω_j is the frequency bin of the localized positive peaks above a certain threshold and δ_k is the discrete delta function. Although this representation shows the form of the signal, it must be generated as a function of $s_i(\omega)$, which can be done in the following way:

$$D_i(\omega) = \frac{\partial}{\partial\omega}\left\{sign\left[\frac{\partial}{\partial\omega}\left\{\frac{1}{2}S_T(1 + sign\{S_T\})\right\}\right]\right\}$$

where S_T is defined as:

$$S_T = s_i(\omega) - A_T$$

and A_T is the magnitude threshold value. Selection of the threshold value will depend on the desired system tradeoffs. In the case of manual classification of signals, the threshold could be made variable so that the user could see different image results as the threshold is adjusted. The optimization and/or adaptability of this threshold value is a topic for continued research in the case of automated signal classification.

To obtain the resulting signal $y_i(\omega)$ with localized peaks isolated, simply take the product:

$$y_i(\omega) = s_i(\omega) \cdot D_i(\omega)$$

The final step in creating the desired image is to create a two dimensional histogram of the magnitudes of each localized peak for each frequency bin. In order to develop the 2D histogram over magnitude and frequency, the magnitude results of the frequency signal $y(\omega)$ need to be quantized. By doing so, magnitude bins that can be used to develop the amplitude frequency histogram will be generated. The selection of the magnitude bin size will depend on the system characteristics including scaling of the magnitude (dB vs. linear), desired resolution, etc. In the case of this paper, and the simulations that follow, dB scaling of the magnitude squared is used (power in dB). The selection of the magnitude bin size can be dynamic as follows:

$$\Delta q = \frac{\max\{y\} - \min\{y\}}{R}$$

where R is the desired number of magnitude bins (resolution). From this, we can create a new index r, over which we will quantize the magnitude into R bins, thus the r index will range from 0 to R-1:

$$q_r = min\{y\} + r\Delta q$$

where

$$r = 0,1,2,\cdots,(R-1)$$

and the result u_r takes a value of 1 if the y value being quantized falls into the magnitude range:

$$u_r = \begin{cases} 1 & q_r \leq y < q_{r+1} \\ 0 & otherwise \end{cases}$$

A matrix is then formed by counting the occurrences of events that fall into the joint frequency – magnitude bins as follows:

$$U_{k,r} = \sum_{i=0}^{I-1} u_{k,r}$$

where magnitude bin index

$$r = 0,1,2,\cdots,(R-1)$$

and frequency bin index

$$k = 0,1,2,\cdots,(K-1)$$

Figure 1 shows the basic flow of operations to produce the proposed two dimensional image that will be used to identify the features of several widely used signal formats.

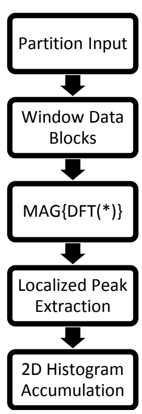

Figure 1: Process Flow Block Diagram

4. SIMULATIONS

Simulations were performed to present the image patterns for different types of signals used in communications and RADAR processing. The following types of signals were used in the stimulus for the simulation: 1) two level Frequency Shift Keyed (FSK) signal, 2) two level Amplitude Shift Keyed (ASK) signal, 3) analog linear FM (LFM) signal, 4) 16 point Quadrature Amplitude Modulated (QAM16) signal, 5) Offset Quadrature Phase Shift Keyed (OQPSK) signal, and 6) An OFDM-like (Orthogonal Frequency Division Multiplexed) signal. The last signal may not conform to the strict definition of an OFDM signal, but for the purpose of this paper, the differences will be considered negligible. Each of the baseband modulated data signals are formed from a set of random numbers, such as 1s and -1s for binary modulation, or {-1, -1/3, 1/3, 1} for QAM16. The LFM signal will be generated from a linear ramp signal. Each baseband signal will be denoted A_{bb}. A_{bb} is generated from an oversampled series of these values that are passed through low pass filters to shape the signal for realistic bandwidth limiting. The signal construction proceeds from there as follows:

1. Two level FSK baseband:

$$S_1 = e^{j(2\pi T_s f_d \varphi_F)}$$

where T_s is the sampling period, f_d is the frequency deviation constant, and:

$$\varphi_{F_j} = A_{bb_j} + \varphi_{F_{j-1}} \quad j = 1,2,3 \ldots \infty$$

is the accumulated phase of the baseband FSK that is derived from the pulse shaped data signal A_{bb} described above.

