Evaluation of Beamforming and Direction Finding for a Phased Array HF Ocean Current Radar

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ABSTRACT

The errors in the current radial velocity measurements are examined using Bartlett beamforming and Multiple Signal Classification (MUSIC) direction-finding algorithms with a linear phased array antenna system. A variety of radar and environmental parameters are examined. Suggestions for the optimal choice of operating parameters are proposed. The MUSIC algorithm has shown promising performance in current measurement when beamforming is used to first establish the maximum current velocity. Comparisons of radar field data and current meter measurements show RMS radial velocity differences in magnitude of 7.44 and 6.64 cm s\(^{-1}\) for the Bartlett beamforming and MUSIC–Bartlett algorithms, respectively. The results indicate that there are advantages to using a MUSIC–Bartlett approach in operational applications.

1. Introduction

For decades, high-frequency surface wave radar (HFSWR), operating in the 3–30-MHz frequency band, has been utilized to provide ocean surface current measurements. Depending on the radar parameters and the conditions of the radio environment, these radars may be used to obtain useful current information up to ranges of 300 km from the shore. Such information has been widely used for oceanography applications (Kohut et al. 1999), data assimilation (Paduan and Shulman 2004), and model validation (Oke et al. 2002). Since vector current measurements are deduced from the radial components supplied by each of two radars, it is important to determine errors in these components. To obtain radial current measurements, radar signal processing involves the resolving of radar signals in range, Doppler, and azimuth. Angular resolution is typically addressed by either beamforming (BF) for phased arrays or direction finding (DF) for antennas of compact size and complex configuration, for example, one monopole collocated with two cross loops. Bartlett beamforming and Multiple Signal Classification (MUSIC) are well-accepted algorithms for BF and DF systems, respectively. A query worthy of some consideration is whether there are circumstances in which MUSIC, a DF method, may be used to enhance results obtained using a phased array system. Except for an early study by Laws et al. (2000) in which Bartlett BF was compared with the MUSIC algorithm, there is a dearth of literature on the evaluation of BF against DF methods for phased arrays. Wyatt et al. (2013) compared current measurements from phased array radar using a BF algorithm with those from radar with a compact antenna using the MUSIC method. Laws et al. (2010) continued the study in current error analysis with application to a compact-antenna system rather than a phased array system. Issues addressed here that were not treated in Laws et al. (2000) include the effect of overlapping percentage of consecutive time segments before Doppler processing, the dependence on time series length, and an investigation of the measurement capabilities of the combined MUSIC–Bartlett algorithm. The investigation of the combined MUSIC–Bartlett algorithm includes the influence of target signals, the effects of coarse radial current resolution in weak and moderate current conditions, and more complex variations in current speed. Under these conditions, it is shown that the combined algorithm overcomes weakness in each of the individual pointing techniques. This investigation forms an important part of this study. A second aspect of the study involves seeking means to
improve current measurement estimation by attempting to optimize the radar-associated parameters for DF and BF methods.

As pointed out by Graber et al. (1997), there are difficulties associated with comparing radial current measurements obtained from in situ measurements with those obtained from radar data because both sets of instrumentation contain measurement errors, and they also provide information from different depths and spatial scales. From this perspective, when seeking to establish the various influences on the measurements and whether the Bartlett and MUSIC methods can be combined to form a better technique for a particular combination of conditions, it is useful to employ simulated data, for which all parameters may be controlled and fine-tuned. Here, backscatter is simulated under various sea conditions, including a uniform current flowing parallel to shore and a uniform current superimposed with a Gaussian variation over an azimuthal region (i.e., Gaussian current). The dependence of RMS error between simulated and retrieved radial currents on the look direction of the radar is examined for each case. Environmental parameters used in the simulation include signal-to-noise ratio (SNR) and current speed. Other parameters in the investigation include time series length or coherent integration time (CIT), overlapping percentage of consecutive time series, the window filter used for time averaging, the number of individual Doppler spectra to be averaged, and the operating frequency. In section 2 of the paper, the two pointing algorithms (i.e., Bartlett and MUSIC), and the combined MUSIC–Bartlett method are briefly explained. Section 3 contains a simulation of the first-order sea clutter and stipulates the radar and environmental parameters that are relevant to the estimation of the radials. The performance of the pointing algorithms as applied to the simulated data is examined in sections 4 and 5. Radial currents computed from field data using the Bartlett-only method and the suggested MUSIC–Bartlett method are compared to radial components from a current meter in section 6. Conclusions appear in section 7.

2. Pointing algorithms

a. Beamforming algorithm (Bartlett)

Conventional beamforming (or the Bartlett method) is normally applied in HF radar systems where receive antennas are operated as uniform linear arrays. After fast Fourier transformation (FFT) of a signal, the time delays between antenna elements become phase shifts. The weighted signal at each element is summed to steer a narrow beam to a desired direction in such a way that signals from particular directions sum constructively, while signals from other directions sum destructively. The weighted and summed signal $S(\theta)$ for the azimuthal look direction $\theta$ is given by

$$S(\theta) = w(\theta)^H x, \quad w = a(\theta) \cdot \omega(\theta)$$

and

$$a(\theta) = [1, e^{-jk \sin(\theta)}, \ldots, e^{-jk(N-1) \sin(\theta)}]^T,$$

where $x$ is the signal at each element, $k$ is the wavelength over the number of transmitted radio waves, $d$ is the spacing between antenna elements, and $N$ is the total number of elements in the uniform linear array. The term $H$ represents the conjugate transpose and $\omega(\theta)$ is the steering vector. The term $w$ represents the beamformer weights equal to the inner product of the steering vector and the gain function of each antenna element $\omega(\theta)$. The term $\theta$ is referenced to the perpendicular to the array axis (i.e., broadside), positive clockwise. In this study, the gain functions for all of the monopole elements are assumed to be the same for all directions. Sidelobes of the formed beam are generally reduced at the expense of beamwidth by the application of an amplitude taper over the elements. Using different amplitude tapers to control the beam shape for different steering angles is not considered here but can be used to calibrate antenna patterns when they are greatly distorted.

