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다중경로 페이딩 환경에서 HOS와 WT을 이용한 디지털 변조형태 인식

(Digital Modulation Types Recognition using HOS and WT in Multipath Fading Environments)

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요 약

본 논문은 다중경로 페이딩 채널 조건에서 사전 정보없이 입사하는 디지털 신호 10종의 변조형태를 고정확도로 인식할 수 있도록 고차 통계량(HOS)과 웨이브릿 변환(WT)에서 선정된 특징(key features)을 이용한 견실한 하이브리드 분류기를 제안하였다. 제안된 분류기는 실제 시나리오를 고려하여 다양한 다중경로 환경(즉, 농촌, 소도시, 도심지역)에서 측정된 채널 데이터를 이용하였다. 실제 측정된 다중경로 페이딩 채널 데이터를 이용하여 Holdout-like 방식으로 총 15개 채널 중 9개 채널은 트레이닝용으로 사용하고, 나머지 6개 채널은 테스트용으로 사용하였다. 제안된 분류기는 다중경로 환경에서 높은 변별력을 유지하는 HOS 특징을 기반으로 구현되었고, AMA(Alphabet Matched Algorithm) 또는 MMA(Multi-modulus Algorithm)와 같은 등화기법의 적용없이 분류가 어렵다고 알려진 MQAM신호(M=16, 64, 256)들에 대해서만 WT 특징을 적용하였다. 선정된 특징들을 이용한 변조인식은 입력공간에서 최대 마진을 갖는 하이퍼 공간으로 매핑시킴으로서 분류 능력이 우수하다고 알려진 SVM 메소드를 적용하여 시뮬레이션을 실시하였다. 제안된 분류기의 성능은 트레이닝 채널과 테스트 채널에서 WT 또는 HOS 특징만을 단독으로 사용하는 분류기에 비해 현저한 성능 향상을 보였고, 특히, MQAM 신호의 인식률은 낮은 SNR레벨에서도 거의 완전하게 분류되었다.

Abstract

In this paper, the robust hybrid modulation type classifier which use both HOS and WT key features and can recognize 10 digitally modulated signals without a priori information in multipath fading channel conditions is proposed. The proposed classifier developed using data taken field measurements in various propagation model (i.e., rural area, small town and urban area) for real world scenarios. The 9 channel data are used for supervised training and the 6 channel data are used for testing among total 15 channel data(i.e., holdout-like method). The proposed classifier is based on HOS key features because they are relatively robust to signal distortion in AWGN and multipath environments, and combined WT key features for classifying MQAM(M=16, 64, 256) signals which are difficult to classify without equalization scheme such as AMA(Alphabet Matched Algorithm) or MMA(Multi-modulus Algorithm). To investigate the performance of proposed classifier, these selected key features are applied in SVM(Support Vector Machine) which is known to having good capability of classifying because of mapping input space to hyperspace for margin maximization. The Pcc(Probability of correct classification) of the proposed classifier shows higher than those of classifiers using only HOS or WT key features in both training channels and testing channels. Especially, the Pccs of MQAM are almost perfect in various SNR levels.

Keywords : Modulation Classification(MC), High-Order Statistics(HOS), Wavelet Transformation(WT), Support Vector Machine(SVM)

Ⅰ. Introduction

An automatic radio signal modulation classifier finds its use military and civilian communication

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application including interference identification, spectrum monitoring, signal surveillance, electronic warfare, military threat analysis, electronic counter measure, and software/cognitive radio system.

Most modulation classifiers have been proposed for recognition of signal format in AWGN channels[1~3]. In practical wireless communication, due to the multipath, the level of the received signal is always time-varying and not known. So, classifiers developed in only AWGN channels suffer from severe performance degrade of modulation classification(MC) when they operate in multipath fading environments.

In this paper, data taken real world measurements were used to simulate situations as close to reality as possible, as it considers multipath propagation environments in [4]. These impulse responses represent various wireless propagation channels, from mild fading to severe multipath fading situations.

