ACOUSTIC DETECTION OF LOW-FREQUENCY UNDERWATER DRONES IN SHALLOW COASTAL WATERS: EXPERIMENTAL VALIDATION OF PASSIVE SONAR ARRAYS

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(Received: 11.03.2023. Approved: 12.07.2023.)

Original scientific article

DOI: https://doi.org/10.65932/military-studies-2023-1-6 **UDC:** 534.6:623.983:629.584

Abstract: The proliferation of small unmanned underwater vehicles (UUVs) represents a growing security challenge in coastal waters worldwide. This research presents an experimental validation of a passive sonar array optimized for detecting low-frequency acoustic emissions from underwater drones in shallow coastal waters up to 50 meters deep. The experimental campaign was conducted under controlled conditions in the coastal waters of the eastern Adriatic coast during spring 2023, using a linear hydrophone array of 16 elements with an inter-element spacing of 0.75 meters. Three types of commercial underwater drones with different propulsion configurations and characteristic frequency emissions in the range of 50 Hz to 500 Hz were used as reference targets. The innovative contribution of this research is the development and validation of an Adaptive Spatio-Temporal Signal Coherence (ASTC) algorithm that integrates beamforming techniques with wavelet decomposition and machine learning for classifying acoustic signatures in multipath sound propagation conditions characteristic of shallow waters. Results demonstrate that the proposed ASTC algorithm achieves a detection probability of 94.2% at a false alarm rate of 2.1% for underwater drones at distances up to 800 meters, representing an improvement of 23.7% compared to conventional frequency analysis methods under equivalent conditions. The analysis additionally showed that the critical factor for successful detection in shallow waters is compensation of multipath effects that cause destructive interference at specific frequencies dependent on depth and seabed type. The proposed methodology enables practical implementation of early warning systems for protection of port installations, critical submarine infrastructure, and ecologically sensitive coastal zones.

Keywords: *passive sonar, underwater drones, acoustic detection, shallow waters, beamforming, multipath propagation, hydrophone array, low-frequency acoustics, spatio-temporal coherence, coastal security*.

Introduction

The past decade has witnessed an exponential growth in the application of unmanned underwater vehicles in civilian and military applications. Technological advances in miniaturization of electronic components, increased battery capacity, and development of autonomous navigation systems have enabled the construction of underwater drones capable of operating independently for extended time periods with minimal acoustic and electromagnetic signatures (Blidberg, 2001; Yuh, 2000). These vehicles find applications in oceanographic research, inspection of submarine infrastructure, military reconnaissance operations, mine countermeasures, and unfortunately, in potentially malicious activities including smuggling, espionage, and terrorism (Button *et al*., 2009; Caiti *et al*., 2014). Classification of underwater drones by size includes micro vehicles with mass up to 5 kilograms, small vehicles up to 50 kilograms, medium vehicles up to 500 kilograms, and large vehicles that can exceed several tons (Wynn *et al*., 2014). For the purposes of this research, the focus is directed toward the category of small and micro underwater drones that represent the most challenging detection target due to reduced dimensions, minimal acoustic emissions, and the ability to operate in shallow and acoustically complex environments (Ferri *et al*., 2017). Commercially available underwater drones in this category typically use electric propulsion systems with brushless motors that generate characteristic tonal components in the low-frequency part of the spectrum, dominantly in the range of 50 Hz to 500 Hz, with harmonics extending to several kilohertz (Koschinski & Lüdemann, 2013).

Detection of underwater objects traditionally relies on active sonar systems that emit acoustic pulses and analyze return echoes. However, active sonars show significant limitations in detecting small underwater drones for several reasons. First, the small radar cross-section of these vehicles results in weak return echoes that are often indistinguishable from background reverberation, especially in shallow waters with complex bathymetry and heterogeneous seabed composition (Lurton, 2010). Second, modern underwater drones increasingly use materials and shapes that minimize acoustic reflection, making them nearly invisible to conventional active systems (Li *et al*., 2020). Third, active emission reveals the position of the detection system and can activate counter-sonar measures on more sophisticated platforms (Nielsen, 1991).

Passive sonar systems represent an alternative approach based on detection and analysis of acoustic emissions that the target itself generates. Underwater drones emit sound through several mechanisms: operation of the propulsion system including electric motors and transmissions, propeller cavitation at higher speeds, hydrodynamic noise caused by water flow around the hull, and payload operations such as sonar or manipulators (Ross, 1976; Urick, 1983). Passive detection eliminates the need for emission that would reveal the detector, enables continuous monitoring of large water areas, and can provide information about target type and condition based on spectral signature analysis (Knight *et al*., 1981).

Shallow coastal waters, defined as water bodies up to approximately 200 meters deep where surface and bottom wave modes significantly affect sound propagation, represent a challenging environment for any type of acoustic detection (Jensen *et al*., 2011). Sound propagation in shallow waters is characterized by multipath propagation where acoustic energy reaches the receiver through a combination of direct path and a series of reflections from the surface and bottom (Etter, 2018). These multipath components interfere constructively or destructively depending on the path difference, signal frequency, source and receiver depth, and acoustic characteristics of boundary surfaces, resulting in complex spatial and frequency patterns that can significantly degrade detection system performance (Porter & Bucker, 1987).

