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A Study on the Detection of Hazardous Weather Conditions by a Doppler Weather Radar

正會員 이 종 길*

도플러 레이다를 이용한 기상위험 탐지에 관한 연구

Jong Gil Lee* *Regular Member*

ABSTRACT

In a Doppler weather radar, high resolution windspeed profile measurements are needed to provide reliable detection of a hazardous weather condition. For this purpose, the pulse-pair method is generally considered to be the most efficient estimator. However, this estimator has some bias errors due to asymmetric spectra and may yield meaningless results in the case of a multimodal return spectrum. In this paper, bias errors were anlyzed and an improved method was suggested to reduce these errors. For the case of a multimodal or seriously skewed spectrum, the modes of spectrum may provide more reliable information than the statistical mean. Therefore, the idea of a relatively simple mode estimator is also developed.

要 約

기상용 도플러 레이다의 경우 기상이변 등을 탐지하기위해서는 대상지역의 강우량, 풍속의 변화, turbulence정도 등을 거리및 방위각별로 세밀하게 측정, 표시하여줄 수 있어야 한다. 이러한 목적으로 쓰여지고 있는 알고리즘으로는 pulse pair추정방법이 가장 효율적인 것으로 인정되어지고 있다. 그러나 이 방법은 레이다 반사신호의 스펙트럼이 비대칭일 경우 bias오차가 크게 생길 수 있으며 두개이상의 peak점을 갖는 스펙트럼의 경우에는 무의미한 결과가 얻어질 수 있다. 따라서 본 논문에서는 이와 같은 bias오차에 대해서 분석하였으며 이러한 오차를 줄이기 위한 개선된 방법을 제시하였다. 또한 여러개의 peak점을 갖는 스펙트럼이나 비대칭성의 정도가 심할 경우 mode추정 방법을 이용한 탐지 기법에 대해서도 연구, 검토되어졌다.

I. Introduction

One of the important potential applications of Doppler weather radar is in a windshear detection system. When the wind abruptly shifts its speed

*仁川大學校 情報通信工學科
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or direction, it can mean deadly difficulty for an airliner particularly at low altitude such as on approach or take-off. This dangerous weather conditions are frequently caused by microbursts. Microbursts are sudden downdrafts of highly turbulent air which appear as if they are designed to cause airline crashes. Since microbursts can occur within a very small geographical scale and the reflectivity of dry microbursts may be very weak, the weather surveillance radar for microburst detection, shoud have high sensitivity and high resolution of both range and Doppler frequency. For this purpose, the pulse pair algorithm is considered to be the most economical since it is simple to implement and fast enough to process huge amounts of data for real time mapping of the weather situation in an interested area. It is also shown in [1] that the performance of the pulse pair estimator is even better than that of the DFT (Discrete Fourier Transform) estimator at low SNR (signal-to-noise ratios) and narrower widths. However, the pulse pair method was derived and has been evaluated most often under the assumption that the weather spectrum is symmetric and relatively narrow. With the turbulent situations associated with windshear, these assumptions may not be valid. Some observed weather spectra [2] show that nearly 25% are seriously skewed and can not be considered to be symmetric. This effect was analyzed using the skewed Gaussian spectrum model.

The poly-pulse pair method was originally suggested as a way of enhancing the accuracy of spectrum moment estimation, but this method may be also useful in reducing the bias errors of a skewed spectrum. Bsed on the similar concept, a new modified pulse pair mean estimator was developed in this paper where it shows an improvement over a conventional method by reducing the bias errors. In the symmetric spectrum, the mean and the mode are same. However, in the case of a skewed spectrum, it may be questionable that the mean is a more representative value than the mode. Hence the difference between the mode and the true mean due to skewness effect was also presented. Since the estimation of a few strong modes may be more meaninqful for the case of a seriously skwed or multimodal spectrum, a modified Prony method was applied to estimate peak points of weather return spectra. This method may not need any preliminary processing such as clutter filtering by locating strong peak points in the spectrum which may well represent the velocity spectrum modes of wind and clutter signals in each range cell. These peak values may be adequate to identify the hazardous weather conditions by showing the spatial gradient of wind velocity in an interested area. Using a NASA simulation model, some validating results were shown.