b. Direction-finding algorithm (MUSIC)

The direction of arrival (DOA) determination in MUSIC was introduced by Schmidt (1986). Although it can be used with any antenna geometry, MUSIC has been widely investigated [see Laws et al. (2000), Barrick and Lipa (1999), de Paolo and Terrill (2007) for details] in conjunction with antennas of compact configuration as, for example, in the Coastal Ocean Dynamics Applications Radar (CODAR) (Lipa and Barrick 1986), which consists of two collocated cross loops and one monopole. Antenna patterns of each element are employed to sort out directions of incoming signals. The MUSIC algorithm determines a signal space by diagonalization of the covariance matrix formed from the measured signals on each antenna, and it determines the most likely signal bearing by projecting all the bearings associated with a particular range annulus onto that signal space. The procedures associated with the MUSIC algorithm are as follows: 1) the received signal at each antenna is first range gated and Doppler filtered—this is referred to as the “signal” in the remainder of the discussion regarding the application of the principles of the MUSIC algorithm; 2) each shifted Bragg frequency in a radar Doppler spectrum obtained by averaging $K$ spectra from one of $n_{\text{ant}}$ antenna elements corresponds to a radial current velocity; 3) eigenvectors of the covariance matrix of
the signal at antenna element $n_{\text{ant}}$ belong either to the $M$-dimensional signal subspace (assuming the number of DOAs of the signal is $M$) or to the $(n_{\text{ant}} - M)$-dimensional noise subspace. The $M$ eigenvectors are determined by choosing the eigenvectors corresponding to the highest $M$ eigenvalues and the remaining are for the noise subspace. The key is not only that the signal subspace vector is orthogonal to all noise subspace vectors, but also the steering vector is orthogonal to all noise subspace vectors. By searching through steering vectors at all azimuthal directions, MUSIC attempts to find the directions from which the steering vectors give the $M$ smallest noise subspace projections. The maximum $M$ that can be resolved is the lesser of $n_{\text{ant}} - 1$ and $K$. For HFSWR, near-surface current sensing, the $M$ for current estimation is usually less than three, which means $K$, the number of Doppler spectra to be averaged, must be at least $3$ when applying the MUSIC algorithm.

A challenge associated with the implementation of the MUSIC algorithm is outlier detection. It is found that solutions with outliers tend to originate from the mismatch between the number of peaks found in the DOA spectrum and the assumed number $M$ (Laws et al. 2000). The original MUSIC algorithm employs a statistical approach to determine the number of peaks in the DOA spectrum for a given current speed. This can result in the frequent selection of multiple DOAs, even when there is only one DOA of the current. A modification of this method involves iterating $M$ from $1$ to $4$ and evaluating the DOA spectrum for each iteration. If the number of peaks in the spectrum is found to be greater than $M$, then the spectrum is rejected. Laws et al. (2000) introduced a technique for determining the number of peaks: first, all positive extrema in the DOA spectrum are selected as possible peaks; next, a histogram of the points within the spectrum is analyzed to separate peaks from noise by defining cutoffs where the number of points in a histogram bin has fallen by $e^{-3}$; last, extrema that are greater than the cutoff are classified as true peaks to determine the DOA of the currents. Examination of results with simulated data revealed that $e^{-3}$ represents a good rejection threshold under high SNR. When the SNR is low, this threshold results in the rejection of too many peaks and the number of current results is substantially reduced. In this work, a modification has been made to the threshold. The cutoff threshold is found by calculating the centroid of the histogram of the DOA spectrum. This idea has been tested using the simulated data and has shown better results, especially for low SNR conditions.

Another method for removing the outliers involves a criterion for rejecting error-prone solutions. Barrick and Lipa (1997) presented theory describing the DOA metric. These metrics are directly related to the quality of the bearings produced by the MUSIC algorithm. Eliminating data with low DOA metrics can remove outliers and decrease the RMS error. In this work, a practical quality metric suggested by CODAR (de Paolo et al. 2007) has been used in the $M$ iterations to determine whether the DOA spectrum should be accepted or rejected.