Since it is known that HOS key features such as moments and cumulants are relatively robust to signal distortion, we mainly used HOS key features for MC. But it is known that HOS key features are difficult to discriminate among MQAM[4].

The wavelet transform (WT) is a powerful tool for analyzing non-stationary signals, which include digital communication signals, and the WT magnitude of communication signals vary with modulation types[1]. The WT coefficients have the property of insensitive to the changing of noise. So we tried to discriminate among MQAM using WT key features having the property of insensitive of noise and the capability for analyzing non-stationary signals.

In this paper, we investigate the performance of the hybrid classifier with HOS and WT key features for 10 types of digital modulated signals using data taken real world measurements.

The paper is organized as follows. In Section Ⅱ, the HOS key features for classification are presented. In Section Ⅲ, the wavelet key features for classification are presented. In Section Ⅳ, the modulation classification using SVM is presented. In Section Ⅴ, we investigated the performance of the proposed hybrid classifier with HOS and WT key features using numerical simulations in multipath fading environment, and in Section Ⅵ, the paper is concluded.

Ⅱ. HOS Key features for MC

In many paper, the higher-order moments and higher-order cumulants were used for identification of digital signals. These features can provide a fine way to describe the shape of the probability density function.

1. Moments

Probability distribution moments are a generalization of the concept of the expected value, and can be used to define the characteristics of a probability density function. Recall that the general expression for the ith moment of a random variable is given by[4~5]

$$\mu_i = \int_{-\infty}^{\infty} (s-\mu)^i f(s) ds \tag{1}$$

where is μ the mean of the random variable. The definition for the ith moment for a finite length discrete signal is given by

$$\mu_i = \sum_{k=1}^{N} (s_k - \mu)^i f(s_k) \tag{2}$$

where N is the data length.

In this paper, signals are assumed to be zero mean. Thus Eq. (2) becomes

$$\mu_i = \sum_{k=1}^{N} s_k^i f(s_k) \tag{3}$$

Next, the auto-moment of the random variable may be defined as

$$E_{p+q,p} = E\left[s^p (s^*)^q\right] \tag{4}$$

where p and q represent the number of the non conjugated terms and number of the conjugated terms, respectively, and $p+q$ is called the moment order.

For example, for p = 2 and q = 0, Eq. (4) becomes

$$E_{2,2} = E[s^2(s^*)^0] = E[s^2] = \mu_2 = \sum_{k=1}^{N} s_k^2 f(s_k), \tag{5}$$

which is the second moment or the variance of the random variable.

In a similar way, expression for $E_{2,1}$, $E_{4,4}$, $E_{8,8}$, etc. may be easily derived. Note that the normalized moments $E_{3,3}$ and $E_{4,4}$ are called skewness and kurtosis, respectively.

2. Cumulants

Consider a scalar zero mean random variable s with characteristic function[4~5]

$$\hat{f}(t) = E\{e^{its}\}, \tag{6}$$

Expanding the logarithm of the characteristic function as a Taylor series, one obtains

$$\log \hat{f}(t) = k_1(it) + \frac{k_2(it)^2}{2} + \ldots + \frac{k_r(it)^r}{r!} + \ldots \tag{7}$$

where the constant k_r are called the cumulants (of the distribution) of s. Note that the first three cumulants (for zero-mean variables) are identical to the first three moments

$$\begin{aligned} k_1 &= E\{s\} \\ k_2 &= E\{s^2\} = E_{2,2} \\ k_3 &= E\{s^3\} = E_{3,3}. \end{aligned} \tag{8}$$

The symbolism for the nth order cumulant is similar to that of the nth order moment. More specifically

$$C_{p+q,p} = Cum\left[\underbrace{s,\ldots,s}_{p\ terms},\underbrace{s^*,\ldots,s^*}_{q\ terms}\right] \tag{9}$$

For example:

$$C_{8,4} = Cum(s, s, s, s, s^*, s^*, s^*, s^*) \tag{10}$$

We have computed all moments and cumulants up to the 8th order for 10 modulated signals. Robustness of the candidated features was investigated next by studying their behavior when

