Parameters of radial wind velocity components as measured by a Volna-3 sodar

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Algorithms for determination of the first four moments and the related standard deviations, as well as the asymmetry and excess coefficients of radial wind velocity components, measured with a Volna-3 sodar are described. In addition to point estimates, interval estimates of these parameters are calculated to characterize objectively the degree of reliability of the information obtained.

In recent three decades, acoustic radars (sodars) have been actively used for determination of various characteristics of the wind velocity field in the atmospheric boundary layer. In spite of such a long history of sodar measurements, the significance of the information obtained is often low because there are no objective characteristics of the degree of its reliability. Let us present some typical examples.

Thus, Ref. 1 presents profiles of the vertical component of turbulence intensity I_w for different classes of thermodynamic stability of the atmosphere acquired with sodar. However, these profiles are not accompanied by the corresponding estimates of the measurement errors, neither interval nor point ones. Without these data it is almost impossible to judge on the actual significance of differences in the altitude dependences of I_w measured with sodars under various atmospheric stratification. The same is also true for other interesting paper,[2] which, in particular, presents the profiles of the asymmetry coefficients of the vertical wind velocity acquired with a sodar under convection and inversion conditions. This list of examples can be extended further.

Thus, we can conclude that in acoustic sensing there exists some neglect of the problems of metrological support of measurements, what, in our opinion, is inadmissible. To characterize objectively the quality of sodar data, every measuring algorithm should include an algorithm for assessing errors (at least roughly, e.g., providing an upper estimate of the possible error). One of the possible causes for the absence of such accuracy characteristics is likely the difficulty of their obtaining, especially, if the relationship between the atmospheric parameters sought and sodar data is nonlinear.

An attempt to eliminate these shortcomings was undertaken in the processing system of Volna-3 sodar.[3] First, let us note the following. Most sodars in each ith sensing cycle measure directly instantaneous altitude profiles of the radial components of wind velocity $\mathbf{V}(i)$, that is, its projection $V_r(i)$ onto the corresponding axes of the directional patterns of the antenna systems. Then, taking into account the sensing geometry used, it is possible to determine the characteristics of different components of the vector $\mathbf{V}$ needed: the orthogonal components (Cartesian V_x, V_y, longitudinal u, and cross v components), the absolute value V_h, and the direction φ_h. The vertical component $w(i)$ is usually measured through mere zenith orientation of one of the sodar antennas.

In this paper, we describe the process of obtaining the most important statistical characteristics of radial components of the wind velocity $V_r(i)$: mean values $M(V_r)$, standard deviations $\sigma(V_r)$, asymmetry coefficients $\gamma(V_r)$, and excess $\varepsilon(V_r)$. To objectively characterize the degree of reliability of the obtained information, one should calculate both the standard errors and the corresponding confidence intervals for the parameters to be estimated. The need in this is caused by the fact that the quality of measurement of these characteristics largely determines the quality of assessments of other atmospheric parameters connected with u, v, V_h, and φ_h. (This analysis is planned to be presented in the future papers). On the other hand, the information on the vertical wind velocity w is of independent interest as well.

The problem formulated above is solved using the methods of classical mathematical statistics.[4,5] Toward this end, assume that $V_r(i)$ measured with a sodar at every fixed height form a set of independent sample values corresponding to some continuous distribution $W_r(V_r)$.

The quality of measuring the above parameters of the radial components V_r strongly depends on the accuracy of estimating the centers of the distributions $W_r(V_r)$. The experience of operation of a Volna-3 sodar and the data from Ref. 2 indicate that the distribution of the radial wind velocity components in the atmospheric boundary layer is not always Gaussian (normal). Consequently, application of the classical optimal assessment methods that assume $W_r(V_r)$ to be Gaussian is unjustified. Thus, the estimate of the distribution center as a sample (arithmetic) mean is the best only in case of Gaussian distribution of the sample processed. If the distribution differs from the Gaussian one, this estimate strongly deteriorates and loses its efficiency.