II. Analysis of Bias Errors in a Skewed Spectrum

The pulse pair estimator calculates the first two moments of the Doppler spectrum from estimates of the complex autocorrelation function at lag T_s. Goodness of this estimator is typically determined by examination of the bias and the variance of the moment estimates. To analyze the bias in the pulse pair estimates, consider the process autocorrelation function $R(T_s)$ expressed in terms of the true mean Doppler frequency f_d [3]:

$$R(T_s) = e^{j2\pi f_d T_s} \int_{-\frac{1}{2T_s}}^{\frac{1}{2T_s}} S'(f)\, e^{j2\pi f T_s}\, df \qquad (1)$$

where $S'(f)$ is the zero-mean representation of the weather Doppler spectrum. Unbiasedness of pulse pair estimates is based on the assumption that a spectrum is symmetric or so narrow that the imaginary part of the integral in (1) can be considered as zero, i.e. [4],

$$\int_{-\frac{1}{2T_s}}^{\frac{1}{2T_s}} S'(f) \sin(2\pi f T_s)\, df = 0.$$

However, the weather return Doppler spectrum is often broad and not symmetric thus causing a bias. This bias effect is analyzed here using a skewed Gaussian spectrum model with various spectrum widths.

In this analysis, a skewed spectrum will be modelled as piecewise Gaussian with appropriate normalization, given by

$$S_n(f)=\frac{2}{1+p}\frac{1}{\sqrt{2\pi}w_1}e^{-\frac{f^2}{2w_1^2}} \quad \text{when} \quad f\le 0$$

$$S_n(f)=\frac{2p}{1+p}\frac{1}{\sqrt{2\pi}w_2}e^{-\frac{f^2}{2w_2^2}} \quad \text{when} \quad f>0 \tag{2}$$

where the standard deviation ratio $p=w_1/w_2$ defines the degree of skewness, g, i.e. [5],

$$g=\frac{4\sqrt{2}}{\sqrt{\pi}}[(p^{-2}+1)^{-\frac{3}{2}}-(p^2+1)^{-\frac{3}{2}}].$$

This skew parameter varies proportionally to skew from $g=0$ for no skew ($p=1$) to larger values, e.g., $g=3.14$ for a case which may be considered large skew ($p=10$). Figure 1 shows the relationship between the parameter, p and the degree of skewness, g. For a narrow Gaussian spectrum with symmetry, i.e., $w_1=w_2=w$, the integral in the autocorrelation function (1) can be reduced to one simple term, $\exp(-2\pi^2w^2T_s^2)$, but the results for the skewed spectrum model will include both a real term

$$a=\int_{-\frac{1}{2T_s}}^{\frac{1}{2T_s}} S_n(f)\cos(2\pi fT_s)\,df$$

$$=\frac{2}{1+p}\left(\frac{1}{2}e^{-2\pi^2w_1^2T_s^2}+\frac{w_2}{2w_1}e^{-2\pi^2w_2^2T_s^2}\right)$$

and an imaginary term

$$b=\frac{2}{1+p}\int_0^{\frac{1}{2T_s}}\left[\frac{1}{\sqrt{2\pi}w_1}\left(e^{-\frac{f^2}{2w_2^2}}-e^{-\frac{f^2}{2w_1^2}}\right)\right].$$

$$\sin(2\pi fT_s)\,df.$$

Using these terms, the bias in the pulse pair mean and width estimates can be represented by

$$\text{mean bias}=\left|\frac{1}{2\pi T_2}\tan^{-1}\left(\frac{b}{a}\right)-f_m\right|$$

$$\text{width bias}=\left|\frac{1}{\sqrt{2}\pi T_s}\left|\ln\left(\frac{1}{\sqrt{a^2+b^2}}\right)\right|^{1/2}-W\right| \tag{3}$$

where true mean, f_m and true width, W are described from Equation (2) as

$$f_m=\int_{-\frac{1}{2T_s}}^{\frac{1}{2T_s}} fS_n(f)\,df=\frac{2}{1+p}\frac{1}{\sqrt{2\pi}}(pw_2-w_1)$$

$$W^2=\int_{-\frac{1}{2T_s}}^{\frac{1}{2T_s}}(f-f_m)^2S_n(f)\,df=\frac{1}{1+p}(w_1^2+pw_2^2)-f_m^2.$$

Estimate biases as given by Equation (3) are plotted as functions of the true width W and the skewness parameter g in Figures 2 and 3. In Figure 2 if there is no skew ($g=0$) the pulse pair estimator is unbiased. As skew is increased there is a sharp increase in the bias. Once the skew parameter $g>0$, the percentage bias error is essentially independent of the specific value of skew but is strongly related to the spectrum width W. As seen, the bias error due to skewness is not negligible if the spectrum is broad. Figure 3 shows that a broad spectrum with a large degree of skewness can degrade the quality of pulse pair width estimates, but it does not seem to be as serious compared to the pulse pair mean estimate error in Figure 2.