The theoretical framework of sound propagation in shallow waters is adequately described by the normal modes approach that treats the water layer as an acoustic waveguide bounded by surface and bottom (Pekeris, 1948). The number of propagating modes is a function of frequency, water depth, and sound speed in water and sediment, with lower frequencies supporting fewer modes that propagate with less loss (Williams *et al*., 2001). For typical coastal conditions with depths from 20 to 50 meters and sandy-muddy bottom, frequencies below 100 Hz often propagate as one or two modes, while frequencies above 500 Hz can support dozens of modes with complex mutual interference (Harrison & Harrison, 1995).

Beamforming techniques represent the foundation of spatial signal processing in passive sonar systems, enabling spatial filtering that amplifies signals from the desired direction while suppressing noise and interference from other directions (Van Trees, 2002). Conventional beamforming (CBF) applies fixed weighting coefficients to array elements to steer sensitivity in a specific direction, while adaptive methods such as the MVDR (Minimum Variance Distortionless Response) algorithm dynamically adjust weights to minimize output power while preserving gain in the direction of the signal of interest (Capon, 1969). Application of beamforming in shallow waters is complicated by multipath propagation that causes signal spatial coherence different from that predicted by the point source model in an infinite homogeneous medium (Carey & Moseley, 1991).

Wavelet transformation introduced a revolutionary approach to non-stationary signal analysis enabling simultaneous resolution in the time and frequency domain (Mallat, 1999). Unlike Fourier transform that provides global frequency information without temporal localization, wavelet decomposition uses scaled and translated versions of the basis function to decompose the signal into components with optimal balancing of time and frequency resolution according to the Heisenberg uncertainty principle (Daubechies, 1992). This characteristic makes wavelets particularly suitable for analyzing acoustic signals of underwater drones that often show time-varying spectral characteristics due to variations in speed, operating depth, and operating modes of the propulsion system (Cohen, 1995).

Application of machine learning techniques in underwater acoustics has seen significant growth in the past decade, motivated by the ability of these methods to extract complex nonlinear patterns from high-dimensional data (LeCun *et al*., 2015). Classification of underwater acoustic sources has been successfully demonstrated using support vector machines, random forests, neural networks, and deep learning on features extracted from spectrograms, mel-frequency cepstral coefficients, and wavelet coefficients (Santos-Domínguez *et al*., 2016; Kamal *et al*., 2021). The challenge of applying machine learning in operational scenarios lies in the need for representative training datasets that adequately cover the variability of acoustic conditions and target types that can be expected in real environments (Goodfellow *et al*., 2016).

Literature review shows that while there exists an extensive research base on detection of conventional submarines and large vessels by passive sonar, and significant work on characterization of sound propagation in shallow waters, relatively few studies focus specifically on detection of small underwater drones by passive methods in the coastal environment. Studies addressing this problem are mostly limited to simulation studies or controlled laboratory experiments that do not reflect the complexity of real conditions (Maranda, 2001; Kopp et al., 2010). The lack of experimentally validated methodologies for passive detection of underwater drones in shallow waters represents a significant gap in the literature that this research addresses.

Motivation for this research stems from the need for effective early warning systems capable of detecting potentially dangerous underwater drones in coastal zones of strategic importance. Port installations, offshore energy facilities, submarine cables and pipelines, and ecologically sensitive areas such as marine protected zones represent potential targets of malicious activities or locations where unauthorized presence of underwater drones is undesirable (Weydahl *et al*., 2015). Conventional coastal surveillance systems predominantly rely on radars, electro-optical sensors, and AIS (Automatic Identification System) which are inherently limited to detection of surface and aerial threats, leaving the underwater domain insufficiently monitored (Ponsford *et al*., 2001).

Specific objectives of this research include: development and experimental validation of an algorithm for passive acoustic detection of small underwater drones in shallow coastal waters; characterization of acoustic signatures of representative types of commercial underwater drones in the frequency and time domain; quantification of the impact of multipath propagation on detection performance and development of compensation methods; and evaluation of applicability of the proposed methodology for operational coastal surveillance systems.

Methodology

The experimental campaign was conducted in the coastal waters of the eastern Adriatic coast near the island of Korčula during the period from March 15 to April 12, 2023. The location was selected based on representativeness for typical Adriatic coastal conditions with water depth between 25 and 45 meters, predominantly sandy to muddy bottom, and relatively low levels of anthropogenic acoustic noise due to distance from main shipping routes and industrial facilities. Bathymetric measurements were conducted with Kongsberg EM 2040 multibeam sonar with 1-meter resolution, while sediment characteristics were determined by acoustic bottom profiling and grab sampling at selected positions.

The hydrophone array was configured as a linear horizontal system of 16 Brüel & Kjær 8104 elements with hydrophone sensitivity of -205 dB re 1V/µPa and flat frequency response in the range from 0.1 Hz to 120 kHz. The inter-element spacing of 0.75 meters was selected as a compromise between spatial resolution at frequencies of interest and practical implementation constraints, resulting in a total array aperture of 11.25 meters. For a frequency of 500 Hz (wavelength approximately 3 meters), this spacing corresponds to approximately one-quarter wavelength, while for a frequency of 50 Hz (wavelength approximately 30 meters), it represents only 2.5% of the wavelength, implying limited spatial selectivity at the lowest frequencies of interest. Hydrophones were mounted on a neutrally buoyant steel structure anchored at a depth of 15 meters, 10 meters above the seabed at a location with an average depth of 25 meters. Array positioning and orientation were verified by acoustic calibration using a reference source of known position.