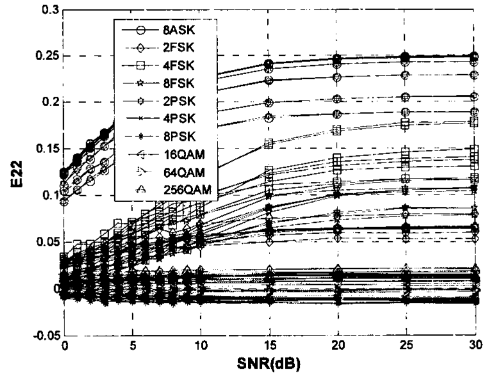

그림 1. 트레이닝 채널(#1-#9)에서 SNR변화에 따른 변조신호별 $E_{2,2}$값의 분포

Fig. 1. $E_{2,2}$ for all modulation scheme w.r.t. SNR in training channels (#1-#9).

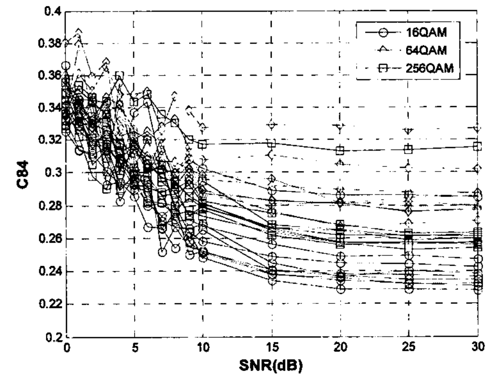

그림 2. 트레이닝 채널(#1-#9)에서 SNR변화에 따른 변조신호별 $C_{8,4}$값의 분포

Fig. 2. $C_{8,4}$ for all modulation scheme w.r.t. SNR in training channels (#1-#9).

the modulation signal is passed through the various fading and multipath propagation model [#1-#9, 6]. These channels cover a variety of different environments, from rural environment model 1 or 2 paths to urban models with more than 3 different propagation paths. Some moments and cumulants can be used to separate different modulation schemes while others have little or no use. Figure 1 and 2 show a closer look of $E_{2,2}$ and $C_{8,4}$ characteristics for a number of the considered digital signal types, respectively. Especially, HOS key feature such as $C_{8,4}$ is difficult to discriminate MQAM signals as shown in Figure 2. The values in these Figures are computed from 9 training channels of real-world measurements [Channels #1-#9, 6], as it considers in [4].

Based on the procedure above, the selected HOS key features are 5 (i.e., $E_{2,2}$, $E_{4,3}$, $E_{4,2}$, $E_{8,4}$, $C_{8,4}$) for classify of non-MQAM in the proposed classifier.

Ⅲ. WT Key Features for MC

The key features for modulation classification in pattern recognition approach must be selected.

Wavelet key feature extraction is proposed here. The main characteristic of wavelet is that it can provide localized frequency information of a signal, which is very useful for classification. Due to some desirable properties, the wavelet basis constructed by Daubechies became the foundation for the most popular techniques for signal analysis and representation in a wide range of applications. Digital modulated waveform is a cyclo-stationary signal that contains transients in amplitude, frequency or phase and the WT is quite suitable at extracting transient information. Another attractive feature of WT is that it can be computed using fast algorithm (e.g., Fast WT) and hence allowing identification of modulation types in real time[3].

The continuous wavelet transform (CWT) of a signal $x(t)$ is defined as

$$CWT(\tau,s) = \int x(t)\psi_s^*$$
$$= \frac{1}{\sqrt{|s|}} \int x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \qquad (11)$$

where the function $\psi(t)$ is called mother wavelet, ψ^* is its complex conjugate, and s is the scaling constant.

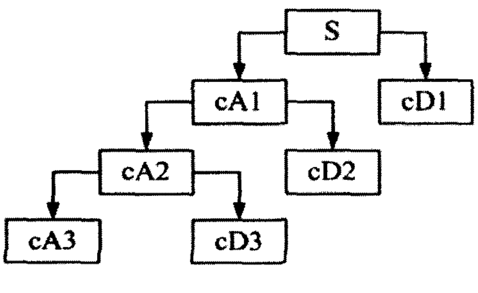

그림 3. 웨이브릿 분해 트리
Fig. 3. Wavelet Decomposition Tree.