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The same is also valid for most parametric estimates and in the presence of spikes, that is, anomalous values disturbing statistical homogeneity of the sample processed. Their presence may be caused by a powerful short-term acoustic noise or too low threshold signal-to-noise ratio specified by the sodar operator at spectral processing.[3] A few anomalous values are sufficient to seriously distort the measurement results. The effect of this factor increases with the increasing order of the moment to be estimated. Therefore, prior to the main statistical calculations, it is necessary to perform censoring of the initial data taking into account that the distribution law of the $V_r(i)$ sample may be different and varying in a rather wide range.

In the processing system of Volna-3 sodar, this problem is solved by applying an iterative method based on the results from Ref. 5. First, we reject the p fraction of extreme values (usually $p = 10\%$) from the variational series $V'_r(i)$ obtained from the initial series $V_r(i)$, $i = 0, 1, \ldots, L - 1$. Then, as a stable estimate of the distribution center of the rest sample having the size $L' = L - [pL/100]$, we take the median of five means $\hat{M}_5(V_r)$: the mean over the range of the variational series, ordinary sample mean, sample mean with rejection of 50% of extreme values, median, and quartile mean. Then we calculate the values (estimates) of the standard deviation $\hat{\sigma}(V_r)$, excess $\hat{\varepsilon}(V_r)$ (see below), coefficient $t_{\lim} = 1.55 + 0.8\sqrt{\hat{\varepsilon} - 1}\log(L'/10)$ and, finally, censoring boundary $V_{1,2}^{\lim} = \hat{M}_5(V_r) \pm t_{\lim}\,\hat{\sigma}(V_r)$. If earlier rejected $V'_r(i)$ fall within the censoring interval, then they are returned into the initial sample. Extra rejection of the data is also possible. Then, for the new series $V''_r(i)$, $i = 0, 1, \ldots, L_1 - 1$ we again calculate $\hat{M}_5$, $\hat{\sigma}$, $\hat{\varepsilon}$, and $V_{1,2}^{\lim}$ and compare $V_{1,2}^{\lim}$ with $V''_r(i)$. The censoring process is completed, if at some iteration step the number of significant readings of the sample N does not change. The procedure described can be applied to a rather wide class of distributions,[5] including various bimodal and exponential ones from $\varepsilon = 1$ to $\varepsilon = 6$ (that is, including the uniform ($\varepsilon = 1.8$), Gauss ($\varepsilon = 3$), and Laplace ($\varepsilon = 6$) distributions). This provides for the efficiency of this algorithm in rejecting anomalous values of radial components of the wind velocity vector.

The system of rejection of sodar data provides also for the possibility of performing careful (responsible) censoring of the data.[5] This is achieved by extending the applicability limits of the censoring range through substitution of the maximum possible values of $\hat{\sigma}$ and $\hat{\varepsilon}$ into the above equation for $V_{1,2}^{\lim}$ at the confidence probability $P = 0.9$.

At the next step of processing of the radial components by the obtained statistically homogeneous series $V_r(i)$, $i = 0, 1, \ldots, N - 1$, their distribution centers $M(V_r)$ are refined. Toward this end, the most effective estimate $\hat{M}(V_r)$ at $N \geq 20$ is selected based on the excess $\hat{\varepsilon}$ calculated at the last censoring step.[4,5]

Thus, at $\hat{\varepsilon} \geq 3.8$ characteristic of distributions with "heavy tails," we take the median as $\hat{M}(V_r)$, that is, $\hat{M}(V_r) = \mathrm{med}(V_r)$. Its standard error $\sigma[\mathrm{med}] = \sqrt{D[\mathrm{med}(V_r)]}$ in most practical cases can be approximated by a simple equation[4,5]:

$$\sigma[\mathrm{med}(V_r)] = \sigma(V_r)/\sqrt{0.12N\,\varepsilon^{1.6}(V_r)}, \tag{1}$$

where $\sigma(V_r) = \sqrt{D(V_r)}$ is the standard deviation of the corresponding radial component of wind velocity; $D(V_r) = \mu_2(V_r)$ is its variance; $\varepsilon = \mu_4(V_r)/\mu_2^2(V_r)$ is excess; $\mu_k(V_r)$ is the kth central moment; N is the number of processed values of $V_r(i)$ for the given averaging time.