2. Two level ASK baseband:

$$S_2 = (A_{bb} + \frac{2}{g} - 1)\frac{2}{g}$$

where g is the modulation depth with value 0 to 1.

3. Linear FM baseband:

$$S_3 = e^{j(2\pi T_s f_a \varphi_{LFM})}$$

where T_s is the sampling period, f_a is the LFM base frequency constant, and φ_{LFM} is the phase accumulation for the LFM signal.

4. 16 point QAM signal:

$$S_4 = mI + jmQ$$

where mI and mQ are both 4 level uniformly distributed random variables from the set {-1, -1/3, 1/3, 1}. The values are upsampled and filtered just as in the case of the binary baseband signals.

5. Offset Quadrature PSK signal:

$$S_5 = mI + jmQ$$

where mI and mQ are both 2 level uniformly distributed random variables from the set {-1, 1}. The values are upsampled and filtered. The delay of the upsampled mI signal is shifted to ½ the symbol period to produce the offset characteristic of the signal. This minimizes the amplitude fluctuation that occurs as a result of the bandwidth limiting.

6. OFDM-like signal:

$$S_6 = Vec\{IFFT_k\{S_{p,k}\}\}$$

where

$$S_{p,k} = mI + jmQ \;\; \| \; \bar{0}$$

is a 16 point QAM signal (with no upsampling or filtering) taken in k blocks of N size and padded with zeros to the length of the IFFT. As in the case of 16QAM, the values for mI and mQ are taken uniformly from the set {-1, -1/3, 1/3, 1}. The $Vec\{\}$ function creates a single vector from the concatenation of the k sequences generated from each IFFT function.

The final stimulus for the simulation is, as described under signal construction, a superposition of all sub-signals as follows:

$$x(n) = N(n) + \sum_{m=1}^{6} S_m(n) A_m e^{j(2\pi n f c_m + \varphi_m)}$$

where $N(n)$ is the AWG noise that is added to the composite signal. A_m is an amplitude factor that is applied independently to each signal to provide variance to the signal levels. f_{cm} is the carrier frequency of each independent signal to separate the spectrum of the signals. As stated in the signal assumption section, these center frequencies are set to avoid spectrum overlap between signals. S_m are the individual test signals described above.

After the PFM histograms are generated for the signals in the simulated bandwidth, a 5X5 pixel smoothing filter is applied to help create an image that facilitates normalized viewing of the individual signals. The selection and performance of the smoothing is subjective in the case of manual identification of the signals. Future research into automated classification would necessitate a methodical approach to filter selection. For the case of the following plots, a simple pyramid shape is used for the filter kernel.

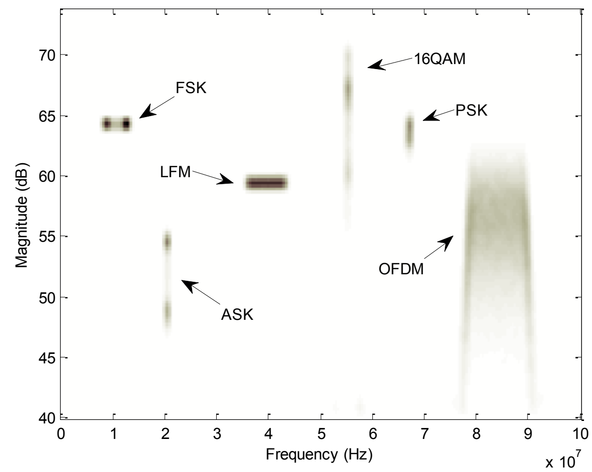

Figure 2: PFM histogram of 6 signals, block size of 100, FFT size of 256 , SNR = 22dB

Figure 2 shows the distinct patterns of the example signals used in the simulation. The two level FSK signal produces a dual hump pattern along the horizontal (frequency) axis, while the two level ASK signal produces a dual hump pattern in the vertical (magnitude) axis. Important to note however is that the dual humps in these patterns are not independent humps. The humps from the modulated signals form connected clusters due to the band limited nature of the modulated signals. The signals do not change from one state to another instantaneously in a practical system, and the PFM histogram shows this feature by displaying connected, albeit lower, "ridges" between the humps. These distinctive characteristics will allow the classifier to isolate different signal formats.