Besides the issues mentioned above, an important task in the MUSIC algorithm is to determine boundaries on the radar spectrum delimiting the region due to first-order scatter from the sea. The details of this are discussed in the next subsection.

c. Supplementing the DF method with the BF method (MUSIC–Bartlett)

To retrieve current information using the MUSIC algorithm, the preprocessing of data involves Doppler resolving of range-resolved time series and Bragg region identification. The Bragg region is taken to be a region of spread around the Bragg peaks whose energy and position are due to Bragg-resonant waves and the underlying current velocity. Then, the Doppler shift (or radial current velocity) is calculated for each frequency bin in the Bragg region, and finally the DOA is determined for that radial current velocity. Laws et al. (2000) noted that the errors resulting from the technique were due to the processing of frequency bins outside the Bragg region. In this case, the algorithm attempts to determine DOAs for frequencies that correspond to currents that are greater in magnitude than any present in the data. It was noted that the errors caused by this problem are particularly significant for the lower-operating frequencies, where the current resolution is lower. In fact, this problem is also significant 1) for low SNR cases, when it is difficult to identify the exact Bragg region from the surrounding noisy spectrum; 2) for weak currents, when the current speed resolution becomes comparable in magnitude to the current speed; and 3) for high sea states, when the second-order energy can rival that of the first order. Calculating the DOA for a frequency deviating by just one bin from the exact Bragg region will cause significant error.

CODAR has its own algorithm for determining the first-order Bragg regions. In this paper, the MUSIC algorithm is first tried on its own, using a sensible simple maximum absolute current speed value (this maximum was established by the observation of currents from field data collected at the radar site for a 1-yr period) to determine the Bragg region [as shown by an earlier dataset (Wang and Gill 2015)]. It is found to give too many errors for the field data experiment. A different approach
is thus sought, in which the beamformer outputs for the maximum and minimum current speed are used as the respective limits of the positive and negative regions for the application of the MUSIC algorithm. Given the robust performance of the beamformer, the Bragg region to be processed by MUSIC can be determined even under low SNR conditions. Having predicted the maximum Doppler shifts and knowing the operational frequency, the Bragg region can be identified with more confidence, and as seen in section 5, the error produced by applying the MUSIC algorithm can be significantly reduced.

Note that, as an important parameter in pointing algorithms, the beam increment for the beamforming algorithm is limited by the physical aperture of the array. For 8- and 16-element “long” linear phased arrays, the broadside 3-dB beamwidth $\phi$ is about 12° and 6°, respectively. This beamwidth is approximated under the assumption of a long array as $\phi = 2.65\lambda/\pi M d$ [see Eq. (3.46) on page 114 in Collin (1985)], where $\lambda$ is the radio wavelength, $d$ is the spacing between monopoles, and $M$ is the number of elements. Note that the beam increment in beamforming is chosen to be smaller than $\phi$ for averaging purpose. The maximum azimuthal view is typically limited to $\pm 60^\circ$ from broadside due to increasing the main lobe width and increasing the sidelobe as the beam is steered from broadside. Curved array configurations can extend the azimuthal view, but these are not discussed here. For application of the MUSIC algorithm, the azimuthal view is typically set as $\pm 90^\circ$.

3. Simulation of radar return from the sea

A simulation of the complex time series of an ideal uniform linear phased array HFSWR system is developed first in this study. The simulation of voltages at each antenna induced by backscatter from the sea due to the first-order mechanism over a surface patch is briefly introduced here. It is well known that the first-order Bragg scattering mechanism (Crombie 1955) for grazing incidence involves scatter from ocean waves having lengths of half the radio wave length. Since HF signals are 3–30 MHz, the frequencies of these ocean waves belong to the gravity wave spectrum. For the deep-water case, these waves propagate at a speed $u_p$ given by

$$u_p^2 = g\lambda_0^2/4\pi,$$

where $g$ is the gravitational acceleration. Scatter from these waves typically produces large signatures (the Bragg peaks) in the radar spectrum at Doppler frequencies of $f_B = \pm \sqrt{g\pi/\lambda_0}$. When the ocean waves propagate in a region for which there exists a surface current having radial velocity components toward ($+u_r$) or away from ($-u_r$) the radar, the entire Doppler spectrum will be further shifted by an amount given by $f_s = \pm 2u_r/\lambda_0$. Because of this, nonstationary or nonhomogeneous surface currents can cause spectral smearing.

With the previous considerations in view, a complex time sequence $s(t)$ for each antenna element in the receive array due to first-order scatter from a single range cell is generated and summed over $\theta$. The result may be written as

$$s(t) = \sum_n A_n(\theta)e^{2\pi i f_s t + jBn} + A_n(\theta)e^{-2\pi i f_s t - jBn}.$$  

(4)

For the ocean surface, the complex amplitudes $A_p$ and $A_n$ may be described by zero-mean Gaussian random variables with variance $\zeta$ proportional to the ocean wave spectral energy at the Bragg frequency (Barrick and Snider 1977), given by

$$A_p = a_p + jb_p \quad \text{and} \quad A_n = a_n + jb_n \quad \text{and} \quad \langle a^2_p \rangle = \langle a^2_n \rangle = \zeta.$$

(5)

(6)

For the assumption of uniform wind and a fully developed sea, suggested by Longuet-Higgins et al. (1963), the directional distribution of spectral energy $\eta$ has the broad cardioid expression of

$$\eta = \cos^4\left(\frac{\theta - \theta^w}{2}\right) + 0.01.$$

(7)

Errors associated with surface current determination are simulated using three typical current scenarios: 1) a uniform current flowing parallel to shore (i.e., a uniform profile); 2) a uniform profile with one, two, and three bursts added (i.e., a burst profile), representing the existence of multiple targets; and 3) a Gaussian profile superimposed onto the uniform profile (i.e., a Gaussian profile), representing nonuniform variations of radial current velocity. (These modeled scenarios are depicted by solid lines in Fig. 4–6.)

