MDC와 kNNC를 이용한 고속 자동변조인식

Fast Automatic Modulation Classification by MDC and kNNC

박 철 순* Park, Cheol-Sun　**양 종 원*** Yang Jong-Won　**나 선 필*** Nah, Sun-Phil　**장 원*** Jang, Won

ABSTRACT

This paper discusses the fast modulation classifiers capable of classifying both analog and digital modulation signals in wireless communications applications. A total of 7 statistical signal features are extracted and used to classify 9 modulated signals. In this paper, we investigate the performance of the two types of fast modulation classifiers (i.e. 2 nearest neighbor classifiers and 2 minimum distance classifiers) and compare the performance of these classifiers with that of the state of the art for the existing classification methods such as SVM Classifier. Computer simulations indicate good performance on an AWGN channel, even at low signal-to-noise ratios, in case of minimum distance classifiers (MDC for short) and k nearest neighbor classifiers (kNNC for short). Besides a good performance, these type classifiers are considered as ideal candidate to adapt real-time software radio because of their fast modulation classification capability.

주요기술용어(주제어) : Modulation Classification(변조 인식), Minimum Distance Classifier(최소 거리 인식기), Nearest Neighbor Classifier(최근접 이웃 인식기)

1. Introduction

SDR (software defined radio) techniques can receive various kinds of modulation signal by very flexible software programming. These are considered as the important radio techniques for reconfigurable radio convergence in mobile systems, and are recently attracted interest from both the military and commercial sectors due to their capabilities of replacing several receivers with one universal receiver.

SDR is the practical applications for example in a wireless network environment where it is required for an unknown incoming signal to be routed to a right demodulator. The advent of realizable software radio allows the implementation of creative transceiver designs, which can dynamically adapt to the communications channel and user applications. One such transceiver design that demonstrates how the flexibility of a software radio may be exploited is a software radio that automatically determines the modulation

† 2007년 7월 31일 접수~2007년 10월 18일 게재승인
* 국방과학연구소(ADD)
주저자 이메일 : csun@add.re.kr

scheme used in an unknown signal. For a software radio implementation employing fast modulation classifier, the techniques must have a processing time overhead that still allows the software radio to maintain its real-time objectives.

The aim of this paper is to recognize simultaneously analog and digital modulation types, although there is a tendency to move towards using digital modulation schemes, there are currently still analog methods (i.e., legacy radios) in use. It is also possible to extract simply the message from an analog signal once it has been demodulated, which is more useful than the coded message which is received from a demodulated digital signal.

In this paper, we investigate the performances of the two types of fast modulation classifiers (i.e., 2 minimum distance classifiers and 2 k-nearest neighbor classifiers) with 7 features for 9 types of modulation signals and compare the performance of these classifiers with that of decision theoretic classifier (MDC for short) and support vector machine classifier (SVC for short). The probability of correct classification (Pcc) and the classification time of these classifiers are compared through numerical simulations.

The paper is organized as follows. In Section 2, the 7 key features used in classifiers are presented. In Section 3, the classifiers using normalized Euclidean distance (refer MDC-1) and weighted distance (refer MDC-2), and classifiers using kNNC with k=3 (refer kNNC-1) and k=5 (refer kNNC-2) are presented. In Section 4, the performances of these classifiers are evaluated and analyzed using numerical simulations, and in Section 5, the paper is concluded.

2. Key Features for Classification

The key features to be used for modulation classification must be selected so that they are sensitive to the modulation types of interest. These features also have robust properties of sensitive with modulation types and insensitive with SNR variation. Then the key features must be processed to enhance modulation dependencies and to suppress message dependencies.