At $2.4 \leq \hat{\varepsilon} < 3.8$ characteristic of close-to-normal distributions, as $\hat{M}(V_r)$ we take the ordinary sample mean with the standard error:

$$\sigma[\hat{M}(V_r)] = \sigma(V_r)/\sqrt{N}. \tag{2}$$

At $1 < \hat{\varepsilon} < 2.4$ characteristic of flat-topped and steeply decreasing distributions, as $\hat{M}(V_r)$ we use the median of the three means $\hat{M}_3(V_r)$: sample mean, quartile mean, and mean over the range of the variational series $V_r(i)$. It can be shown that the upper estimate for $\sigma[\hat{M}_3(V_r)]$ is given by Eq. (2).

At $N < 20$ the median of the five means listed above $\hat{M}_5(V_r)$ is taken as an estimate of the distribution center $\hat{M}(V_r)$.

Note that all the equations for standard errors of estimates of the $V_r(i)$ distribution parameters (in particular, Eqs. (1) and (2) for the distribution centers) are the functions of the true values of the moments $\mu_k(V_r)$. In practice, we always have to replace these unknown parameters with their sample values $\hat{\mu}_k(V_r)$, which can lead to distortion of the degree of measurement objectivity, especially, with the growing order of the moment to be estimated. One of the possible ways to obtain acceptable practical results is discussed below.

Let us consider now the estimates of the higher moments of radial wind velocity components using their known unbiased versions.[4,5] The unbiased estimate of variance is

$$\hat{D}(V_r) = \hat{\mu}_2(V_r) = m_2(V_r)\,N/(N - 1), \tag{3}$$

where $m_k(V_r) = \frac{1}{N}\sum_{i=0}^{N-1}[V_r(i) - \hat{M}(V_r)]^k$ is the central sample moment of the kth order. As the unbiased estimate of the standard deviation, we use

$$\hat{\sigma}(V_r) = \begin{cases} \tilde{\sigma}(V_r)\sqrt{(N-1)/(N-1.5)}, & 2 \leq N < 20 \\ \tilde{\sigma}(V_r), & 20 \leq N, \end{cases}$$

where $\tilde{\sigma}(V_r) = \sqrt{\hat{D}(V_r)}$. Since the variance of the variance estimate is[4]:

$$D[\hat{D}(V_r)] = \frac{D^2(V_r)}{N}\left[\varepsilon(V_r) - \frac{N-3}{N-1}\right], \quad (4)$$

the equation for the standard error of the estimate of standard deviation in the first approximation has the form

$$\sigma[\tilde{\sigma}(V_r)] = \frac{\sigma(V_r)}{2\sqrt{N}}\sqrt{\varepsilon(V_r) - \frac{N-3}{N-1}}.$$

The unbiased estimates of the third and fourth central moments are:

$$\hat{\mu}_3(V_r) = \frac{N^2}{(N-1)(N-2)} m_3(V_r), \quad N \geq 3, \quad (5)$$

$$\hat{\mu}_4(V_r) = \frac{N}{(N-1)(N-2)(N-3)} \times$$

$$\times\left[(N^2 - 2N + 3)m_4 - 3(2N-3)m_2^2\right], \quad N \geq 4. \quad (6)$$

Then, taking Eq. (3) into account, the estimates of the asymmetry coefficients $\gamma(V_r)$ and excess $\varepsilon(V_r)$ take the form

$$\hat{\gamma}(V_r) = \frac{\sqrt{N(N-1)}}{N-2}\tilde{\gamma}(V_r);$$

$$\hat{\varepsilon}(V_r) = \frac{N-1}{N(N-2)(N-3)}\left[(N^2 - 2N + 3)\tilde{\varepsilon}(V_r) - 3(2N-3)\right],$$

where

$$\tilde{\gamma}(V_r) = m_3(V_r)/m_2^{3/2}(V_r), \quad \tilde{\varepsilon}(V_r) = m_4(V_r)/m_2^2(V_r)$$

are the corresponding initial biased estimates of γ and ε. The relation between the standard errors becomes evident:

$$\sigma[\hat{\gamma}(V_r)] = \frac{\sqrt{N(N-1)}}{N-2}\sigma[\tilde{\gamma}(V_r)],$$

$$\sigma[\hat{\varepsilon}(V_r)] = \frac{(N-1)(N^2-2N+3)}{N(N-2)(N-3)}\sigma[\tilde{\varepsilon}(V_r)].$$