To get a more complete measure of the effect of skewness on the pulse pair mean estimate, Figure 4 compares the estimate r.m.s. error for the case of the skewed spectrum with that of a symmetric Gaussian spectrum having an equivalent width. As seen from Figure 4, the error caused by the skewness may seriously degrade the pulse pair estimation quality if the return Doppler spectrum width is 40% or more of the Nyquist bandwidth.

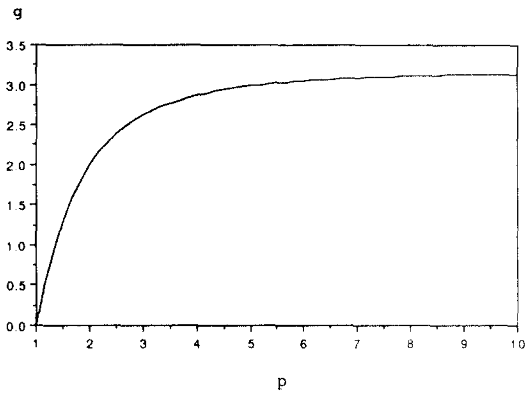

Figure 1. Relationship between the Parameter, p and the Degree of Skewness, g

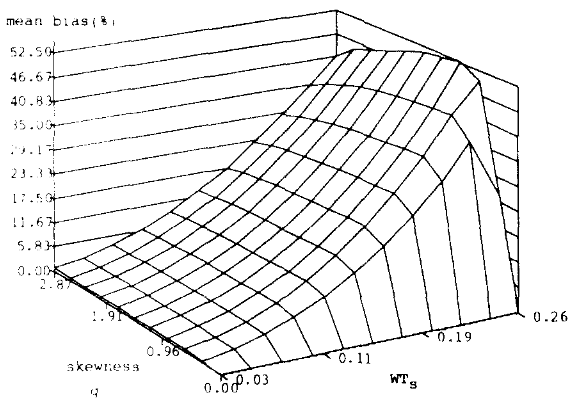

Figure 2. Mean Bias Error in Pulse Pair Estimates

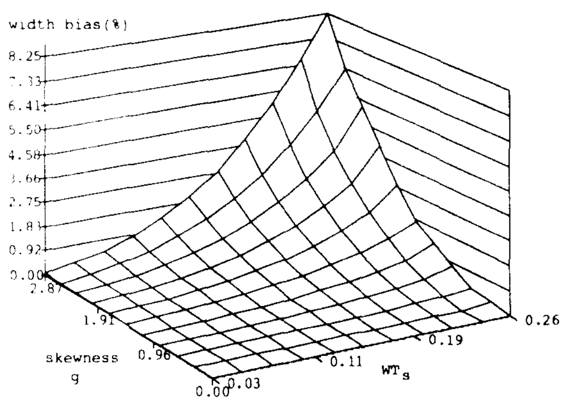

Figure 3. Width Bias Error in Pulse Pair Estimates

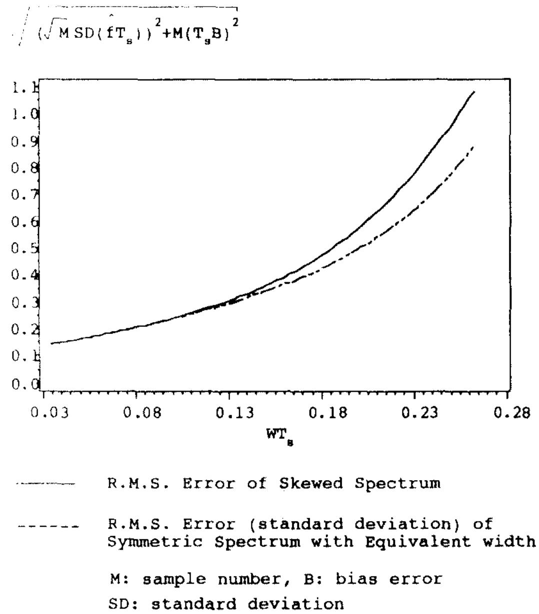

Figure 4. R.M.S. Error of Skewed Gaussian Spectrum for a Certain Degree of Skewness ($g = 1.99$)