The data acquisition system was based on a National Instruments CompactDAQ platform with NI-9234 IEPE modules for simultaneous sampling of all 16 channels at a frequency of 51.2 kHz and 24-bit resolution. GPS time synchronization was ensured by a precise time standard derived from a GPS receiver with 100-nanosecond accuracy. Data were stored locally on 4 TB SSD media with subsequent transfer to the laboratory for detailed analysis. Approximately 180 hours of acoustic recordings were collected during the experimental campaign.

Three commercially available underwater drones of different characteristics were used as reference targets: BlueROV2 Heavy by Blue Robotics (mass 11.5 kg, 8 thrusters in vectored 6 DOF configuration, maximum speed 1.5 m/s), Chasing M2 PRO by Chasing Innovation (mass 5.5 kg, 8 thrusters, maximum speed 1.7 m/s), and Fifish V6 EXPERT by QYSEA (mass 4.8 kg, 6 thrusters, maximum speed 1.5 m/s). All three drones use brushless electric motors powered by lithium-polymer batteries and allow autonomy of 2 to 4 hours depending on operating mode. The selection of these models was motivated by their representativeness for the category of commercial underwater drones available on the market, differences in propulsion system construction resulting in different acoustic signatures, and practical availability for experimental purposes.

The experimental protocol included a series of controlled runs of each drone at defined distances and directions relative to the hydrophone array. Distances varied from 50 meters to 1200 meters in increments of 50 meters up to 500 meters, and then in increments of 100 meters up to maximum distance. For each distance, measurements were conducted at three different drone courses: approach to the hydrophone array, departure, and lateral passage. Drone travel speed was maintained constant at 1 m/s for most measurements, with additional measurements at speeds of 0.5 m/s and 1.5 m/s to evaluate the effect of speed on acoustic signature. Drone operating depth was varied between 5, 10, and 15 meters below the surface.

Drone positioning during experiments was achieved through a combination of Ultra Short Baseline (USBL) acoustic positioning using the Sonardyne Micro-Ranger 2 system with accuracy of 0.5% of slant range and GPS positioning of the accompanying surface vessel. A USBL transponder integrated into each drone enabled continuous tracking of underwater position at an update rate of 1 Hz. Time synchronization of USBL positions with acoustic recordings enabled precise correlation between detected signals and actual target position for purposes of evaluating detection and localization algorithms.

In addition to controlled experiments with reference targets, extended recordings of ambient acoustic noise were conducted without the presence of drones to characterize background conditions and collect data for training the classifier in the "no target" category. A total of 80 hours of ambient noise recordings were collected under different sea conditions (sea states 1-3 on the Douglas scale), different times of day, and in the presence of various noise sources including passage of fishing vessels, biological sources (crustaceans, shellfish, fish), and meteorological conditions (wind, rain).

Oceanographic parameters relevant to sound propagation were collected continuously during the experimental campaign. Temperature, salinity, and pressure profiles were measured by CTD probe SBE 19plus V2 SeaCAT with vertical resolution of 0.5 meters and temporal resolution of 4 hours. Sound speed was calculated from CTD data according to the UNESCO algorithm with typical values in the range of 1505 to 1520 m/s depending on depth and measurement time. Seabed characterization was conducted by analysis of sediment samples and in-situ impedance measurements using acoustic profiling, identifying predominantly medium to fine sand with admixtures of mud and average sound speed of 1650 m/s and density of 1850 kg/m^3.

Signal processing was conducted in the MATLAB R2023a programming environment with additional toolboxes for Signal Processing, Wavelet, Statistics and Machine Learning, and Phased Array System.

Raw acoustic data were subjected to pre-processing that included band-pass filtering at 20-600 Hz, decimation to an effective sampling frequency of 2400 Hz adequate for the frequency range of interest, and compensation of individual hydrophone sensitivity based on calibration data. Data segmentation was performed into non-overlapping frames of 1-second duration (2400 samples) for frequency domain analysis.

Conventional beamforming was implemented as phase-delayed summation of signals with weighting windows for side-lobe control of the directivity pattern. Beam steering was achieved by calculating appropriate phase delays for each array element according to the expression $\tau_m = md \sin(\theta)/c$, where m is the element index, d is the inter-element spacing, θ is the steering angle, and c is the sound speed. Space scanning was performed in the azimuthal range from -90° to +90° in 1° increments, generating a time-varying spatial spectrum. The beamformer output power for each direction and time frame was used as one of the input features for the classification algorithm.

MVDR adaptive beamforming was applied as an advanced spatial processing method with potential for better interference and noise suppression. The algorithm calculates optimal weighting coefficients according to the expression $w = R^{-1}a(\theta) / (a^H(\theta)R^{-1}a(\theta))$, where R is the estimate of the input signal covariance matrix, a(θ) is the steering vector for the desired direction, and H denotes Hermitian transpose. Covariance matrix estimation was performed by time averaging over 100 samples with diagonal loading of 0.1 of the matrix trace to ensure numerical stability. Comparison of CBF and MVDR beamforming performance was conducted on a subset of data to evaluate relative advantages in shallow-water propagation conditions.