Let us present the equations obtained in Ref. 4 for the variances $D[\tilde{\gamma}]$ and $D[\tilde{\varepsilon}]$. To make the presentation clearer, we omit the arguments of the corresponding estimates and central moments:

$$D[\tilde{\gamma}] = \frac{4\mu_2^2\mu_6 - 12\mu_2\mu_3\mu_5 - 24\mu_2^3\mu_4 + 9\mu_3^2\mu_4 + 35\mu_2^2\mu_3^2 + 36\mu_2^5}{4\mu_2^5 N}, \quad (7)$$

$$D[\tilde{\varepsilon}] = (\mu_2^2\mu_8 - 4\mu_2\mu_4\mu_6 - 8\mu_2^2\mu_3\mu_5 + 4\mu_4^3 - \mu_2^2\mu_4^2 +$$

$$+ 16\mu_2\mu_3^2\mu_4 + 16\mu_2^3\mu_3^2)/(\mu_2^6 N). \quad (8)$$

It follows from Eqs. (7) and (8) that the standard errors $\sigma[\tilde{\gamma}]$ and $\sigma[\tilde{\varepsilon}]$, along with the sample size N, are mostly determined by the excess and moments of higher orders up to the eighth one inclusive. However, replacement of μ_6 and μ_8 with the sample values $\hat{\mu}_6$, $\hat{\mu}_8$ can lead to large errors in estimation of $\sigma[\tilde{\gamma}]$ and $\sigma[\tilde{\varepsilon}]$, because of the very low accuracy of their determination from the limited number of observations N. Reduction of the above equations to the Gaussian case through replacement of μ_6 and μ_8 with the sufficiently accurately measured μ_2 using known functional dependences is also inaccessible because of a sharp change of $\sigma[\tilde{\gamma}]$ and $\sigma[\tilde{\varepsilon}]$ as the distribution of the processed sample deviates from the normal one. Thus, for the normal distribution $\sigma[\tilde{\varepsilon}] = 4.9/\sqrt{N}$, and for the Laplace distribution $\sigma[\tilde{\varepsilon}] = 34.47/\sqrt{N}$. Therefore, following recommendations from Ref. 5, to obtain more realistic values of the standard errors considered, we approximated $\sigma[\tilde{\gamma}]$ and $\sigma[\tilde{\varepsilon}]$ as functions of ε. For this purpose, analytical equations (7) and (8) were used to calculate $\sigma[\tilde{\gamma}]$ and $\sigma[\tilde{\varepsilon}]$ for different symmetric distribution laws, whose excess values cover practically all observable values. In particular, the uniform (ε = 1.8), normal (ε = 3), and Laplace (ε = 6) distributions were used, as well as the bilateral exponential distribution with the exponent $\alpha = 0.5$ ($\varepsilon = 25.2$). As a result, the following approximations were obtained with the error no more than 10% at the node points (for $1 < \varepsilon \leq 25.2$):

$$\sigma[\tilde{\gamma}] \cong \log\varepsilon(31.16 - 193.06\log\varepsilon + 470.57\log^2\varepsilon -$$

$$-453.94\log^3\varepsilon + 156.19\log^4\varepsilon)/\sqrt{N}, \quad (9)$$

$$\sigma[\tilde{\varepsilon}] \cong \varepsilon\log\varepsilon(7.09 - 40.94\log\varepsilon + 115.99\log^2\varepsilon -$$