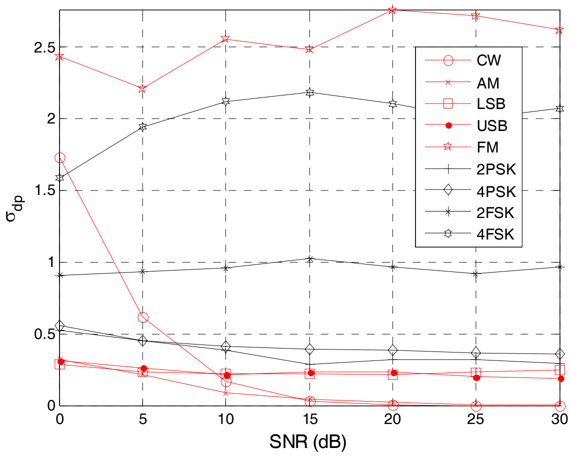
In this paper, we selected 7 key features for modulation classification. The 6 key features among them are used in [1] and 1 key feature is used in [2]. These 6 key features are gamma max (γ_{max}), symmetry of frequency (P), sigma of direct phase (σ_{dp}), sigma of absolute frequency (σ_{af}), sigma of absolute phase (σ_{ap}) and frequency compactness (μ_{42}^{f}). The 1 key feature that were used in [2] is Occupied bandwidth (oBW). The two features (i.e., σ_{dp} and μ_{42}^{f}) among these 7 key features set are given briefly and other 5 key features are skipped here for brevity's sake.

A. Sigma of direct phase (σ_{dp})

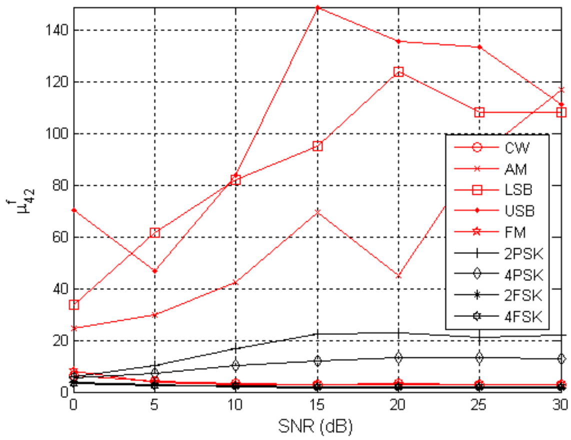
This key feature, σ_{dp}, is the standard deviation of the centered non-linear component of the direct (not absolute) instantaneous phase, evaluated over the non-weak intervals of a signal segment[1]. This key feature is used to discriminate between types without direct phase information such as AM and CW, and types with direct phase information such as 2/4PSK and FM (see Figure 1).

B. Compactness (μ_{42}^{f})

This key feature, μ_{42}^{f}, is the kurtosis of the normalized-centered instantaneous frequency[2]. The instantaneous frequency distribution can be used to identify the modulation type for frequency



[Figure 1] Graph of the SNR versus the σ_{dp}



[Figure 2] Graph of the SNR versus the μ_{42}^{f}

modulated signals. The instantaneous frequency is obtained by computing the phase derivative of the observed signal. The kurtosis of the normalized-centered instantaneous frequency, μ_{42}^{f}, defined by

$$\mu_{42}^{f} = \frac{Ef_n^4(t)}{E(f_n^2(t))^2} \tag{1}$$

where $E(\cdot)$ is the expectation operation, and $f_n(t)$ is the normalized-centered instantaneous frequency at time t.

The kurtosis coefficient is a measure of the flatness of the distributions. Since this is usually different for frequency and phase modulated signals, it is used as a feature for distinguishing between 2/4FSK and FM signals, and 2/4PSK. It is known that the kurtosis coefficient gives good results, and it is used here (see Figure 2). Also, this key feature can be used to discriminate between the FM signal, in which the instantaneous frequency (related to the speech signal) have high compact distribution, and 2/4FSK, in which the instantaneous frequency (related to the symbol sequence) have less compact distribution.