It is also clear that the LFM example forms a solid line across the horizontal axis. This is to be expected when considering the derivation of the LFM. It is fairly easy for a classifier to identify the LFM.

Figure 3 shows the PFM histogram of the same composite input signal but with a reduction in the signal to noise ratio (SNR) by 6 dB. It is important to note that the signal to noise ratio is calculated over the composite signal which contains the superposition of 6 signals of differing power levels. The SNR of any individual signal is less than the composite.

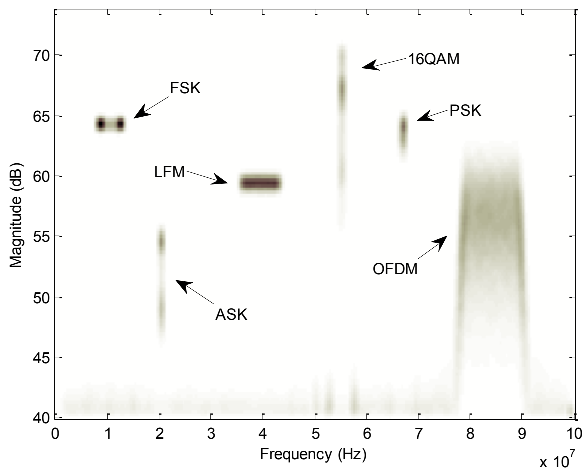

Figure 3: PFM histogram of 6 signals, block size of 100, FFT size of 256 , SNR = 16 dB

It is clear from Figure 3 and Figure 4 that the reduction in SNR results in a smearing effect on the signal clusters and a cloud of noise appears at the bottom of the image.

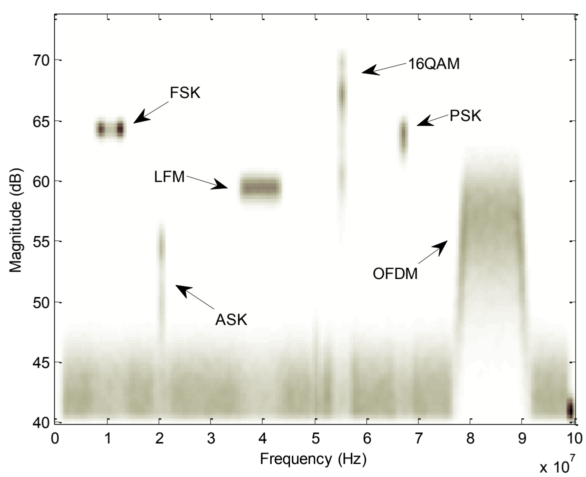

Figure 4: PFM histogram of 6 signals, block size of 100, FFT size of 256 , SNR = 10 dB

Figure 5, Figure 6, and Figure 7 show plots of the same composite signal with nothing changed other than the block size and DFT length. In this case, 128 point DFT is used to contrast against a 256 point DFT. The same features exist in this plot, but with less resolution. It is clear from these images that the distinct humps of multilevel modulation could be merged together if the resolution relative to the state separation is insufficient to distinguish the humps.

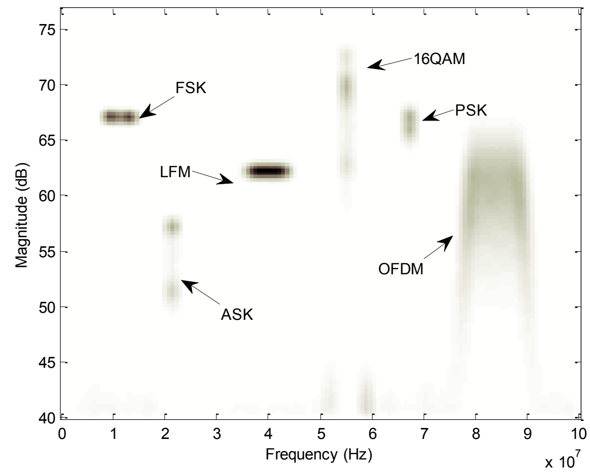

Figure 5: PFM histogram of 6 signals, block size of 70, FFT size of 128 , SNR = 22 dB