$$-116.39\log^3\varepsilon + 45.76\log^4\varepsilon)/\sqrt{N}. \quad (10)$$

For a control purpose, we have calculated $\sigma[\tilde{\gamma}]$ and $\sigma[\tilde{\varepsilon}]$ by the exact equations (7) and (8) and by the approximate equations (9) and (10) for a strongly asymmetric single-sided exponential distribution ($\gamma = 2$, ε = 9). As a result, the relative error for $\sigma[\tilde{\varepsilon}]$ was 5%, and for $\sigma[\tilde{\gamma}]$ it was 18%, which is much better than with the use of the two approaches described earlier. Thus, at the Gaussian approach, calculated $\sigma[\tilde{\gamma}]$ is roughly 3.5 times smaller than the true value, while $\sigma[\tilde{\varepsilon}]$ is even 18 times smaller. The above-said leads to excessively optimistic conclusions about the degree of reliability of the information obtained, and this can finally depreciate the measurement results. On the other hand, if ε of the initial distribution is much less than three, then the conclusions concerning the experimental results can be excessively pessimistic. At the same time, application of Eqs. (9) and (10) yields more adequate values of the standard errors in the asymmetry and excess of the radial wind velocity components measured.

For getting a more complete idea of the accuracy and reliability of the considered point estimates $\hat{g}$ of the parameters of the radial components V_r, it is necessary to pass on to the corresponding interval values. For this purpose, we should determine the random interval I_P, which covers the true value of the estimated parameter g with the given confidence probability P. At an arbitrary P, calculation of I_P requires knowledge of not only the initial distribution $W_r(V_r)$, but also the distribution of the estimates $W(\hat{g})$, which is practically unfeasible, in particular, because of the variability of $W_r(V_r)$. Even if we succeed in the determination of the exact form of $W(\hat{g})$, then it becomes necessary to search the quantile factor z_P corresponding to determined $W(\hat{g})$ and the given value of the confidence probability P in the probability tables. As a result, the process of I_P determination becomes very inconvenient for the automated data processing needed.

A possible way out of this situation is the use of Chebyshev inequality,[4] in which the knowledge of only $\sigma(\hat{g})$ is needed. However, the confidence intervals obtained in this case prove to be too wide and inconvenient for practical use. Therefore, to estimate the degree of reliability of the information obtained in the processing system of Volna-3 sodar, we have implemented different approach that makes use of the known unique properties of 90% confidence intervals.[5,6] Indeed, for a very wide class of distributions (uniform, triangular, trapezoidal, normal, Laplace distributions and all other exponential distributions with the exponent $\alpha \geq 2/3$, as well as bimodal distributions with the antimodal depth less than 1.5) only $\Delta_{0.9}$ (halflength of the interquantile interval with the 90% probability) has a simple unique relation to the standard deviation σ in the form $\Delta_{0.9} = 1.6\sigma$ with the error no more than $\pm 0.05\sigma$. Consequently, the confidence interval for the estimated parameter g at $P = 0.9$ can be written in the form

$$I_{0.9} = [\hat{g} - 1.6\sigma(\hat{g}) \text{ to } \hat{g} + 1.6\sigma(\hat{g})]. \quad (11)$$