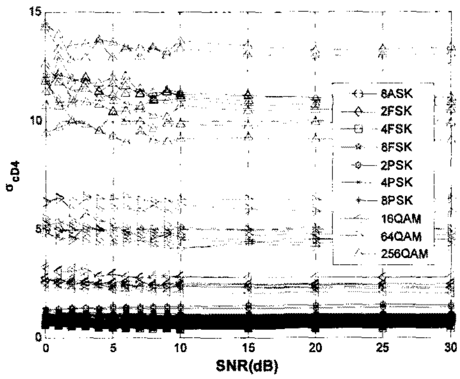

그림 4. 트레이닝 채널(#1-#9)에서 SNR변화에 따른 변조신호별 sd_cD4의 분포
Fig. 4. sd_cD4 for all modulation scheme w.r.t. SNR in training channels (#1-#9).

The baby wavelet $\psi_s(t)$ comes from time-scaling and translation of the mother wavelet.

The WT decomposition process can be iterated with successive approximations being decomposed in turn, so that one signal is broken down into many lower-resolution components as shown in Figure 3.

This is called the WDT (wavelet decomposition tree). In this paper, WDT with scale factor 4 (i.e. standard deviation of approximation and detail coefficients at each level) is used for modulation classification.

We selected 5 key features (i.e., cA1, cA2, cA3, cA4, and cD4) for MC using Haar WT because these key features have robust properties of sensitive with modulation types and insensitive with SNR variations. Figure 4 shows the characteristics of sd_cD4 (i.e., σ_{cD4}) among these selected key features. Note that MQAM signals can almost perfectly classified using sd_cD4 as shown in Figure 4.

Ⅳ. Classification using SVM

Support Vector Machine (SVM) is an empirical modeling algorithm and is the state-of-the-art for the existing classification methods. The SVM is basically a two-class classifier based on the ideas of “large margin” and “mapping data into a higher dimensional space,” and the kernel functions in the SVM.

The first objective of the SVM classification is the maximization of the margin between the two nearest data points belonging to two separate classes. The second objective is to constraint that all data points belong to the right class. It is a two-class solution which can use multi-dimensions features. SVMC (SVM Classifier) classifies the points from two linearly separable sets in two classes by solving a quadratic optimization problem in order to find the optimal separating hyperplane between these two classes. This hyperplane maximizes the distance from the convex hulls of each class. These techniques can be extended to the nonlinear cases by embedding the data in a nonlinear space using kernel functions. The robustness of SVMC originates from the strong fundamentals of statistical learning theory.

Another degree of freedom in the SVMC is the kernel function used. Since similarities need not follow properties of Euclidean space, SVM must firstly transform the similarity space to a manageable space. This is done by defining a "kernel" which is an inner product to convert points in the input space to points in the feature space.

In modulation classification using SVM, we used only exponential radial basis function (RBF) kernels. One of examples using exponential RBF kernel in SVMC shows as shown in Figure 5.

Since SVM is basically a binary classifier, it is not

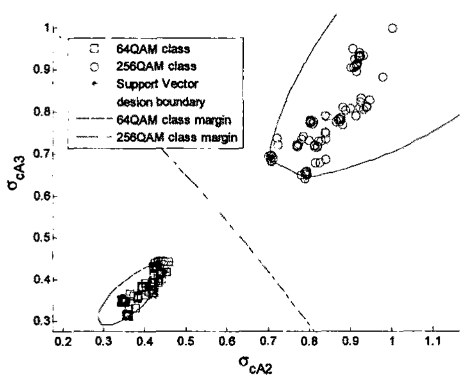

그림 5. SVM에서 eRBF 커널을 이용한 64QAM 대 256 QAM의 분리 (sd_cA2와 sd_cA3 특징 이용)
Fig. 5. Classification of 64QAM and 256QAM signals using eRBF kernel in SVM (key features : sd_cA2 vs. sd_cA3).