Wavelet decomposition was applied to beamformer output signals using discrete wavelet transform with Daubechies 4 (db4) basis function selected based on previous acoustic classification studies (Santos-Domínguez *et al.*, 2016). Decomposition was performed at 6 levels, separating the signal into details D1 to D6 and approximation A6 with corresponding frequency subbands from 600-300 Hz (D1) to 9.4-4.7 Hz (D6) and 4.7-0 Hz (A6). For each level, energy statistics were calculated as the sum of squared coefficients, and skewness and kurtosis coefficients of coefficient distribution, forming a 24-dimensional feature vector from the wavelet domain.

Additional features were extracted from the frequency domain using the periodogram with Welch's method with Hanning windows of 512 samples and 50% overlap. Spectral peak locations in the 50-500 Hz range were identified, along with their magnitudes and bandwidths at 3 dB below peak. Harmonic structure was analyzed by detecting series of peaks at multiples of the fundamental frequency, characteristic of tonal emissions from underwater drone electric motors. The frequency domain feature vector comprised 15 elements including 5 dominant frequencies, their magnitudes, widths, and harmonicity coefficient.

The innovative Adaptive Spatio-Temporal Coherence (ASTC) algorithm developed in this research integrates spatial processing by beamforming, time-frequency analysis by wavelet decomposition, and machine learning classification into a coherent framework optimized for shallow-water propagation conditions. The key novelty of the algorithm consists in adaptive compensation of multipath effects achieved by estimating signal coherence between hydrophone pairs as a function of frequency and time delay. For a given pair of hydrophones separated by distance d, multipath propagation causes frequency-dependent fluctuations in mutual coherence that can be modeled as an interferometric pattern determined by differences in phase paths of direct wave and reflected components.

The ASTC algorithm estimates the coherence matrix $\Gamma(f,\tau)$ whose elements $\gamma_{ij}(f,\tau)$ represent the normalized cross-correlation of signals at hydrophones i and j for a frequency band centered at f and time delay τ. Theoretical predictions of the coherence matrix for different source scenarios and propagation conditions are derived from the normal modes model using the KRAKEN software package for solving the characteristic equation of the acoustic waveguide. Comparison of measured and theoretical coherence matrices identifies the scenario with the best match, providing more robust geometry estimation than direct interpretation of beamformer output. This estimation is used to adaptively adjust beamforming parameters and correct extracted features for multipath effects characteristic of the estimated geometry.

Classification was performed using the Random Forest algorithm that forms an ensemble of decision trees trained on different subsets of data and features, with final prediction made by majority vote of trees (Breiman, 2001). The choice of Random Forest algorithm was motivated by its robustness to noise, ability to handle high-dimensional feature space without need for selection, and interpretability in terms of importance of individual features. The model was configured with 200 trees, maximum depth of 20 levels, and minimum number of samples for node splitting of 5. Alternative classifiers including support vector machines (SVM) with radial basis function kernel and a simple neural network with one hidden layer were evaluated for comparison.

The training and testing dataset was formed from controlled experiments categorized into positive examples (drone present) and negative examples (ambient noise without drone). Positive examples comprise 2400 one-second segments evenly distributed across three drone types, different distances, directions, and depths. Negative examples comprise 2400 segments of ambient noise under different conditions. Division into training and test sets was performed in a 70:30 ratio with temporal separation ensuring that segments from the same experimental run are not present in both sets, eliminating potential bias due to temporal correlation.

Evaluation of detection algorithm performance was conducted using standard binary classification metrics including accuracy (ratio of correct classifications to total number of examples), precision (ratio of true positives to all positive predictions), recall or detection probability (ratio of true positives to actual positive examples), and false alarm rate (ratio of false positives to actual negative examples). The Receiver Operating Characteristic (ROC) curve was constructed by varying the classification threshold, and the area under the ROC curve (AUC) was used as an integral measure of class separability. Statistical significance testing of differences in performance between methods was conducted using McNemar's test at a significance level of 0.05.

Research Results

Characterization of ambient acoustic noise at the experimental site showed spectral power density levels consistent with literature data for typical coastal waters of temperate climate zone. In the frequency range from 50 to 500 Hz, the average spectral level was 68 dB re 1 $\mu Pa^2/Hz$ at sea state 1 (calm), increasing to 75 dB re 1 $\mu Pa^2/Hz$ at sea state 3 (moderately rough). Dominant sources of ambient noise included passage of vessels at distances of several kilometers (characteristic low-frequency signature with maximum around 80-120 Hz), biological sources (snapping shrimp in the 2-200 kHz range, fish vocalizations below 1 kHz), and surface noise generated by wind and waves. Temporal variations in ambient noise showed pronounced day-night modulation of the biological component, with increased activity during night, and correlation with vessel passage according to AIS records.

Acoustic signatures of the three tested underwater drones showed characteristic spectral profiles enabling mutual distinction. BlueROV2 Heavy emits a dominant tonal component at 127 Hz corresponding to the rotational speed of main thrusters at nominal load, with pronounced harmonics at 254 Hz and 381 Hz. Additional components were identified at 340 Hz related to electric motors of controllable thrusters and broadband cavitation noise in the 400-600 Hz range at higher travel speeds. Chasing M2 PRO showed a thruster fundamental frequency at 156 Hz with harmonics, while Fifish V6 EXPERT had the lowest fundamental frequency of 98 Hz. Differences in spectral signatures correlate with differences in propulsion system construction, particularly the number of poles of brushless motors and propeller diameters.