In Ref. 4 it was shown that (under rather general conditions) the distributions $W(\hat{g})$ of any sample quantile (including the median) and the functions of sample moments are asymptotically normal regardless of the form of the distribution of the initial sample. Thus, the distribution law of the sample mean is close to the normal one at $N \geq 30$ and any distribution law of the processed data having the finite excess value.[5] In the particular case of a Gaussian initial sample at $N < 30$, the Student distribution is used to determine I_P of the parameter mentioned above. The quantiles of this distribution can be replaced in practice with the quantiles of the normal distribution already at $N \geq 8$ (Ref. 5). Similarly, to estimate the variance, the chi-square distribution can be approximated by the Gaussian one at $N \geq 30$ (Ref. 4). However, in our case for determination of $I_{0.9}$, fulfillment of the condition of $W(\hat{g})$ normality is not obligatory. For Eq. (11) to be valid, it is necessary for the distribution of the estimated parameter $W(\hat{g})$ to be continuous and symmetric with the excess falling in the range $1.8 \leq \varepsilon \leq 12.3$. To determine the minimum sample size $N_{\min}$, from which Eq. (18) is fulfilled with an acceptable accuracy, we modeled various initial distributions $W_r(V_r)$ (with the parameters characteristic of sodar measurements) and all the above estimates $\hat{g}$: $\hat{M}(V_r)$, $\hat{\sigma}(V_r)$, $\hat{\gamma}(V_r)$, $\hat{\varepsilon}(V_r)$, using the uniform, Gaussian, Laplace, and Rayleigh distributions. For each $W_r(V_r)$ and selected value of N, we formed $L_r = 1000$ realizations of V_r and, correspondingly, calculated L_r values of $\hat{g}$. Then we determined the 5% ($p_{0.05}$) and 95% ($p_{0.95}$) quantiles of the obtained sample distributions $W(\hat{g})$. With the given L_r, these quantiles are calculated rather accurately,[5,6] which allows us to take their values as the reliable upper and lower boundaries of the sought 90% confidence intervals. From the corresponding accurate estimates, following Eq. (11), we determined similar approximate values of the confidence boundaries I_d and I_u with their absolute Δ and relative δ deviations from $p_{0.05}$ and $p_{0.95}$. As $N = N_{\min}$, we took such size of the initial sample, starting from which the condition $|\delta|_{\max} < 15\%$ was fulfilled, where $|\delta|_{\max}$ is the maximum value among all $|\delta|$ obtained for all $W_r(V_r)$. Only for the estimate $\hat{\gamma}(V_r)$, in the particular case of the asymmetric Rayleigh distribution $W_r(V_r)$, because at some N the 5% quantile of $W(\hat{\gamma})$ is close to zero, $N_{\min}$ was selected to correspond to fulfillment of the condition $|\Delta|_{\max} < 0.1$. As a result of modeling, we have obtained the following values of $N_{\min}$.

1. For estimation of the V_r distribution center, $N_{\min} \approx 5$. (For example, at $N = 4$ $|\delta|_{\max} \leq 18\%$).

2. For estimation of the standard deviation, $N_{\min} \approx 9$. Note that $N_{\min}$ for estimation of the variance is much higher because of the higher initial asymmetry of the distribution $W(\hat{D})$ with respect to $W(\hat{\sigma})$. Thus, for the initial Laplace distribution $W_r(V_r)$ even at $N = 20$, the lower boundary of the 90% confidence interval is determined with $\delta \approx -50\%$.

3. For estimation of the asymmetry coefficient, $N_{\min} \approx 8$.

4. The distribution of the estimated excess $W(\hat{\varepsilon})$ at small N has a pronounced unimodal positively asymmetric character. This determines also the asymmetric arrangement of the 5% and 95% quantiles with respect to the center of $\hat{\varepsilon}$ grouping. Therefore, the accuracy of calculation of the lower I_d and upper I_u confidence boundaries by the approximate equation (11) will be different. In this case, at a given N I_u is determined with higher accuracy and $N_{\min} \approx 15$ for that. The accuracy of I_d calculation strongly depends on the form of the initial distribution $W_r(V_r)$, that is, on the value of the excess to be estimated. Thus, this relative error $|\delta| < 15\%$ starting from $N \approx 19$ for the uniform distribution, $N \approx 40$ for the normal distribution, $N \approx 130$ for the Rayleigh distribution, and even $N \approx 550$ for the Laplace distribution. It is important to note that at smaller N the values of I_d are always smaller than the corresponding values of $p_{0.05}$. Consequently, the length of the left part of the 90% confidence interval estimated by Eq. (11) can be believed the upper estimate for its true value. In this case, for the Laplace distribution $W_r(V_r)$ the difference Δ between I_d and $p_{0.05}$ can achieve −1.5. For other initial distributions this shift is

much smaller. Thus, for the normal distribution $W_r(V_r)$ $\Delta \approx -0.5$ even at $N = 15$. Taking into account the above notes, we accept $N_{\min} \approx 15$ as $N_{\min}$ for estimation of the excess.

Thus, at $N \geq N_{\min}$ the result of measurement of some parameter g with the 90% confidence probability can be presented as $g_{0.9} = \hat{g} \pm 1.6\sigma(\hat{g})$. At smaller N, as a measure of uncertainty in determination of g, we can take the corresponding standard error.

All the algorithms described above we implemented in the processing software for Volna-3 sodar[3] and have demonstrated their practical consistency.

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