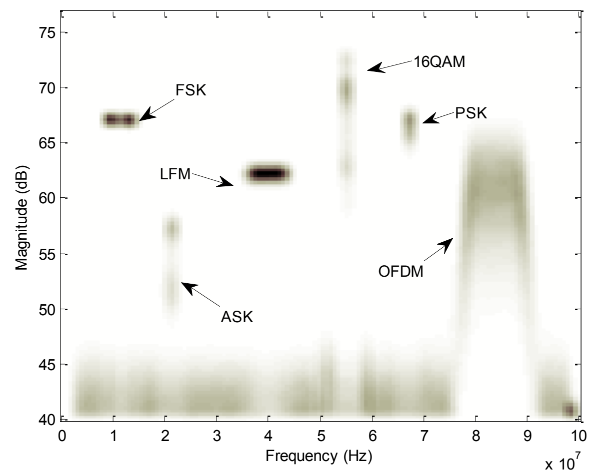

Figure 6: PFM histogram of 6 signals, block size of 70, FFT size of 128 , SNR = 16 dB

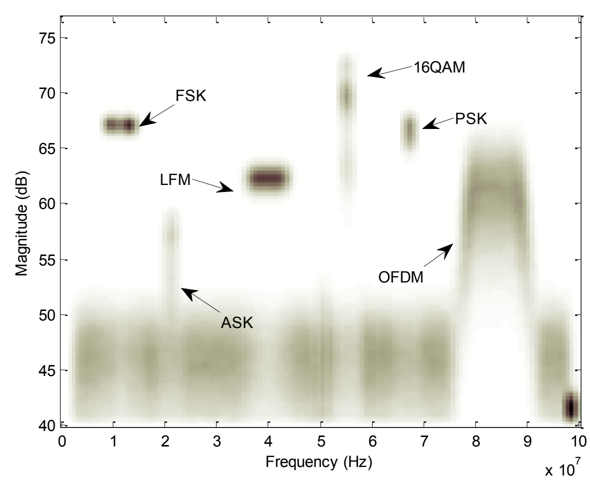

Figure 7: PFM histogram of 6 signals, block size of 70, FFT size of 128 , SNR = 10 dB

Figure 8, Figure 9, and Figure 10 display the results of images produced from 512 point DFTs for the same three signal to noise ratios. One main difference that can be seen in these images is the feature of the hump connection in the two level FSK signal. The connection is somewhat offset in magnitude from the two humps, forming an arched ridge instead of a straight line. This indicates that the transition between FSK levels incurs some reduction in the DFT power for those bins which can be seen at higher frequency resolutions.

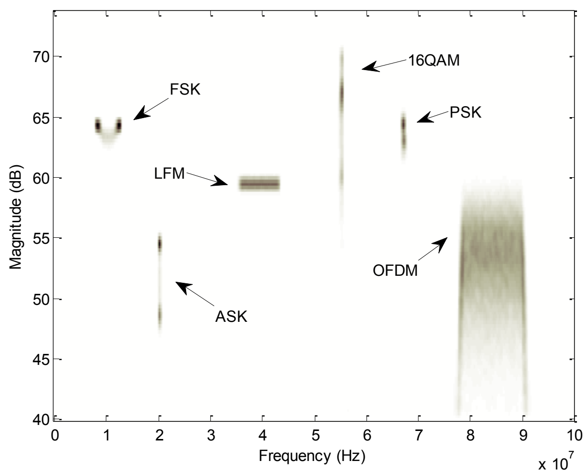

Figure 8: PFM histogram of 6 signals, block size of 200, FFT size of 512 , SNR = 22 dB