3. Fast Modulation Classifiers

In this Section, we propose that 2 Minimum Distance Classifiers and 2 k-nearest neighbor classifiers capable of fast classifying both analog and digital modulation signals. The following section presents the detailed review of these classifiers including basic classification principles.

A. Minimum Distance Classifier

The recognition algorithm used by the modulation classifiers is based on what is known as the degree of similarity in pattern recognition theory. To use this algorithm, the key features that help to make each signal unique must be identified. In many cases the underlying distributions are not known in practice. One can then use simpler classifier like the parametric classifiers which are parameterized in a few of parameters. The most commonly used parametric classifiers are the linear and quadratic classifier.

If the underlying distributions are Gaussian, the Bayes classifier will have a quadratic structure in general, and especially if the covariance matrices for the different classes are identical, the optimal classifier will be linear.

It has been known for a while that the minimum distance classifier (MDC for short) is robust and efficient in parameter estimation. In modulation classification, MDC seems to be an ideal candidate for real-time reconfigurable software radio, because sometimes we do not have the perfect knowledge about the noise model in field and need to fast and robust processing. For example, the noise may not be Gaussian, or the estimated SNR may not be accurate, and so on. In MDC, all the key features are considered simultaneously. So, the time order of the key features dose not affect on the probability of correct classification (Pcc) of on the modulation type of a signal. The MDC can automatically overcome moderate degree of model distortion. For that reason, it implies that the use of the MDC approach for solving the modulation recognition process may have better performance than the one of decision theoretic approach. As well as achieving robustness, MDC also possesses efficiency. Under the right model assumption, at least asymptotically (when the number of received signals is large), MDC is as efficient as likelihood method is.

Once these features are determined, a sample feature set of all identified features must be collected for each signal of interest. The sample set for one signal is treated as a class of data. There is one class for each signal. After all the sample sets have been collected, the data is reduced by calculating the mean and standard deviation of each feature for a given class. To classify an unknown incoming signal, the same feature set is used as is used for the known signals. This set of data points is treated as an N dimensional vector (for N features).

When the variance of features within each class are not homogeneous but vary from case to case, the performance of the MDC deteriorates. One technique for increasing the similarity of the samples in the same class is to weight each attribute in the distance equation.

The basic distance equation is distributing small relative weights to those features with large variances because these particular features have little in common over the samples of the k th class. Conversely, large weights are given to those key features with small variances. To equalize the importance of each key feature within a class, our MDC used the normalized Euclidean distance formula which follows[2]

$$\mathrm{H1}(\mathbf{x}) = \prod_{l=1}^{N} \sigma_{kl}^{2/N} \sum_{l=1}^{N} \left(\frac{x_{kl} - \mu_{kl}}{\sigma_{kl}} \right)^2 \tag{2}$$

where, μ_{kl} and σ_{kl} are the mean and variance respectively of the key feature element l in class k.

In a classification problem, good key features should have the natural characteristic of separating different classes form one another while at the same time keeping each cluster as tightly packed as possible. Equation (2) uses only intraclass information of the feature space. On the other hand, the certain key features are of greater importance in discriminating between classes of modulated signals. This property (i.e., interclass information) can be measured using Wilks' Λ, defined as [3] :

$$\Lambda = \frac{|\mathbf{E}|}{|\mathbf{E}+\mathbf{H}|} \tag{3}$$

where $\mathbf{E}$ is "within" matrices and $\mathbf{H}$ is "between" matrices.

Wilks' Λ compares the within sum of squares and products matrix $\mathbf{E}$ to the total sum of squares and products matrix $\mathbf{E}+\mathbf{H}$. To evaluate the overall goodness of a feature subset, we give different weights to each key feature in the minimum distance classifier using Wilks' Λ as

$$\mathrm{H2}(\mathbf{x}) = \prod_{l=1}^{N} \sigma_{kl}^{2/N} \sum_{l=1}^{N} w_{kl} \left(\frac{x_{kl} - \mu_{kl}}{\sigma_{kl}} \right)^2 \qquad (4)$$

where w_{kl} is weight using Wilks' Λ.