In this study, wind speed, duration, and fetch were assumed to be sufficient for fully developed Bragg resonant waves at all radar frequencies. The wind was chosen to be onshore and perpendicular to the array axis. The angles are all referenced to the broadside. The simulated time series from each of $n_{\text{ant}}$ antennas, containing $N_{\text{total}}$ samples, are subdivided into $K$ time segments of length $n_{\text{dop}}$ samples, with an overlapping percentage $p_{\text{per}}$. The four parameters are related by

$$K = \frac{N_{\text{total}} - n_{\text{dop}}}{\text{floor}\left[\frac{n_{\text{dop}}(1 - p_{\text{per}})}{n_{\text{dop}}(1 - p_{\text{per}})}\right] + 1},$$

(8)

where floor means rounding toward the nearest smaller integer. Each segment containing $n_{\text{dop}}$ samples is weighted.
by a temporal window. Then, a Doppler spectrum is obtained using the FFT on each segment.

To investigate the performance of HF current mapping in various cases, six different operating frequencies, increasing from 7.5 to 28 MHz are used, and the SNR is set incrementally from 10 to 35 dB. The parameters and parameter space are summarized in Table 1. For each possibility, the simulation is run 100 times repeatedly to show statistical significance. The number is reduced to 30, since the result was found not to differ from that of 100. Current estimates in each simulation are compared with the simulated reference current profile to calculate RMS differences, and then the resulting 30 RMS errors are averaged to reduce statistical variations. The mean RMS differences between the actual simulated currents and their estimates (errors) are used as indicators of the performance of both pointing algorithms. The term $n_{ant}$ is set as 8, a typical value in many radar installations. The radial velocity resolution, $\Delta v_c$, of the surface current is inversely proportional to the sampling rate $\tau$, the segment length $n_{\text{dep}}$, and the operating frequency $f_r$, since

$$\Delta v_c = \frac{c}{(2f_r n_{\text{dep}})}, \quad (9)$$

where $c$ is the speed of light.

### 4. Dependence of pointing algorithm on radar parameters

In this section, details are given on the effects of a variety of HF radar parameters on errors in current radial velocity measurements. The performances of the two azimuth-resolving algorithms are evaluated with the goal of better characterizing these errors.

#### a. Temporal window and time segment overlap

Since the sea echo is a random variable, its Doppler spectrum is also random and should be obtained from an averaged periodogram in order to reduce the variance in the resulting surface current estimates. Each Doppler spectral estimate is a $\chi^2$-distributed variable with $v$ degree of freedom (Barrick and Snider 1977). The number of degrees of freedom depends on the number of individual spectra and the degree of overlap of their respective time segments (each time segment is overlapped by $p_{\text{per}}$ and is windowed). Hence, the impacts of the window function and the overlap percentage $p_{\text{per}}$ on current measurements are examined.

The periodic extension of the sea echo signal in a finite observation interval not consistent with its natural period produces discontinuities at the boundaries of the observation interval and these give rise to spectral leakage in the entire Doppler domain. Windowing is typically applied to reduce this spectral leakage. A simple approach is to bring a window filter to zero at boundaries so that the periodic extension of the data is continuous. After range resolving, in HF applications, each range-resolved time series is often weighted by a window, for example, a Hanning window (Laws et al. 2000), a Hamming window (Atwater and Heron 2010), or a Blackman–Harris four-term window (Wyatt et al. 2009). Given that windowing attenuates samples at the boundaries to zero, overlapping of consecutive finite time series is also required due to the loss of samples [50% and 75% overlap is normally used (Harris 1978)]. Simulations are conducted to examine the dependence of error on the choice of windowing and the overlap percentage of the time segments. Errors in beamforming using five windows for various overlap percentages are shown in Figs. 1a,c,e. The leakage factor of the main lobe and sidelobe level of the windows’ spectrum decreases from 1 to 5. For the BF method, Figs. 1a,c,e show that a 75% overlap leads to the lowest radial errors in more than 85% of the cases. Particularly, for window 3, a 75% overlap is the best in all cases.

On the premise of the 75% overlap, the effect of windows on the RMS error is examined. For a uniform profile, errors when using the rectangle window are slightly lower than those when using any other window. Investigation for the low SNR condition and Gaussian current cases show that the Hamming window (3 on the x axis) performance exceeds that of the other windows. This is not difficult to understand, since the rectangle window that has the narrowest main beam and highest sidelobe level is ideal when 1) the current profile is simple and 2) SNR is moderate. Other than these two cases, the Hamming window with a moderate main beamwidth and sidelobe level shows the best performance.