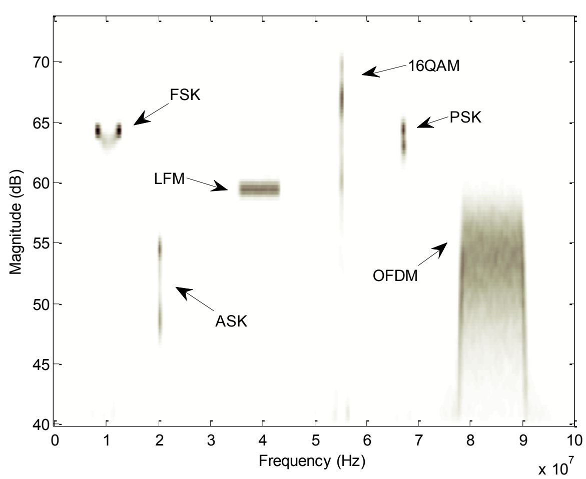

Figure 9: PFM histogram of 6 signals, block size of 200, FFT size of 512 , SNR = 16 dB

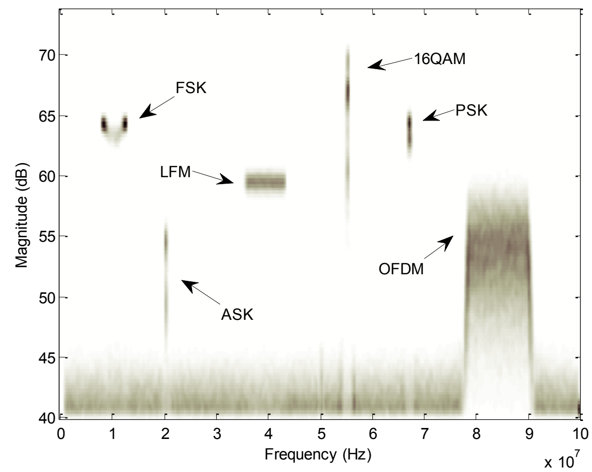

Figure 10: PFM histogram of 6 signals, block size of 200, FFT size of 512 , SNR = 10 dB

Three dimensional images are included from the simulation to provide alternate views of the characteristic features of the different signal types.

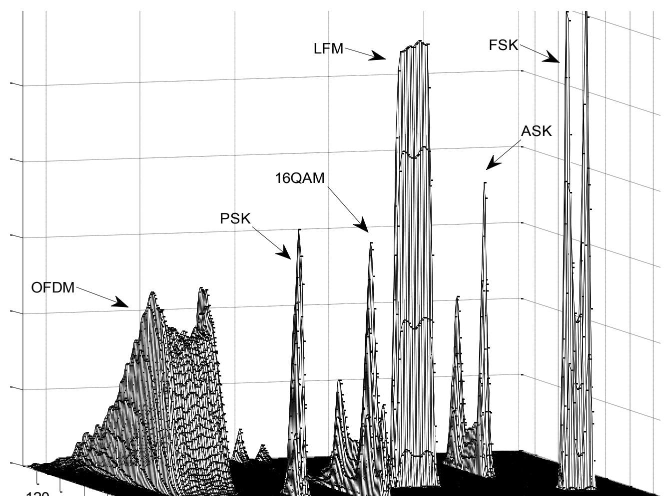

Figure 11: 3D emulation of PFM histogram for SNR = 22 dB, block size of 100, and FFT size = 256

The plot of Figure 12 is a different angle of the same 3D plot of Figure 11, where other signal features are more visible.

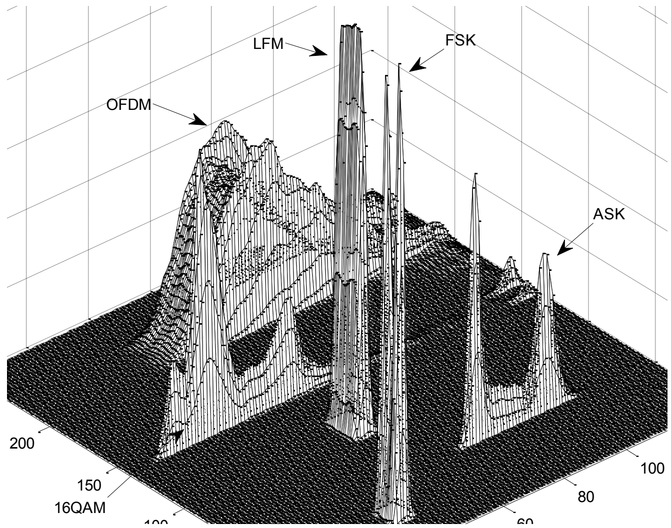

Figure 12: 3D emulation of PFM histogram for SNR = 22 dB, block size of 100, and FFT size = 256, alternate angle