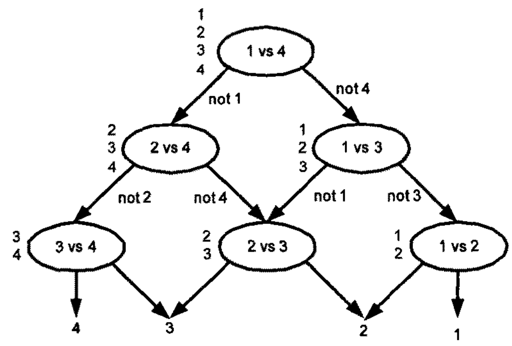

그림 6. 4-클래스 분류를 위한 SVM-DDAG 구조
Fig. 6. SVM-DDAG for 4-classes.

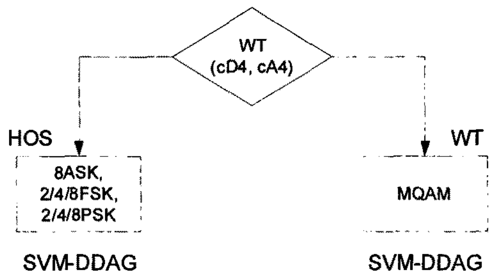

그림 7. HOS와 WT을 이용한 하이브리드 분류기
Fig. 7. Hybrid classifier using HOS and WT.

straight forward to apply it to multi-class classification problems. The SVM-DDAG (Decision Directed Acyclic Graph) method yields comparable accuracy and memory usage to the other two standard methods (i.e., 1-v-1 and 1-v-r), but yields substantial improvement in both training and evaluation time[7]. We applied SVM-DDAG method using HOS (refer C2) and WT (refer C1) for our 10 multi-class modulation classification problem (See Figure 6).

We developed hybrid SVM-DDAG classifier (refer C3) using both HOS and WT features for our 10 multi-class MC problem as depicted in Figure 7.

V. Numerical Simulation

In this Section, the performance of the proposed classifiers is investigated in the MATLAB environment. The 10 digital modulation types (i.e. 8ASK, 2/4/8FSK, 2/4/8PSK, and 16/64/256QAM) are classified. We assumed that carrier frequencies were estimated correctly and signals were complex

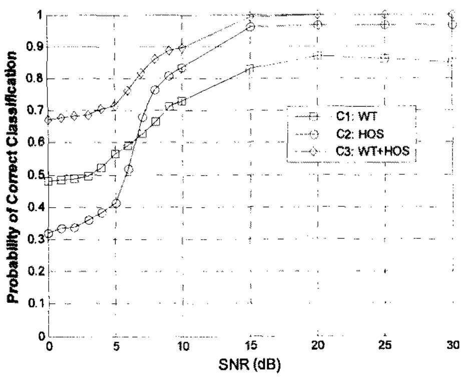

그림 8. 트레이닝 채널을 적용한 SNR 변화에 따른 3 분류기의 인식률

Fig. 8. Pccs of 3 classifiers at SNR from 0dB-30dB in training channels.

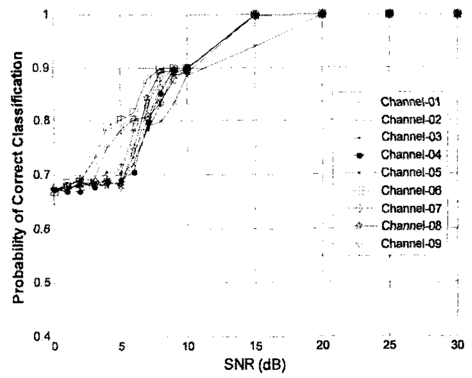

그림 10. 제안된 분류기에서 SNR 변화에 따른 인식률 (트레이닝 채널 조건)

Fig. 10. Pccs of training channels at SNR from 0dB-30dB in the proposed classifier.