Source Level (SL) of underwater drones was estimated by compensating for transmission loss at known distances using spherical divergence and absorption. For BlueROV2 Heavy at a speed of 1 m/s, the estimated source level is 125 dB re 1 μPa at 1 m in the 100-200 Hz frequency band, 118 dB in the 200-400 Hz band, and 115 dB in the 400-600 Hz band. Chasing M2 PRO and Fifish V6 EXPERT show lower source levels by approximately 3-5 dB in all bands, consistent with their smaller mass and propulsion system power. Variation of source level with travel speed follows approximately cubic law, with an increase of approximately 6 dB for doubling of speed, in accordance with theoretical predictions of dominance of hydrodynamic and cavitation noise at higher speeds.

Analysis of multipath propagation at the experimental site was conducted by comparing measured impulse responses with normal mode model predictions. For a typical depth of 30 meters with source at 10 meters and receiver at 15 meters, the model predicts significant reflections from surface and bottom with time delays of 3 to 15 milliseconds relative to the direct path for distances up to 500 meters. Constructive interference of direct and reflected waves occurs at frequencies where path difference corresponds to an integer number of wavelengths, while destructive interference causes significant spectral notches at intermediate frequencies. Experimentally measured spectra of underwater drone signals show characteristic oscillations around the average level with period in the frequency domain consistent with theoretical predictions for the measurement geometry.

Impact of multipath propagation on conventional beamforming performance was quantified by comparing estimated and actual source position. For distances up to 200 meters, conventional beamforming achieves azimuthal estimation accuracy within ±2° for all frequencies of interest. At larger distances, multipath propagation causes progressive increase in error, reaching ±8° at 500 meters and ±15° at 800 meters for frequencies above 200 Hz. Lower frequencies show less performance degradation due to simpler modal structure of propagation. Adaptive MVDR beamforming provides 20-30% improvement in estimation accuracy at larger distances thanks to ability to suppress coherent multipath components, but with increased computational complexity and sensitivity to errors in covariance matrix estimation.

The ASTC algorithm developed in this research demonstrates significant improvement in compensating multipath effects compared to conventional methods.

Estimation of coherence matrix as a function of frequency and spatial delay enables identification of dominant propagation modes and their relative amplitudes. Comparison with library of theoretical coherence matrices for different combinations of source depth and distance identifies the scenario with best match, providing more robust geometry estimation than direct interpretation of beamformer output. Experimental validation on controlled drone runs shows that ASTC achieves distance estimation accuracy within ±15% for distances up to 600 meters, compared to ±30% for conventional beamforming under the same conditions.

Features extracted by wavelet decomposition show high discriminative value for classifying drone presence and identifying type. Energy in detail coefficients D3 and D4, corresponding to the frequency range of 75 to 300 Hz, shows the most pronounced difference between examples with drone and ambient noise. Skewness coefficient of wavelet coefficient distribution at level D2 (150-300 Hz) shows characteristically positive value for underwater drone signals due to tonal components, while ambient noise shows approximately symmetric distribution. Feature importance analysis in the Random Forest classifier identifies energy at levels D3 and D4 and skewness coefficient at D2 as the three most informative features, together contributing 45% of total discriminative power of the model.

Frequency domain features complement wavelet features with information about harmonic structure of the signal. Presence of series of spectral peaks at multiples of fundamental frequency, quantified by harmonicity coefficient, shows high predictive value for detecting underwater drones whose electric motors generate pronounced tonal emissions. Ambient noise, including ship traffic at greater distances, typically shows less pronounced harmonic structure or harmonics at different fundamental frequencies, enabling distinction. Frequency features contribute the remaining 35% of classifier discriminative power. ASTC coherence features contribute 20% of discriminative power, but their value is particularly pronounced at larger distances where standard features lose reliability. At distances over 500 meters, classification based solely on wavelet and frequency features shows significant performance degradation, while inclusion of ASTC features maintains performance relatively stable up to 800 meters. This characteristic makes the ASTC approach particularly valuable for applications requiring detection at larger distances in shallow-water conditions.

Classification results for the complete ASTC algorithm on the test dataset are presented in the summary metrics table. Overall classification accuracy is 96.1%, with precision of 94.8%, recall (detection probability) of 94.2%, and false alarm rate of 2.1%. Area under the ROC curve is 0.987, indicating excellent class separability. The confusion matrix details the distribution of classifications across categories: of 720 test examples with drone present, 678 were correctly classified as positive (true positives), 42 were incorrectly classified as negative (false negatives); of 720 examples without drone, 705 were correctly classified as negative (true negatives), 15 were incorrectly classified as positive (false positives).

Comparison of ASTC algorithm performance with conventional methods was conducted on the identical test dataset. Conventional method based solely on frequency analysis (detection of spectral peaks in characteristic bands without spatial processing and wavelet decomposition) achieves detection probability of 70.5% at a false alarm rate of 5.3%. Adding beamforming without adaptive coherence compensation improves detection probability to 82.3% at a false alarm rate of 3.8%. Adding wavelet features without coherence compensation reaches 89.1% detection probability at 2.8% false alarm rate. The complete ASTC algorithm achieves 94.2% detection probability at 2.1% false alarm rate, representing an improvement of 23.7 percentage points compared to conventional frequency analysis and 5.1 percentage points compared to the approach without coherence compensation.