Ⅲ. Poly-pulse Pair Method

Since the pulse pair mean estimator bias is sensitive to skew, an alternative may be desirable. The poly-pulse pair method using several autocorrelation lag estimates was originally suggested in [6] to improve estimation quality by reducing the variance of pulse pair estimates through averaging of various lag estimates. Although the same term, poly-pulse pair method, is used in this paper to mean that the same various lag estimates are needed, the poly-pulse pair method is investiqated here from the totally different point of view as a possible way of minimizing mean bias errors which may occur in skewed spectra. The pulse pair mean estimator algorithm uses the first lag of the complex autocorrelation estimate and is based on a linear approximation to the derivative of the phase function of the complex autocorrelation estimate, i.e.,

$$\hat{f} = \frac{1}{2\pi} \frac{d\hat{\theta}(T_s)}{dT_s} \Big|_{T_s=0} \cong \frac{1}{2\pi} \frac{\hat{\theta}(T_s)}{T_s}$$

where $\hat{\theta}(T_s)$ is the phase function. There will be no approximation error for a symmetric spectrum, but a large error can occur in a skewed spectrum since $\hat{\theta}(T_s)$ is no longer a linear function of T_s. An alternative which may reduce these errors is to approximate $\hat{\theta}(T_s)$ as a low order polynomial (greater than first order, $n=1$), i.e.,

$$\hat{\theta}(T_s) \cong \sum_{i=1,\,odd}^{n} a_i T_s^i \tag{4}$$

where $\theta(T_s)$ is an odd function of T_s [7]. An odd function representation is needed since $R(T_s)$ is the Fourier transform of a real valued spectrum. Then the mean estimate of a skewed spectrum will be

$$\hat{f} = \frac{1}{2\pi} \frac{d\hat{\theta}(T_s)}{dT_s} \Big|_{T_s=0} \cong \frac{1}{2\pi} \hat{a}_1.$$

To estimate a_1 for a particular $n>1$, the complex autocorrelation function must be estimated for lags other than the first lag value T_s. Figure 5 shows that the mean bias error for a spectrum skew of $g=1.99$ ($p=2$) can be significantly reduced over a range of spectrum widths using the poly-pulse pair method. To more completely evaluate the poly-pulse pair method the variance of these estimates should be compared to the conventional pulse pair method ($n=1$).

Considering a third order polynomial model in Equation (4), i.e.,

$$\hat{\theta}(T_s) = \hat{a}_3 T_s^3 + \hat{a}_1 T_s$$

the poly-pulse pair mean estimate variance can be shown to be

$$\mathrm{var}'(\hat{f}) = \mathrm{var}(\hat{f}) - \frac{T_s^2}{2\pi^2} E\left[\hat{a}_3\hat{a}_1 - a_3 a_1\right] - \frac{T_s^4}{4\pi^2} E\left[\left(a_3 - \hat{a}_3\right)^2\right]$$

where $\mathrm{var}(\hat{f})$ is the variance of the conventional pulse pair method. The second term may be positive or negative and the third term will actually reduce the pulse pair estimate variance. In any case, since the pulse interval T_s is generally very small, the higher order terms may be ignored to yield

$$\mathrm{var}'(\hat{f}) \cong \mathrm{var}(\hat{f}).$$

From these results, it appears that the poly-pulse pair method can improve the quality of mean estimates by reducing bias errors in a skewed spectrum.

In the pulse Doppler radar signal processor, when estimating the "average" windspeed in a given range cell, there may be a question as to whether "average" should be the statistical mean or the statistical mode (most probable value). The pulse pair algorithm will estimate the statistical mean. In the symmetric case the mean and the mode are the same. However, with skewness in the spectrum this is not true as seen in Figure 6 which shows that these two values can differ very largely due to the increased skewness and spectrum width. Figure 7 illustrates the difference between the mode of the skewed spectrum and the pulse pair mean as a function of skew and spectrum width. As the spectrum width increses, this difference is more sensitive to spectrum skew. Therefore, the pulse pair mean estimate tends not to be a good mode estimator for broad spectra. The idea of a mode estimator is developed further in the following chapter. A new approach of characterizing a summary statistic of windspeed within a rang cell is presented using a classical harmonic decomposition technique. This indicates potential for overcoming the biased mean estimation problem with a skewed spectrum.