In equation (4), the attributes for features which have large discriminatory power will take large weights, while small weights will be given to the attributes whose features have small discriminatory power. Using interclass information (i.e., Wilks' Λ), we can evaluate the overall goodness of a feature set and expect to achieve the higher Pcc in classifier.

B. k-Nearest Neighbor Classifier

Near Neighbors is the simplest example of nonparametric techniques of classification[4]. The k-nearest neighbor classification rule is that classify test point as being in the class that the maximum of its k nearest neighbors belong to. The k nearest neighbors are k training points that are closest to test point. When the points are in Euclidean space, "closest" is defined as the minimum Euclidean distance to test point. In a similarity context, "closest" is defined as the maximum similarity (or, minimum dissimilarity).

The kNNC labels an unknown modulated signal with the label of the majority of the k nearest neighbors. A neighbor is deemed nearest if it has the smallest distance, in the Euclidean sense, in feature space. For k=1, this is the label of its closest neighbor in the learning set. The k-nearest neighbor method is intuitively a very attractive method, but one major drawback of this method is its complexity. Calculating the kNN is computationally intensive when compared to the nearest neighbor (i.e., k=1). The complexity increases with increasing k. But it should be noted that the accuracy of classification increases with increasing k (up to a certain level). So a tradeoff has to be made in selecting the value of k for classifying an object. In this paper, our kNNCs give the limit of k=3 and k=5 for fast modulation objectives.

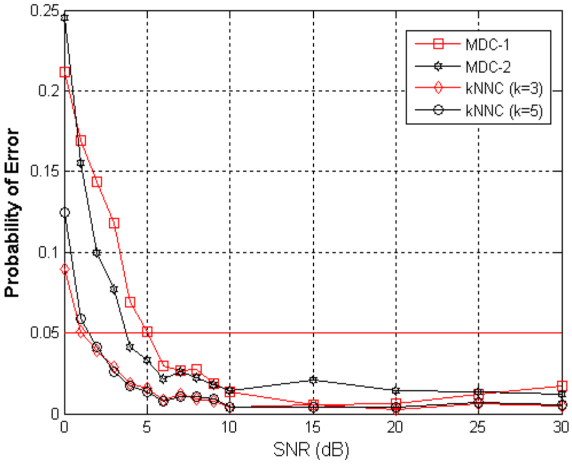
4. Numerical Simulations

In this section, the numerical simulations are performed for all type of modulation signals of interest in order to evaluate the Pcc and processing time of the classifiers. It has known that none of many classification approaches have been proven to work reliably with signals that have low SNR (below 10dB), or when a large range of modulation types including both digital and analog is being considered. Existing technology is able to classify reliably (accuracy >= 90%) only at SNR above 10dB[5].

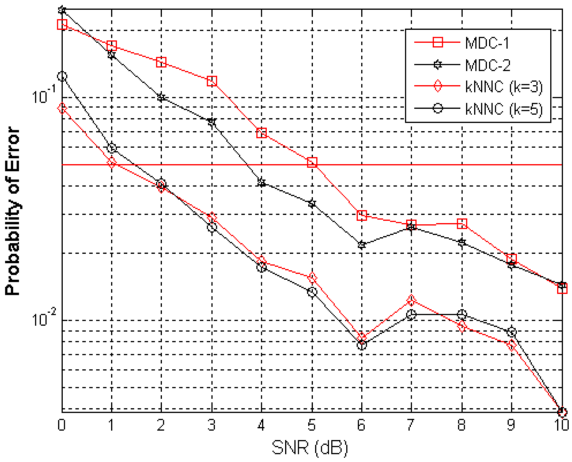
For performance evaluation purpose, we developd 2 MDCs, and 2 kNNCs. The MDC is based on mean and covariance of the feature vectors in multidimensional feature space. There are 2 types of MDC according to whether it is to use only intraclass weight (refer MDC-1) or it is to use intraclass and interclass weights as defined Wilks' Λ (refer MDC-2) in between classes. There are 2 types of kNNC according to the value of k, that is, using k=3 (refer kNNC-1), and using k=5 (refer kNNC-2).