Statistical significance of performance differences was evaluated by McNemar's test on pairs of classification results for individual test examples. The difference between the ASTC algorithm and all alternative methods is statistically significant at $p < 0.001$ level, confirming that the observed improvement is not an artifact of random variability in the test set. Confidence intervals for ASTC algorithm detection probability calculated by bootstrap method with 1000 repetitions are 92.8% to 95.6% at 95% confidence level.

Analysis of performance as a function of distance reveals expected degradation with increasing distance between drone and hydrophone array. At distances up to 200 meters, detection probability is 99.3% for all tested methods, reflecting high signal-to-noise ratio at small distances. At distances from 400 to 600 meters, conventional methods show dramatic drop to 65-75%, while ASTC maintains detection probability above 92%. At maximum tested distances of 800 to 1000 meters, ASTC achieves 85-88% detection probability, compared to 45-55% for conventional approaches. This superiority at larger distances is directly attributable to adaptive compensation of multipath effects that become the dominant factor of performance degradation in shallow-water propagation.

Classifier performance varied depending on the type of underwater drone. BlueROV2 Heavy, with the strongest acoustic signature, shows the highest detection probability of 96.8% averaged across all distances. Chasing M2 PRO achieves 93.5%, while Fifish V6 EXPERT has the lowest detection probability of 92.1%, consistent with its weakest acoustic emissions. Differences between drones are statistically significant ($\chi^2 = 14.3$, $df = 2$, $p < 0.001$), suggesting that propulsion system characteristics affect detectability. Classification of drone type among correctly detected examples shows accuracy of 87.3%, with most errors between Chasing M2 PRO and Fifish V6 EXPERT which have the most similar spectral signatures.

Impact of environmental conditions on detection performance was evaluated by stratification of the test set by sea state and presence of other noise sources. At sea state 1, average detection probability is 95.8%, degrading to 93.1% at sea state 2 and 91.5% at sea state 3. Presence of ship traffic at distances less than 2 km causes additional degradation of 2-4 percentage points depending on traffic intensity. These results confirm the robustness of the ASTC algorithm to typical variations in environmental conditions in coastal waters, although they identify sea state and ship traffic as factors that need to be considered in operational implementation.

Alternative classifiers evaluated for comparison with the Random Forest algorithm show competitive but generally inferior performance. SVM with RBF kernel achieves 92.8% detection probability at 2.5% false alarm rate, while simple neural network with 100 nodes in the hidden layer achieves 93.5% at 2.3% false alarm rate. Random Forest combines the best performance with interpretability through feature importance analysis and robustness to suboptimal hyperparameter tuning. Deep learning with convolutional neural networks directly on spectrograms was preliminarily evaluated, showing potentially superior performance (95.1% detection probability), but with significantly greater training data requirements and computational resources that complicate practical application.

Computational complexity of the ASTC algorithm was evaluated on a standard workstation with Intel Xeon processor (3.5 GHz, 8 cores) and 64 GB RAM. Processing of one-second segment requires an average of 45 milliseconds, of which beamforming consumes 15 ms, wavelet decomposition 8 ms, coherence matrix estimation 18 ms, and classification 4 ms. This enables real-time processing with a safety factor greater than 20, with the possibility of parallel processing of multiple scan directions to increase spatial coverage. Memory footprint of the algorithm is approximately 500 MB for storing the model and intermediate results, compatible with implementation on embedded computing platforms for autonomous systems.

Conclusion

This research presented the development and experimental validation of an adaptive spatio-temporal coherence algorithm for passive acoustic detection of small underwater drones in shallow coastal waters. The fundamental contribution of the work consists in demonstrating that integration of spatial processing by beamforming, wavelet analysis, and machine learning classification, with innovative adaptive compensation of multipath propagation effects characteristic of shallow waters, enables significant improvement in detection performance compared to conventional approaches. The experimental campaign conducted in the coastal Adriatic validated the methodology under realistic conditions, demonstrating detection probability of 94.2% at a false alarm rate of 2.1% for commercial underwater drones at distances up to 800 meters.

The key result that constitutes the innovative contribution of this study is the quantification of ASTC algorithm superiority over conventional methods particularly at larger distances where multipath propagation dominantly degrades performance. Improvement of 23.7 percentage points in detection probability compared to standard frequency analysis represents a practically significant advance that can imply the difference between timely warning and missed detection in operational scenarios. The mechanism of this improvement was identified as the ability of coherence analysis to distinguish propagation characteristics that are correlates of source distance and depth, providing implicit compensation of multipath effects that degrade conventional methods.

Characterization of acoustic signatures of the three tested underwater drones provided an empirical database useful for future research and development of operational systems. Identified differences in fundamental frequencies, harmonic structure, and source levels between drone types reflect constructional characteristics of propulsion systems and enable not only detection but also type classification with 87.3% accuracy. These results suggest potential for development of acoustic signature libraries that could integrate information about known types of underwater vehicles for improved identification in operational context.

Analysis of multipath propagation impact on signal propagation in shallow coastal waters confirmed theoretical predictions from the literature and provided empirical data specific to the Adriatic Sea. Characteristic patterns of constructive and destructive interference identified in experimental data are consistent with the normal modes model for shallow-water propagation, validating the theoretical framework used for ASTC algorithm development. This consistency between theory and experiment increases confidence in applicability of results to other locations with similar bathymetric and sedimentological characteristics.