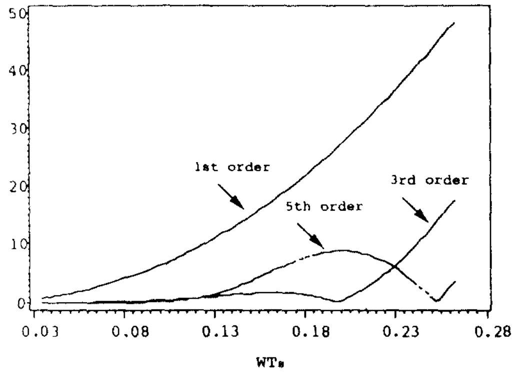

Figure 5. Performance Comparison between Polypulse Pair and Conventional Method

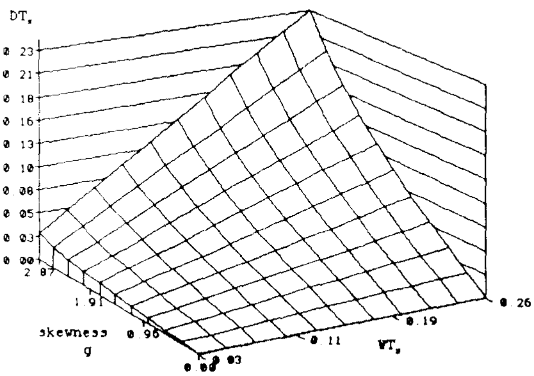

Figure 6. Normalized Difference Value between True Mean and Mode of Skewed Spectrum

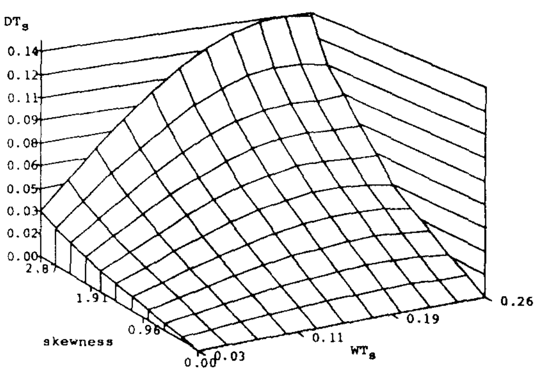

Figure 7. Normalized Difference Value between Pulse Pair Mean Estimate and Mode of Skewed Spectrum

Ⅳ. Spectrum Modes Estimation by Modified Prony Method

The aviational hazard often caused by microbursts can frequently be identified from a Doppler radar return by an S curve characteristic which describes mean windspeed changes along the radar range radial. The mean value of the weather return spectrum is generally considered as representing the windspeed in each range cell. However, based upon the results from the previous chapter, in the skewed spectrum case or with the multimodal return spectrum, the modes of spectrum may provide more reliable information than the statistical mean for the purpose of windshear detection. Therefore, the mode estimation technique using the modified Prony method is presented here. Also this mode estimator may be useful in recognizing the windshear hazard without the need for clutter rejection filtering.

As has been noted earlier, one of the more popular methods of estimating mean Doppler or mean wind speed within a range resolution cell is the pulse pair estimation technique. This is computationally much more efficient than DFT based methods although spectrum parameter estimates involving the DFT are generally considered to be more robust. With an airborne Doppler radar wet microburst return, where signal-to-clutter ratio is large enough, the simple pulse pair estimator, for example, generally yields a very accurate estimate of mean wind velocity in each range cell. However, difficulties arise in a dry microburst case since a very low signal-to-clutter ratio may seriously bias the mean velocity estimates without effective and efficient clutter filtering. To make matters worse, the removal of clutter may not be an easy task though several methods have proven to be useful [8], [9], [10]. It has been shown [8] that efficient clutter suppression can be done using an autoregressive least squares method, but mean estimates from clutter-only range cells often fluctuate randomly, because there remain only weak background noise signals after filtration. This can also occur when the weather return spectrum falls largely within the clutter filter notch and is mostly removed with clutter rejection processing. Another problem is that radar system phase noise may limit the clutter rejection capability yielding a too low signal-to-clutter ratio in the filtered spectrum thus causing an inaccurate estimation of the mean velocity.