To distinguish 9 modulation types, simulation runs were carried out with 4,096 samples at SNR ranging from 0 dB to 30 dB. The probabilities of classification error (Pe) obtained from 200 runs at each SNR are plotted in Figure 3 for an AWGN channel. The results indicated an overall success rate of over 95% at SNR ranging from 5 to 30 dB in all classifiers proposed. It is also shown that the Pcc of kNNCs is globally better than that of MDCs. Especially, it was shown that kNNCs (k=3, and k=5) can achieve the Pcc of over 95% for a SNR of 2dB as shown in Figure 4. It is noted that the Pcc of kNNC-1 and kNNC-2 is comparable with that of SVC[2,6,7] as shown in Table 1.

As it is important to know if the classifiers will be suitable for real-time software radio



[Figure 3] SNR vs Pe for MDCs and kNNCs



[Figure 4] SNR vs Pe for MDCs and kNNCs in the region below SNR of 10dB (log scale)

application or not, the modulation classification time was measured using the MATLAB software on the DaqPC with dual XEON 2.66 GHz processor. The values of the processing time (measured in mili-seconds) evaluated are shown in Table 2.

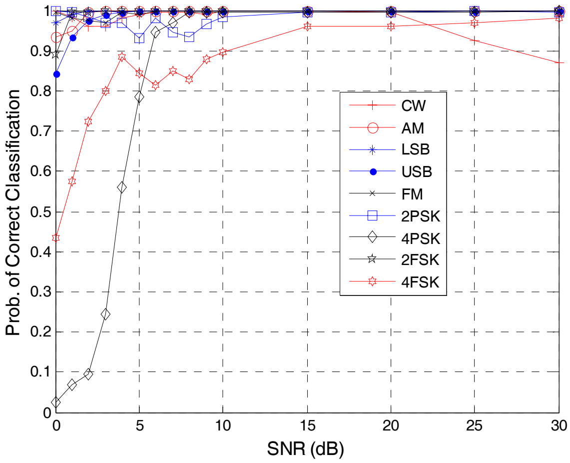
In Table 2, the processing time required to take a decision about the modulation type corresponds to only one unknown signal in each case. The numbers in Table 2 are the average values of the measurements for 200 different realizations of each modulation type of interest at 0~30 dB SNR. We verify that the processing time of MDCs and kNNCs is much faster than that of SVC, but slightly slow than that of DTC. We confirmed that MDCs and kNNCs had fast and robust

[Table 1] Performance of classifiers

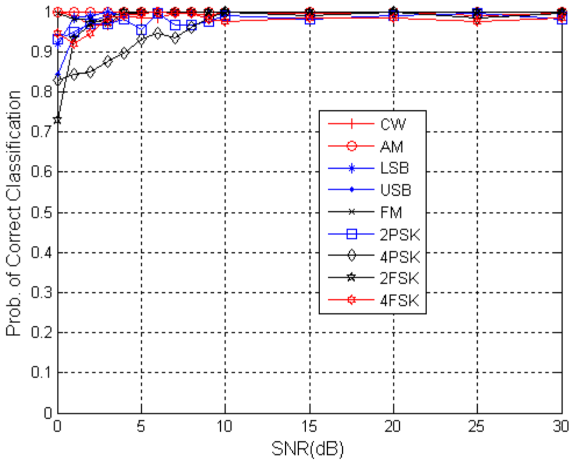
Classifier	Details	Pcc @5dB SNR	Pcc @10dB SNR
MDC-1[2]	normalized	94.89	98.61
MDC-2	weighted	96.67	98.56
kNNC-1	k=3	98.44	99.61
kNNC-2	k=5	98.67	99.61
DTC[2]	Mahalanobis	79.67	95.39
SVC[2,6]	1-v-1	97.33	98.83