Errors in MUSIC measurements are shown in Figs. 1b,d,f. For the uniform current case, the Blackman–Harris window (see Fig. 1b) exhibits stable and low errors for all overlap percentages. This window shows better
performance than the others, in particular when a low SNR condition and a Gaussian current profile are considered (see Figs. 1d,f). For this window, a 75% overlap is seen to produce the lowest errors in all cases. For example, for the low SNR condition, Fig. 1d shows that when overlap increases from 0% to 75%, the number of errors decreases. A possible reason is that the noise is reduced by averaging more segments when using a larger overlap. However, as the overlap continued to increase—for example, to 95%—the error trended higher. This is probably because that excess overlap causes excess sidelobe smearing of the spectral events (Tektronix 2009). In addition, if the field data contain short time bursts, then the spectral information of the short time bursts will be stretched to all the overlapped FFT, and thus the spectral smearing effect will be even worse.

b. Effects of the coherent integration time on current measurements

Another dominant radar-associated parameter to be examined is the CIT, expressed as $t_{\text{CIT}} = n_{\text{dop}} \times \tau$. Assuming that the sea echo is present in the returns of all $n_{\text{dop}}$ chirps, the coherent integration over $n_{\text{dop}}$ chirps will

Fig. 1. Errors in estimates from BF and DF using five temporal windows for five different overlap percentages, with $n_{\text{dop}} = 1024$ and $f_c = 13.385$ MHz. Number on the x-axis represents different windows, where 1 is rectangle, 2 is Hanning, 3 is Hamming, 4 is Blackman, and 5 is Blackman–Harris.
enhance the SNR by a factor of $n_{dop}$. HFSWR relies on long CIT to increase SNR to a sufficiently high level for detection. There is a dilemma in setting the parameter CIT or $n_{dop}$. On the one hand, the larger the $n_{dop}$, the smaller the spectral leakage and the higher the Doppler resolution. On the other hand, the larger the $n_{dop}$, the smaller the number of segments $K$ (to increase $K$, $n_{dop}$ should be set small for a fixed $N_{total}$ and $p_{per}$). The number of degrees of freedom of each Doppler variable increases with $K$. Also, averaging $K$ Doppler spectra will increase the SNR. Therefore, a trade-off may be required for the two parameters. Note that $K$ should be no less than 3 for MUSIC to resolve at most two bearings of current. Considering this, $n_{dop} = 768, 1024, 1280,$ and $1862$ are four typical values used in the following investigations, which are calculated according to $p_{per} = 25\%$, $50\%$, $75\%$, $95\%$ in Eq. (8), respectively, given that $K = 3$, and $N_{total} = 2048$.

The dependence of error on $n_{dop}$ is investigated for both the Bartlett and MUSIC approaches. Results for errors in Figs. 2a,c,e show the Bartlett-derived radials to have lower errors when $n_{dop} = 768$ and 1024 (i.e., the circle and triangle curves, respectively) than $n_{dop} = 1280$ and 1862 for all scenarios. It is implied that a large $K$ is a more dominant factor than a large $n_{dop}$ in producing low errors. As for the two cases $n_{dop} = 768$ and 1024, it is also

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**FIG. 2.** Errors in estimates from BF and DF using five temporal windows for four values of $n_{dop}$, with $p_{per} = 75\%$ and $f_c = 13.385$ MHz. The number on the x-axis represents different windows, where 1 is rectangle, 2 is Hanning, 3 is Hamming, 4 is Blackman, and 5 is Blackman–Harris.
seen that Hamming window produces a more stable performance than the other windows and \( n_{\text{dop}} = 1024 \) is slightly better than 768. Errors in MUSIC measurements in Figs. 2b,d,f show that \( n_{\text{dop}} = 1024 \) is the best setting of the CIT in all cases, using a 75% overlap. It is expected that \( n_{\text{dop}} = 1024 \) will provide a better performance than 768, because of the higher resolution. However, larger errors are seen when \( n_{\text{dop}} \) increases to 1280 and 1862. This can be explained by the trade-off effect that the improvement due to the increase of \( n_{\text{dop}} \) does not compensate for the lack of averaging due to the decrease of \( K \). This trade-off effect does not depend on the window applied. Blackman–Harris windowing shows better performance than the others. Therefore, \( n_{\text{dop}} = 1024 \), a 75% overlap, and the Blackman–Harris window are the recommended optimal settings for the MUSIC algorithm for all the cases investigated.

c. Dependence on SNR and radar operating frequency

The dependence of error on SNR (10–30 dB) and \( f_r \) (7.5–28.8 MHz) for the BF and DF methods for the uniform profile is depicted in Fig. 3. For cases where SNR \( \approx 15 \) dB, errors in the Bartlett beamforming case seem random, fairly low, and not obviously dependent on either SNR or radar frequency, while errors with MUSIC are dependent on SNR over this range. Compared with the results that the errors with MUSIC are independent
of SNR (see Laws et al. 2000), these results may be more expected, because the performance of the MUSIC algorithm relies on the noise subspace decomposition of the signal; that is, higher SNRs should result in more accurate estimates when using MUSIC. For the BF method, the errors associated with accurate estimates when using MUSIC. For the BF method, the errors associated with higher frequencies when SNR \( \leq 15 \) dB. This suggests that a 20-dB SNR may be established as a threshold for the stable low-error performance of the BF method when operating in the lower HF band under a uniform current profile. However, at the lowest SNR, the MUSIC error is 25 cm s\(^{-1}\), which is significantly higher than the BF error by 9 cm s\(^{-1}\). Above 25 dB, MUSIC errors associated with 13.4 MHz are around 1 cm s\(^{-1}\), consistently lower than the BF errors of 2 cm s\(^{-1}\). For a given SNR, higher errors are observed for 7.5 MHz, since the radial current resolution drops significantly. However, MUSIC errors associated with 28.8 MHz are not seen to be lower than 13.4 MHz. A possible reason is that the parameters used (\( n_{\text{dop}} = 1024, p_{\text{per}} = 75\% \)) are fine-tuned for the frequency of 13.4 MHz. For each given \( f_r \), the frequency resolution is different and the trade-off problem needs to be optimized with fine-tuned parameters.