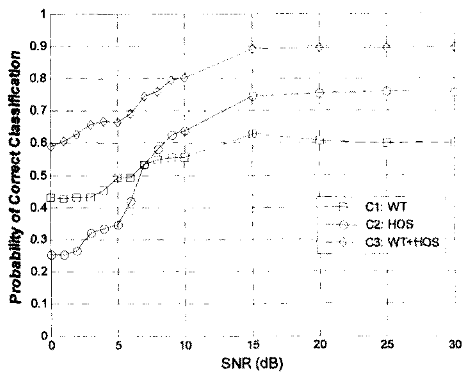

그림 9. 테스팅 채널을 이용한 SNR변화에 따른 3 분류기의 인식률

Fig. 9. Pccs of 3 classifiers at SNR from 0dB-30dB in testing channels.

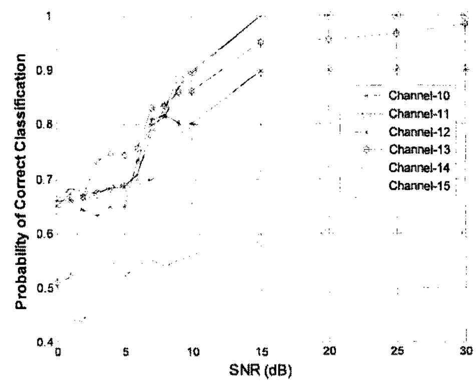

그림 11. 제안된 분류기에서 SNR 변화에 따른 인식률(테스팅 채널 조건)

Fig. 11. Pccs of testing channels at SNR from 0dB-30dB in the proposed classifier.

baseband.

In numerical simulation, the sampling frequency was chosen in such a way that all schemes are sampled with 4 samples/symbol. To distinguish 10 digital modulation types, simulation runs were carried out with 4,096 samples at SNR range from 0 dB to 30 dB. The probabilities of correct classification (Pcc) of 50 independent ensembles at each SNR and each channel in 3 classifiers are plotted for each modulation types as shown in Figure 8 - 13.

Results indicated an overall success rate of over 95% the SNR of 15dB in 2 classification schemes (i.e. C2 and C3) as shown in Figure 8. Especially, it was shown that the proposed classifier(C3) can achieve the good results with high Pcc (i.e., Pcc >= 90%) over region of 10dB SNR in training channels [#1-#9, 6] (See Fig. 8 and Fig. 10).

Figure 9 shows the Pccs of classifiers in testing channels[#10-#15, 6]. The Pcc of the proposed classifier in testing channels is about 10% lower than that of training channels because the Pcc is heavily degraded in channel #14 (See Fig. 9 and Fig. 11).

Figure 10 shows the Pccs of C3 in training channels are good and uniform.

Figure 11 shows that overall classification performances are affected by the amount of multipath distortion and noise in channels. The 6 propagation channels that are chosen for testing are channels #10-#11, #12-#13, and #14-#15 and represent a rural, a small town and urban propagation environments, respectively. These simulations cover a wide spectrum of possible noise and multipath propagation

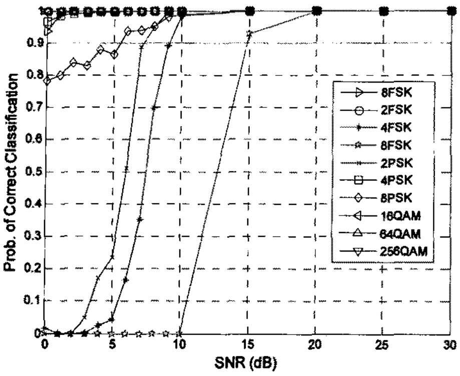

그림 12. 제안된 분류기에서 SNR 변화에 따른 개별 변조신호별 인식률 (트레이닝 채널 조건)

Fig. 12. Pccs of digital modulation types at SNR from 0dB-30dB in the proposed classifier (training channels condition).