[Table 2] Processing time of classifiers (ms)

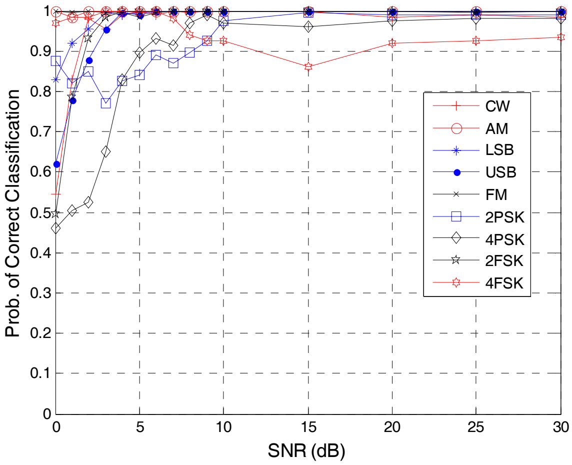
Classifier	Feature Generation	Classification Time	Total Execution Time
MDC-1[2]	43.10	0.03	43.13
MDC-2	43.10	0.03	43.13
kNNC-1	43.10	0.25	43.35
kNNC-2	43.10	0.31	43.41
DTC[2]	26.13	0.13	26.26
SVC[2,6]	43.10	56.20	99.30



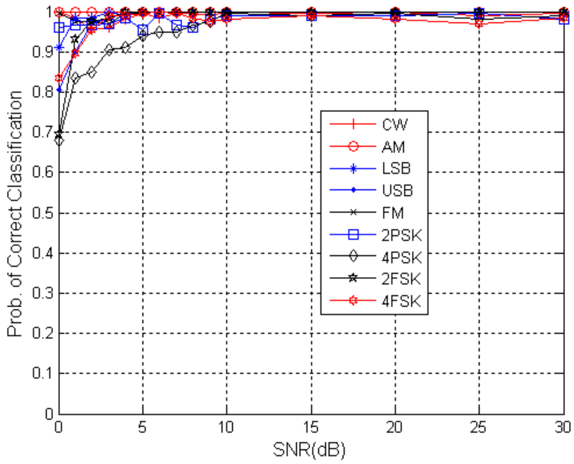
[Figure 5] SNR vs Pcc w.r.t modulation signals in MDC-1



[Figure 7] SNR vs Pcc w.r.t modulation signals in kNNC-1 (k=3)



[Figure 6] SNR vs Pcc w.r.t modulation signals in MDC-2



[Figure 8] SNR vs Pcc modulation signals in kNNC-2 (k=5)

capability, so these are the best candidates for real-time software radio applications.

Figure 5~8 show the Pcc of the modulated signals at each SNR in MDC-1 (normalized), MDC-2 (weighted), kNNC-1 (k=3) and kNNC-2 (k=5), respectively.

The detailed classification results at the SNR of 5 dB are provided in the confusion matrix shown in Table 3~6.

6. Conclusion

In this paper, the two minimum distance classifiers and two k-nearest neighbor classifiers to simultaneously recognize different analog and digital modulated signals have been presented to investigate for real-time software radio application.