5. LIMITATIONS

There are limitations in this method that should be pointed out. First, as noted early in the assumptions, the method is most useful when the signals being analyzed are narrow band relative to the sample rate. Specifically, if the signals under test have a symbol rate higher than the ratio of the sample rate to the block size (DFT block size), then the DFT will merge the spectrum shapes across different symbols and the technique will not be able to create the distinct signatures for the different modulation types.

Another limitation to the method is its inability, for the most part, to distinguish between a narrowband constant envelope phase modulated signal and a sinusoidal (unmodulated) signal. With the exception of small distortions in frequency, depending on the modulation characteristics, the signature of a constant envelope signal with minimal frequency deviation will appear as a single dot in the image, which is the same as an unmodulated sinusoid. Fortunately, however, communication systems almost never use unmodulated carriers because they contain no information. So it is safe in most cases to assume that a single dot is a phase modulated signal in this classifier.

In addition to the above limitations, other conditions under which the method is less effective are cases where the power of the signals is fluctuating rapidly. In systems where the channel is fluctuating at high rates such as mobile systems, the images will become skewed if the power of the signal is fluctuating rapidly compared to the capture time of the image (in large part due to multipath fading). Likewise, in the case where signals being analyzed are present in very short bursts, such that the rising and falling edges of the power envelope are frequently caught in the DFT blocks, they could skew the magnitude and have similar affects. This last condition is not likely under the narrow band assumption because the bursts would not be problematic unless they are only a few symbols long. Most communication systems employ packets with much higher symbol counts. This limitation could be mitigated however through use of time domain power triggering techniques in which the blocks that are sampled are only those which the average power has exceeded a certain threshold.

6. CONCLUSION

This paper introduces a new mechanism for signal classification/modulation detection of multiple signals within a given bandwidth by making use of the magnitude and frequency density features of the signals. Simulations were shown for six different modulation formats and 2D images were displayed for varying signal to noise ratios and block size parameters. Several areas of further research are suggested. Research on autonomous classification through pattern recognition, image template matching and image processing algorithm optimization of the resulting 2D images is proposed. Also some limitations of the method were pointed out in the paper. Resolving some of the limitations should be examined in future work. In addition, the examples were performed under specific parameters in the technique such as bandwidth, block size, FFT size, threshold values, etc. Optimization of these parameters is another area for further investigation. The proposed method employs only the DFT magnitude. Another area of further research is to utilize the phase output of the DFT to enhance the results and provide further differentiation between signal types.

7. REFERENCES

[1] X. Tan, H. Zhang, W. Lu, "Automatic Modulation Recognition of Mixed Multiple Source Signals", *Frequenz*, Vol. 65, pp. 37-45, 2011.

[2] O.A. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, "A Survey of Automatic Modulation Classification Techniques: Classical Approaches and New Trends" pp. 1-43, August 1992.

[3] A.K. Nandi, and E.E. Azouz "Algorithms for Automatic Modulation Recognition of communication Signals" *IEEE Transactions On Communications*, Vol. 46, No. 4, pp. 431-436, April 1998.

[4] M.L.D. Wong, and A.K. Nondi, "Automatic Digital Modulation Recognition Using Spectral And Statistical Features With Multi-Layer Perceptrons", *International Symposium on Signal Processing and its Applications (ISSPA) Kuala Lumpur Malaysia*, pp. 390-393, August, 2001.

[5] A. Shklyaeva, P. Kovar, and D. Kubanek. "Classification of Digital Modulations Mainly Used in Mobile Radio Networks by means of Spectrogram Analysis", *IFIP International Federation for Information Processing*, Vol. 245, pp. 341-348, 2007.