An alternate approach to identifying the presence of a weather return is to locate strong peak points in the spectrum which may well represent the velocity spectrum modes of wind and clutter signals in each range cell. These peak values may be adequate to identify the microburst S curve signature and detect a hazardous windshear condition. This new approach is particularly attractive since it does not require processing to estimate the entire spectrum but only involves finding a few peak points of the spectrum. The modified Prony method [11] is investigated here to find strong peak points of simulated weather spectra that include microburst and static clutter signals.

The modified Prony method involves approximating a complex data sequence by a model consisting of undamped complex sinusoids. It is similar to Pisarenko Harmonic Decomposition (PHD) method [12], but the Prony algorithm is generally better than PHD procedure since it needs neither autocorrelation lags nor a more computationally complex eigen equation solution. The Prony method requires only the solution of two sets of simultaneous linear equations and a polynomial rooting. It is summarized briefly in the following :

1. Find the coefficients of a complex polynomial minimizing the squared smoothing error.
2. Root a complex polynomial to determine frequencies.
3. Solve for the amplitude of each frequency.

A second order Prony model was used here to find peak points of simulated weather spectra. This data set had been previously analyzed using adaptive clutter rejection filtering and pulse-pair mean estimation [8]. Marple's programs [11] were slightly modified to avoid numerical illconditioning in some cases. A 512 point complex data sequence from each range cell was processed. Some typical FFT spectrum plots are shown in Figures 8 through 11 with the Prony method peak estimates also indicated. As seen in Figures 8, 9 and 10, the Prony method is able to locate spectrum peak points. However, Figure 11 shows somewhat inaccurately estimated peak points because of strong clutter power and the closeness of weather and clutter spectral peaks.

In order to check the usefulness of this new approach for detection of windwhear, data from all 40 range cells including a dry microburst and clutter were processed and peak velocity points were plotted versus range. The resulting Figure 12 clearly shows the S curve characteristic around the range cell 27.

Another important consideration is computational complexity which must not prohibit real time processing. Some comparisons with other spectrum estimation methods are made in Table 1. Of course, the Prony method is computationally much more complicated than other classical spectrum estimation techniques as the model order increases, but as it can be seen from Table 1, the second order Prony model used here requires less computation than the FFT method. Therefore, the modified Prony method shows some promise as a component of a windshear detection algorithm.

Also as shown in Figure 4, where clutter and weather spectrum modes are very close together, identification of a weather return is an inherently difficult problem to solve. In these situations, the Prony method appears of limited use. Other more computationally complicated methods such as the PHD may be necessary.