For the Gaussian profile, Figs. 3b,d,f show that 1) errors in this case are larger than the uniform profile for both the BF and DF methods; 2) above a 15-dB SNR, the BF errors remain stable irrespective of the radar operating frequency and SNR; and 3) above a 25-dB SNR, the MUSIC algorithm provides lower errors than the Bartlett method, and this is especially obvious at 13.4 MHz.

5. Supplementing the DF method with the BF method (MUSIC–Bartlett)

a. Effect of target signals

In real data, radar sea echoes are often mixed with target echoes, which may have a radial velocity either larger or smaller than the maximum current radial velocity. Namely, a current profile may contain one point of significant departure from the data trend, such a point being herein referred to as a “burst.” Here, the dependence of RMS errors on target signals in the current profile is examined. In the simulation, as suggested, the existence of a target is represented as a burst in a current profile. The burst magnitudes are set as 35 and 65 cm s\(^{-1}\), one lower and one higher, respectively, than the maximum radial velocity assumed as 50 cm s\(^{-1}\). These two magnitudes are used to examine whether the pointing algorithms can be used to identify targets with velocities smaller and higher than the maximum radial current velocity associated with a particular regime. Results for both cases show that the BF method failed to track the abrupt change, as shown in Figs. 4a,c. This is expected because the azimuthal resolution, due to the limited aperture of the eight-element phased array, is about 12°, while the burst appears at one azimuthal bin of width 2°. Nevertheless, the BF method successfully tracked the current profile itself. When the BF-estimated maximum and minimum radial currents—that is, \( \pm 50 \text{ cm s}^{-1} \)—are used to determine the boundary of the first-order region in the MUSIC algorithm, the existence of a low burst can be precisely detected, as shown in Fig. 4b. In the case of a 65 cm s\(^{-1}\) burst, using the BF-estimated maximum that is smaller than the target velocity, the MUSIC algorithm failed to track the burst (see Fig. 4d), although the derived current profile agrees well with the simulated reference profile. Similar agreement is seen when experiments are extended to three bursts cases. Laws et al. (2000) have shown that the error of the MUSIC algorithm is proportional to the abruptness of the changes in the radial current profile, and so a high RMS error in the order of 10–50 cm s\(^{-1}\) will be expected for a burst width as narrow as that used in this study. Mean RMS errors using the BF–DF algorithm for one and three bursts in this study are 1.5 and 5.6 cm s\(^{-1}\), respectively. This error level is much less than the 10–50 cm s\(^{-1}\) indicated by Laws.

b. Effects of variations of radial currents

1) The resolution of the radial current velocity in weak and moderate currents

The dependence of errors on variations in radial currents represented by a Gaussian profile is examined for two scenarios: the first, and most difficult, case includes a weak current with a maximum speed of 20 cm s\(^{-1}\), a low operating frequency of 7.5 MHz, and a poor SNR for the Bragg signal of 15 dB. A second scenario involves a moderate current with a maximum speed of 100 cm s\(^{-1}\), a radar frequency of 13.385 MHz, and an SNR of 25 dB. In the first case, the current radials varied from \(-10\) to 20 cm s\(^{-1}\). According to Eq. (9), the radial current resolution is determined by \( f_r, \tau, \) and \( n_{\text{dop}} \). If \( n_{\text{dop}} = 1024 \) and \( \tau = 0.52 \) s is fixed, then the use of 7.5 MHz results in a coarse current velocity resolution of 3.76 cm s\(^{-1}\). The minimum current of \(-10\) cm s\(^{-1}\) corresponded to a near-3 spectral bin shift from the theoretical Bragg frequency to the negative side, while the maximum radial current of 20 cm s\(^{-1}\) caused about a 6 spectral bin shift to the positive side. Thus, the first-order region due to current
velocity is spread over nine spectral bins around the theoretical Bragg peak location. This coarse resolution will accentuate MUSIC errors, because even the least deviation in the determination of the first-order region will cause the algorithm to determine the DOA for spectral bins that correspond to currents that are greater/less in magnitude than the weak current present in the data.

Figure 5a show the Bartlett-derived radials for the first scenario. Bartlett radials are seen to successfully track the Gaussian current profile. Referred to as the BF radial estimates, the maximum radial velocity in the MUSIC method is then set as 20 cm s\(^{-1}\). Figure 5b shows the radials estimated by the combination of Bartlett and MUSIC algorithms. It can be seen that the current estimates by the MUSIC–Bartlett algorithm track the Gaussian variation better than the Bartlett method. As for the second case, the resolution of the current velocity is reduced to 2.75 cm s\(^{-1}\). The Bartlett algorithm shows good performance in tracking the maximum current speed of 100 cm s\(^{-1}\) in Fig. 5c. Using the maximum current estimated by the Bartlett method, Fig. 5d shows the MUSIC algorithm to have good tracking of the currents. In addition, the RMS error of the combined MUSIC–Bartlett algorithm is lower than that of the Bartlett algorithm by 4.5 cm s\(^{-1}\), which indicates the promising use of the MUSIC algorithm in conjunction with the Bartlett method.