Practical implications of this research include potential for implementation of cost-effective coastal surveillance systems based on passive sonar arrays. Unlike active systems that require powerful transmitters and reveal their position, passive approaches enable covert surveillance with lower energy requirements and maintenance costs. Demonstrated real-time processing capability with a safety factor greater than 20 on a standard computing platform suggests feasibility of implementation on autonomous underwater or surface platforms for mobile coastal zone surveillance.

Limitations of this research include focus on controlled experimental conditions that, although representative of typical coastal environment, do not cover the full variability of conditions that may be encountered in operational application. Experiments were conducted at moderate sea states (1-3) and water depths (25-45 m) characteristic of the selected location, while extreme conditions such as stormy sea or very shallow waters below 15 meters were not tested. Also, the underwater drones used represent commercial platforms that do not include potential counter-acoustic measures that more sophisticated adversaries might implement to reduce acoustic signature.

Future research can be directed in several directions identified by this study. Extension of experimental validation to different locations with variable bathymetric and oceanographic conditions would provide more robust assessment of ASTC algorithm generalizability. Integration with other sensor modalities, particularly magnetometers for detection of metallic components and electro-optical systems for identification at short distances, could result in a multimodal system with complementary capabilities. Application of deep learning on larger datasets could potentially further improve performance, especially for automatic feature extraction without need for expert design.

Development of an operational system based on this methodology requires additional considerations including optimization of sonar array architecture for specific operational requirements, integration with command and control systems, protocols for alarm validation and coordination with other elements of coastal surveillance, and assessment of reliability in extended operational service. Economic cost-benefit analysis of passive versus active approaches for different applications (port protection, offshore facilities, submarine cables) would provide valuable guidance for decision-makers in the domain of coastal security.

In conclusion, this research demonstrated the feasibility and effectiveness of passive acoustic detection of small underwater drones in shallow coastal waters using the innovative ASTC algorithm that integrates spatial, time-frequency, and coherence analysis. The achieved results represent a significant advance compared to conventional methods and provide a foundation for development of practical coastal surveillance systems. In the context of the growing challenge that underwater drones pose to the security of coastal zones and critical submarine infrastructure, such systems can become an essential component of a comprehensive coastal surveillance and protection strategy.

References

1. Blidberg, D. R. (2001). The development of autonomous underwater vehicles (AUV): A brief summary. *IEEE ICRA*, 4, 4089-4095.
2. Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.
3. Button, R. W., Kamp, J., Curtin, T. B. & Dryden, J. (2009). A survey of missions for unmanned undersea vehicles. RAND Corporation.
4. Caiti, A., Munafò, A. & Viviani, R. (2014). Adaptive online planning for AUVs: A learning approach. *Ocean Engineering*, 78, 32-41.
5. Capon, J. (1969). High-resolution frequency-wavenumber spectrum analysis. *Proceedings of the IEEE*, 57(8), 1408-1418.
6. Carey, W. M. & Moseley, W. B. (1991). Space-time processing: Environmental-acoustic effects. *IEEE Journal of Oceanic Engineering*, 16(3), 285-301.
7. Cohen, L. (1995). Time-frequency analysis. Prentice Hall.
8. Daubechies, I. (1992). Ten lectures on wavelets. SIAM.
9. Etter, P. C. (2018). Underwater acoustic modeling and simulation (5th ed.). CRC Press.
10. Ferri, G., Manzi, A., Fornai, F., Mazzolai, B., Laschi, C., Cianchetti, M. & Dario, P. (2017). Design, fabrication and first sea trials of a small-sized autonomous catamaran for heavy metals monitoring in coastal waters. *Sensors*, 17(8), 1774.
11. Goodfellow, I., Bengio, Y. & Courville, A. (2016). Deep learning. MIT Press.
12. Harrison, C. H. & Harrison, J. A. (1995). A simple relationship between frequency and range averages for broadband sonar. *The Journal of the Acoustical Society of America*, 97(2), 1314-1317.
13. Jensen, F. B., Kuperman, W. A., Porter, M. B. & Schmidt, H. (2011). Computational ocean acoustics (2nd ed.). Springer.
14. Kamal, S., Mohammed, S. K., Pillai, P. R. S. & Supriya, M. H. (2021). Deep learning architectures for underwater target recognition. Archives of Acoustics, 46(2), 213-224.
15. Knight, W. C., Pridham, R. G. & Kay, S. M. (1981). Digital signal processing for sonar. Proceedings of the IEEE, 69(11), 1451-1506.
16. Kopp, B. A., Abraham, D. A. & Lyons, A. P. (2010). Highlights and perspective for sonar technology development: Shallow water sonar. Applied Acoustics, 71(6), 447-454.
17. Koschinski, S. & Lüdemann, K. (2013). Development of noise mitigation measures in offshore wind farm construction. Federal Agency for Nature Conservation.
18. LeCun, Y., Bengio, Y. & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.
19. Li, S., Cao, Y., Zhang, Y. & Chen, J. (2020). Design and analysis of underwater acoustic stealth for AUVs. Ocean Engineering, 218, 108215.
20. Lurton, X. (2010). An introduction to underwater acoustics: Principles and applications (2nd ed.). Springer.
21. Mallat, S. (1999). A wavelet tour of signal processing (2nd ed.). Academic Press.
22. Maranda, B. (2001). Efficient digital beamforming in the frequency domain. *The Journal of the Acoustical Society of America*, 109(1), 360-366.
23. Nielsen, R. O. (1991). Sonar signal processing. Artech House.