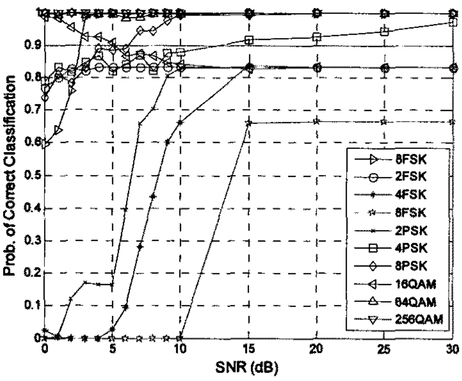

그림 13. 제안된 분류기에서 SNR 변화에 따른 개별 변조신호별 인식률 (테스팅 채널 조건)

Fig. 13. Pccs of digital modulation types at SNR from 0dB-30dB in the proposed classifier (testing channels condition).

environment combinations. Especially, it seems that the distortion condition of Channel #14 is worst.

Figure 12 and 13 show the Pccs of 10 modulated signals in training and testing channels, respectively. Some modulation types (i.e., 2/4FSK, 2PSK) are affected heavily in multipath channel conditions as shown in these figures. It is known that the classification of MQAM type is a problem since no suitable HOS can be found to serve as classification key feature, for the varying environments considered [4]. But, MQAM signals are almost perfectly classified using WT key features in proposed classifier as shown in Figure 12 and 13.

The detailed results of the proposed classifier at

표 1. 채널 11에서의 세부 인식율 (Pcc=90.0%)

Table 1. Confusion Matrix (Pcc=90.0% in Channel #11).

	Estimated Modulation Type @ SNR 10dB									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
T1	100									
T2		100								
T3			100							
T4			100	0						
T5					100					
T6						100				
T7							100			
T8								100		
T9									100	
T10										100

표 2. 채널 13에서의 세부 인식율 (Pcc=85.8%)

Table 2. Confusion Matrix (Pcc=85.8% in Channel #13).

	Estimated Modulation Type @ SNR 10dB									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
T1	100									
T2		100								
T3			100							
T4			100	0						
T5					100					
T6						58.0	42.0			
T7							100			
T8								100		
T9									100	
T10										100

표 3. 채널 15에서의 세부 인식율 (Pcc=80.0%)

Table 3. Confusion Matrix (Pcc=80.0% in Channel #15).

	Estimated Modulation Type @ SNR 10dB									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
T1	100									
T2		100								
T3		98.0	2.0							
T4			100	0						
T5				2.0	98.0					
T6						100				
T7							100			
T8								100		
T9									100	
T10										100

the SNR of 10dB are provided in the confusion matrix shown in Table 1-3. Channel 11, 13, 15 are test channel data and are measured in rural area, small town and urban area, respectively. These Tables showed that the Pcc of the proposed classifier smoothly degrade according to environmental conditions. Note that the classification of MQAM type is perfectly classified in these 5 testing channels except for channel 14. Because of simplifying the indication, the digital signal types of 8ASK, 2/4/8FSK, 2/4/8PSK, and 16/64/256QAM are substituted with T1, T2, T3, T4, T5, T6, T7, T8, T9, and T10, respectively.

VI. Conclusion

In this paper, the robust hybrid classifier which use both HOS and WT key features and can recognize 10 digitally modulated signals without a priori information in multipath fading channel conditions is proposed.

The proposed classifier is developed using data taken field measurements in various propagation model (i.e., rural area, small town and urban area) for real world scenarios. The 9 channel data are used for supervised training and the 6 channel data are used for testing among total 15 channel data like holdout-like method. The proposed classifier is based on HOS key features because they are relatively robust to signal distortion in AWGN and multipath environments, and combined WT key features for classifying MQAM(M=16, 64, 256) signals which are difficult to classify without equalization scheme such as AMA or MMA.

To investigate the performance of proposed classifier, these selected key features are applied in SVM which is known to having good capability of classifying because of mapping input space to hyperspace for margin maximization. The Pcc of the proposed classifier shows higher than those of classifiers using only HOS or WT key features in both training channels and testing channels. Especially, the Pccs of MQAM are almost perfect in various SNR levels.

참 고 문 헌

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