2) ANGULAR WIDTH AND STRENGTH OF THE GAUSSIAN CURRENT PROFILE

The dependence of errors on the angular width and the strength of the current variations for both pointing algorithms was further examined. In the previous examples, the Gaussian profile is generated by adding the Gaussian component to the uniform profile in the radar azimuth region from \(-10^\circ\) to \(10^\circ\). Here, both the angular width of the azimuth region and a strength coefficient (with values of 0.5, 1.5, and 2.5 used to amplify or attenuate the Gaussian component) are changed to examine the performance of the Bartlett and MUSIC techniques in each case. This simulation of the Gaussian profile as having current change in either magnitude or directional extent is intended to widen the investigation in the sense of sea conditions and also to examine the weaknesses of the two pointing techniques. Note that when the angular width and the strength coefficient vary, the same radial magnitude can appear at one, two, or three azimuth bins in the Gaussian profile. It is well known that the MUSIC algorithm is subject to higher errors when resolving multiple directions than one direction for the same current radial, while the Bartlett...
algorithm is not affected in this regard. Meanwhile, the Bartlett algorithm is subject to higher errors due to the broadening of the main beam when the beam is steered further from the broadside, while the MUSIC algorithm is not affected by this issue.

Comparing Figs. 6a,b, the benefit of using the MUSIC–Bartlett algorithm as opposed to the Bartlett algorithm is demonstrated. The weakness of the latter method not being able to track sudden changes within the beamwidth is supplemented by the former method. In the next experiment, the strength coefficient is increased to 1.5. Since the Bartlett method again failed to track the Gaussian component in the current profile, the MUSIC–Bartlett also failed, having no correct reference for the maximum current speed. This finding indicates the limitation of the combined algorithm.

Next, instead of adding the Gaussian component around the broadside of the radar, as was done previously, the variation is added in the angular region between $38^\circ$ and $60^\circ$. This spread is narrower than the width of the main beam when it is steered at $60^\circ$. Figure 6a confirms the weakness of the Bartlett method in tracking current variations within its beamwidth, and also the benefit of this method in providing an estimate of the maximum current speed during this change. Using the estimated maximum current speed, Fig. 6d illustrates the advantage of the MUSIC–Bartlett algorithm in terms of tracking local variations of currents.

6. Field data evaluation

In assessing whether the radar BF and DF algorithms with optimized parameters are suitable for practical radial current velocity retrieval, radar-derived radial current measurements are compared with buoy measurements. An experiment commenced on 29 November 2012, with the deployment of a single Wellen Radar (WERA) installed on the coast of Placentia Bay, at Argentia, Newfoundland and Labrador, Canada, as illustrated in Fig. 7. The radar site consisted of eight identical receiving elements with nominal half-wavelength spacing. The operating frequency was 13.385 MHz and a 50-kHz bandwidth theoretically yielded a 3-km radial resolution. The half-power width of the main lobe and, thus, the ideal broadside azimuthal resolution, is about $12^\circ$. Resolution degrades by a factor of 2 at beam-steering angles of $\pm 60^\circ$, which is taken to be a practical limit. Samples were collected at intervals of 0.39 s per radar beam. A 1024-point FFT (optimal setting of this parameter) is processed to yield a CIT of about 400 s or, correspondingly, a current velocity resolution...
of approximately 2.8 cm s$^{-1}$. During the CIT, signals at the receivers are combined to yield a constructive signal for one beam only. The radar was configured to yield 61 beams, each separated by approximately 2°.

The optimal setting of parameters based on simulations is considered for application of both the Bartlett and MUSIC methods, that is, 75% overlapping for both methods, a Hamming window for the BF method, and the Blackman–Harris window for the DF method.

The in situ measurements used in this paper are from a buoy-mounted Nortek Aquadopp acoustic Doppler single-point current meter, moored at a depth of 0.5–1 m in an area with a water depth of about 153 m. The Nortek current meter is at 47°19.6’N, 54°07.7’W (the location of the buoy is about 10 km from the radar site), shown in Fig. 7. This instrument provided current velocity every half an hour on a daily basis. According to the technical specification of the current meter (CM), the range of the water velocity measurement is $0.5–1$ cm s$^{-1}$ with an accuracy of 1%.

The performance of the Bartlett method illustrated in Fig. 8a shows the radial current speed difference between the CM and the radar from 29 November 2012 to 21 August 2013. Differences between HF radar–derived and CM-derived velocities near 10–15 cm s$^{-1}$ have been reported by Schott et al. (1986). More recent comparisons between HF radar velocities and point measurements show RMS differences between 7 and 19 cm s$^{-1}$ [see Essen et al. (2000), Paduan et al. (2006), and Lorente et al. (2014) for details]. The RMS difference found here