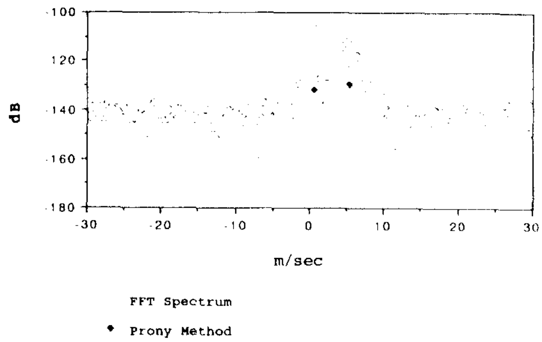

Figure 8. Mode Estimates Shown in Simulated Weather Spectrum of Range Cell 24

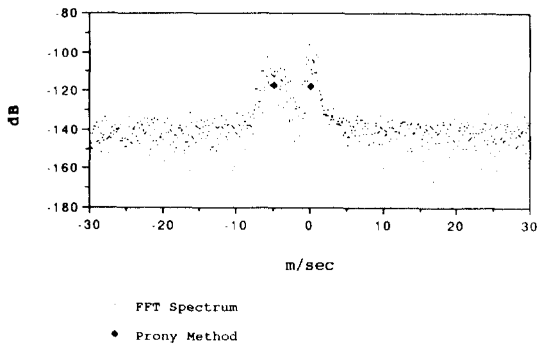

Figure 9. Mode Estimates Shown in Simulated Weather Spectrum of Range Cell 29

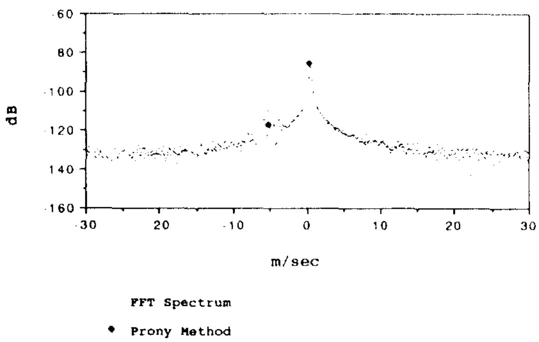

Figure 10. Mode Estimates Shown in Simulated Weather Spectrum of Range Cell 30

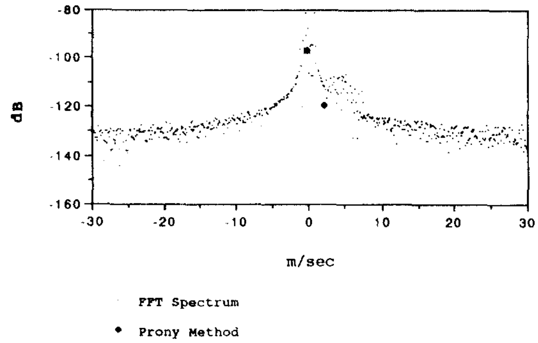

Figure 11. Mode Estimates Shown in Simulated Weather Spectrum of Range Cell 25

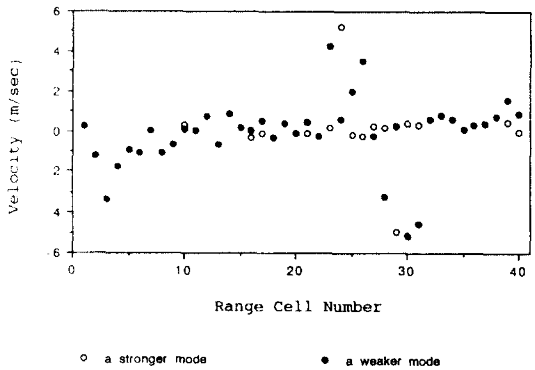

Figure 12. Estimated Spectrum Modes of Simulated Weather Data in All Range Cells

V. Concluding Remarks

The analysis in this paper shows that the mean estimates can be seriously biased due to skewness in the weather spectrum as the spectrum is broadened even though the width bias error can be considered to be negligible. Degradation of estimation quality due to the bias term is less than 15% if WT_s is not larger than 0.15 as seen in Figure 4, but this condition may not always be satisfied. In the skewed spectrum case, the suggested poly-pulse pair method was demonstrated as useful in reducing bias errors of mean estimates. It is also shown that the mode of the skewed spec-

Table 1. Comparison of Computational Complexity Where N = 512)
(f(p) means that the required number of computations depends on the algorithm used for a polynomial rooting)

method	computation requirement	approximate number of calculations for a reasonable model order
FFT	$N\log_2 N$	4700 complex adds/mults
AR LSQ	$2NP + P^2$	10500 complex adds/mults for p = 10
Prony	$2NP + 18P^2 + P^3 + f(P)$	2300 complex adds/mults for p = 2

trum and the pulse pair mean can differ very largely as the spectrum width increases. This may be a problem in some applications such as windshear detection where frequently the mode of a return spectrum may be a more informative statistic than the mean value.

A new approach explained in this paper shows that windshear detection may be possible using a pattern recognition type technique by finding an "S" curve characteristic demonstrated here using the modified Prony method. From the results in Figure 12, it can be said that the very low order Prony model may make it possible to detect the windshear condition without any other preliminary processing. However, this new approach also has the limitation that some valuable weather information such as spectrum width can not be obtained without additional processing.

Future work may include the investigation of characteristic patterns related with hazardous weather conditions other than microbursts which can be represented by the S curve characteristic. This information may help eventually to build a more intelligent system for reliabe detection of the weather hazards.

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이 종 길(Jong Gil Lee)　정회원
1959년 12월 19일생
1982년 2월 : 연세대학교 전자공학과(공학사)
1985년 1월 : Case Western Reserve Univ., 전기공학과(M.S.)
1990년 5월 : Clemson Univ., 전기공학과(Ph.D.)
1991년 1월 ~ 1993년 2월 : 삼성전자 특수연구소
1993년 3월 ~ 현재 : 인천대학교 정보통신공학과 조교수
※주관심분야 : 레이다신호처리, 무선통신, 스펙트럼분석 등임