These all classifiers are relatively simple and

[Table 3] Confusion Matrix (MDC-1, Pcc=94.89%)

Input Signal	Estimated Modulation Type @ SNR = 5dB								
	CW	AM	LSB	USB	FM	2FSK	4FSK	2PSK	4PSK
CW	99.0							1.0	
AM		100							
LSB			100						
USB				100					
FM					99.0			1.0	
2FSK						100			
4FSK					15.5		84.5		
2PSK								93.0	7.0
4PSK								21.5	78.5

[Table 4] Confusion Matrix (MDC-2, Pcc=96.67%)

Input Signal	Estimated Modulation Type @ SNR = 5dB								
	CW	AM	LSB	USB	FM	2FSK	4FSK	2PSK	4PSK
CW	100								
AM		100							
LSB		0.5	99.5						
USB		1.0		99.0					
FM	0.5				98.5		1.0		
2FSK						100			
4FSK					0.5		99.5		
2PSK								84.0	16.0
4PSK								10.5	89.5

have a low computational complexity compared with that of the state of the art for the classification methods such as SVM classifier (SVC for short). These advantages in MDC and kNNCs are due to the inherent properties of Euclidean distance concept in feature space.

Numerical simulations were conducted to the performance of these classifiers. Their classification performances and processing time are compared with that of SVC with 1-v-1 type, which is the state of the art for the existing classification methods and that of DTC, which is best in processing speed.

[Table 5] Confusion Matrix (kNNC-1, Pcc=98.44%)

Input Signal	Estimated Modulation Type @ SNR = 5dB								
	CW	AM	LSB	USB	FM	2FSK	4FSK	2PSK	4PSK
CW	98.5							1.5	
AM		100							
LSB			100						
USB				100					
FM					99.5			0.5	
2FSK						100			
4FSK					0.5		99.5		
2PSK								95.5	4.5
4PSK								7.0	93.0

[Table 6] Confusion Matrix (kNNC-2, Pcc=98.67%)

Input Signal	Estimated Modulation Type @ SNR = 5dB								
	CW	AM	LSB	USB	FM	2FSK	4FSK	2PSK	4PSK
CW	99.5							0.5	
AM		100							
LSB			100						
USB				100					
FM					99.5			0.5	
2FSK						100			
4FSK					0.5		99.5		
2PSK								95.5	4.5
4PSK								6.0	94.0

Results indicated an overall success rate of over 95% at SNR ranging from 5 to 30dB in all classifiers. The processing time of these classifiers is much faster than that of SVC, but slightly slow than that of DTC. Especially, it was shown that *k*NNC-1 and *k*NNC-2 can achieve the Pcc of over 95% at SNR of 2dB. It was shown that the Pcc of *k*NNCs is comparable with that of SVM classifier.

We confirmed that MDCs and *k*NNCs had fast and robust capability, which can automatically overcome moderate degree of model distortion due to capability of simultaneously evaluation of key features, so these are the best candidates for real-time software radio applications.

References

[1] E. E. Azzouz and A. K. Nandi, Automatic Modulation Recognition of Communication Signals, Kluwer, 1996.

[2] 박철순, 장원, 김대영, "소프트웨어 라디오를 위한 고속 변조 인식기," 한국통신학회논문지, Vol. 32, No. 4, pp. 425~432, 2007. 4.

[3] Alvin C. Rencher, Methods of Multivariate Analysis, Wiley, pp. 156~233, 2002.

[4] Richard O. Duda, Peter E. Hart and David G. Stork, Pattern Classification, 2E, John Wiley, pp. 174~192, 2001.

[5] Stefan C. Kremer and Joanne Sheils, "A Testbed for Automatic Modulation Recognition using Artificial Neural Networks", IEEE Canadian Conference on Electrical and Computer Engineering, pp. 67~70, May 1997.

[6] Cheol-Sun Park and Dae Young Kim, "Automatic Recognition for Analog and Digital Modulated Signals using Neural Network and Support Vector Machine", Lecture Notes in Computer Science(Advances in Neural Network), Springer-Verlag, Vol. 4493, pp. 368~373, June 2006.

[7] Cheol-Sun Park, Won Jang, Sun-Phil Nah and Dae Young Kim, "Automatic Modulation Recognition using Support Vector Machine in Software Radio Application", in Proc. IEEE The 9th International Conference on Advanced Communication Technology(IEEE ICACT2007), pp. 9~12, Feb. 2007.