![FIG. 7. Location of the buoy (solid dot) and a single radar site (star). Buoy is at a distance of 10 km from the radar site.](image-url)
is 7.44 cm s$^{-1}$, which is within the aforementioned difference range for CM–radar comparison, and the correlation coefficient is about 82.3% (refer to Fig. 9a). Figure 8 displays the time series of the CM-derived current speeds, together with the radar point estimates by the MUSIC–Bartlett algorithm during the same period. The RMS error as compared to the benchmark CM measurements is 6.64 cm s$^{-1}$, which is lower than that of the Bartlett method, and the correlation coefficient in this case is increased to 88.0% (refer to Fig. 9b). Note that the Bartlett method tends to give a smoothed or averaged estimation, while the MUSIC algorithm can better track abrupt changes in the radial current speed, for example, burstlike radial current measurements in the region marked with a circle in Fig. 8. However, the number of MUSIC-derived and Bartlett-derived valid measurements is 88 and 56, respectively (there were 92 data collections). The MUSIC–Bartlett methodology produces fewer measurements than the Bartlett because the MUSIC method usually requires an hour of data to fill the gap of measurements in azimuth. With 13 min of data, there are sometimes no available current measurements (or there is a gap) for the radar look direction toward the buoy. Then, there are no measurements to be compared with the current meter. A solution to increase the number of measurements is to use 30-min to 1-h data segments to fill the gap in azimuth. However, the data we collected are not continuous and so the gap filling cannot be done. The SNR value of the field data is in the range of 20–35 dB. Even though the statistics suggest a better performance for the “combined” method, the scatterplots do not show consistent superiority. At this stage of the work, it is still too early to conclude whether the MUSIC–Bartlett method or the Bartlett method is better. The aim of this work is more to show the strength of each algorithm and the potential of combining these methods. Another limitation in this study is that the dataset does not represent a large variation in current regimes.

7. Conclusions

In this simulation-based study, which also contains a preliminary experimental validation, we have first examined the effects that various radar and environmental parameters used in the Bartlett and MUSIC algorithms have on errors in radial current measurements. An analysis of errors related to the temporal window shows that the most consistent and reliable performance, for the nonuniform current profile and for low or high SNR conditions, are obtained when the Hamming window is used in the Bartlett approach and when the Blackman–Harris window is used in the MUSIC algorithm. Examination of the overlapping of windowed time segments shows that 75% overlapping is preferable for both pointing techniques.

Examination of error dependence on the length of the time segment $n_{\text{dop}}$, or coherent integration time (CIT), shows a trade-off effect between the CIT and the number of segments used for averaging. In this case, for a total time series of length 2048, a radar working frequency of 13.385 MHz, and a 75% overlap, both techniques indicate that an optimal CIT is associated with $n_{\text{dop}} = 1024$.

This study also indicates that for the Gaussian current profile, 1) the Bartlett performance bears no clear dependence on SNR and the radar frequency when SNR is above 15 dB and $f_s$ is higher than 11.4 MHz; 2) a decrease in the error with SNR increasing from 10 to 30 dB is observed with the MUSIC method for all six frequencies; and 3) above a 25-dB SNR, the MUSIC algorithm provides lower errors than the Bartlett method, and this is especially obvious at 13.385 MHz. Similar results are seen for the uniform current profile.

Using the optimal parameters found in previous examinations, the MUSIC algorithm, which makes use of the maximum current speed measured by the Bartlett algorithm, has been presented for use in a phased array system. This technique was implemented to address the
fact that a major source of error in results obtained using the MUSIC algorithm arises from inaccurate determination of the Bragg region during low SNR operation and under weak current condition. This problem will be even more severe in field data when the second-order continuum is mixed with first order in low SNR conditions or high sea states. In this study, the second-order Doppler continuum is not simulated. Also, the MUSIC–Bartlett technique addresses the fact that a major source of error obtained using the Bartlett method arises from the wide azimuthal extent of the beam. In real data, when currents vary significantly within the azimuthal extent of the radar beam, the Bartlett method will not be able to track the change, while the combined MUSIC–Bartlett method shows the potential to track the abrupt change.

An analysis of the errors associated with target presence in the current profile (represented as the current profile containing a single point of significant departure from the data trend) shows MUSIC to generate multiple false bursts. This prevents the algorithm from tracking the true direction and velocity of the target, and it causes the Bartlett method to miss the target burst. When the MUSIC–Bartlett method is used, the latter shows improved accuracy in capturing the target in the current profile, due to the utilization of the eigenfeature of the target signal and the accurate identification of the maximum current speed. It is found that if the burst exceeds the maximum current speed that is found by the Bartlett method, that the MUSIC algorithm still can be used to track the current trend and fill in the gaps in the Bartlett current measurements.

Investigations into conditions of weak currents, low frequency, low SNR, and poor current resolution indicate that the combined MUSIC–Bartlett algorithm produces improvements in radial current measurements, when compared to results from each of the two pointing methods being applied individually. This is also confirmed for less-challenging conditions. Next, the effects of the broadened main lobe of the Bartlett method on the performance of the combined algorithm are investigated by allowing the angular width and strength of the Gaussian profile to vary. Results show that the MUSIC–Bartlett algorithm to outperform the Bartlett method when the current variation is within an angular region smaller than the beamwidth, irrespective of whether the beam is steered broadside or ±60° from it, and whether the variation is weak or strong. Finally, although this work is presented primarily as a simulation-based study for current mapping techniques, current meter data are employed as a preliminary validation of the combined MUSIC–Bartlett algorithm using radar field data. It has been observed that the Bartlett method could achieve an RMS error of 7.44 cm s⁻¹ based on the 92 current estimates collected from 29 November 2012 to 21 August 2013, while the MUSIC–Bartlett method produced an error of 6.64 cm s⁻¹ but with significantly fewer estimates. While a more robust validation of the technique will require further application of the combined algorithms to more extensive and varied sets of field data, the presented results appear to show some promise for phased array systems.

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