24. Pekeris, C. L. (1948). Theory of propagation of explosive sound in shallow water. Geological Society of America Memoirs, 27, 1-116.
25. Ponsford, A. M., Sevgi, L. & Chan, H. C. (2001). An integrated maritime surveillance system based on high-frequency surface-wave radars. Part 2: Operational status and system performance. *IEEE Antennas and Propagation Magazine*, 43(5), 52-63.
26. Porter, M. B. & Bucker, H. P. (1987). Gaussian beam tracing for computing ocean acoustic fields. *The Journal of the Acoustical Society of America*, 82(4), 1349-1359.
27. Ross, D. (1976). Mechanics of underwater noise. Pergamon Press.
28. Santos-Domínguez, D., Torres-Guijarro, S., Cardenal-López, A. & Pena-Giménez, A. (2016). ShipsEar: An underwater vessel noise database. *Applied Acoustics*, 113, 64-69.
29. Urick, R. J. (1983). Principles of underwater sound (3rd ed.). McGraw-Hill.
30. Van Trees, H. L. (2002). Optimum array processing: Part IV of detection, estimation, and modulation theory. Wiley-Interscience.
31. Weydahl, D. J., Sagstuen, J., Dick, Ø. B., & Rønning, H. (2015). COSMO-SkyMed detector of small vessels. *International Journal of Remote Sensing*, 36(8), 2149-2164.
32. Williams, K. L., Jackson, D. R., Thorsos, E. I., Tang, D. & Schock, S. G. (2001). Comparison of sound speed and attenuation measured in a sandy sediment to predictions based on the Biot theory of porous media. *IEEE Journal of Oceanic Engineering*, 26(4), 571-583.
33. Wynn, R. B., Huvenne, V. A. I., Le Bas, T. P., Murton, B. J., Connelly, D. P., Bett, B. J., Ruhl, H. A., Morris, K. J., Peakall, J., Parsons, D. R., Sumner, E. J., Darber, S. E., Dorrell, R. M. & Hunt, J. E. (2014). Autonomous Underwater Vehicles (AUVs): Their past, present and future contributions to the advancement of marine geoscience. *Marine Geology*, 352, 451-468.
34. Yuh, J. (2000). Design and control of autonomous underwater robots: A survey. *Autonomous Robots*, 8(1), 7-24.

AKUSTIČKA DETEKCIJA NISKOFREKVENTNIH PODVODNIH DRONOVA U PLITKIM OBALNIM VODAMA: EKSPERIMENTALNA VALIDACIJA PASIVNIH SONARSKIH NIZOVA

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(Primljeno: 11.03.2023. Odobreno: 12.07.2023.)

Originalni naučni članak

DOI: https://doi.org/10.65932/military-studies-2023-1-6 **UDK:** 534.6:623.983:629.584

Sažetak: Proliferacija malih bespilotnih podvodnih vozila (BPV) predstavlja rastući bezbjednosni izazov u obalnim vodama širom svijeta. Ovo istraživanje predstavlja eksperimentalnu validaciju pasivnog sonarskog niza optimizovanog za detekciju niskofrekventnih akustičkih emisija podvodnih dronova u plitkim obalnim vodama do 50 metara dubine. Eksperimentalna kampanja sprovedena je u kontrolisanim uslovima u obalnim vodama istočne jadranske obale tokom proljeća 2023. godine, korištenjem linearnog hidrofonskog niza od 16 elemenata s međuelementnim razmakom od 0,75 metara. Tri tipa komercijalnih podvodnih dronova s različitim konfiguracijama pogona i karakterističnim frekventnim emisijama u opsegu od 50 Hz do 500 Hz korištena su kao referentne mete. Inovativni doprinos ovog istraživanja je razvoj i validacija algoritma Adaptivne Prostorno-Vremenske Koherencije Signala (APVKS) koji integriše tehnike formiranja snopa s wavelet dekompozicijom i mašinskim učenjem za klasifikaciju akustičkih potpisa u uslovima višeputnog prostiranja zvuka karakterističnog za plitke vode. Rezultati pokazuju da predloženi APVKS algoritam postiže vjerovatnoću detekcije od 94,2% pri stopi lažnih alarma od 2,1% za podvodne dronove na udaljenostima do 800 metara, što predstavlja poboljšanje od 23,7% u poređenju s konvencionalnim metodama frekventne analize u ekvivalentnim uslovima. Analiza je dodatno pokazala da je kritični faktor za uspješnu detekciju u plitkim vodama kompenzacija višeputnih efekata koji uzrokuju destruktivnu interferenciju na specifičnim frekvencijama zavisnim od dubine i tipa morskog dna. Predložena metodologija omogućava praktičnu implementaciju sistema ranog upozoravanja za zaštitu lučkih postrojenja, kritične podmorske infrastrukture i ekološki osjetljivih obalnih zona.

Ključne riječi: *pasivni sonar, podvodni dronovi, akustička detekcija, plitke vode, formiranje snopa, višeputno prostiranje, hidrofonski niz, niskofrekventna akustika, prostorno-vremenska koherencija, obalna bezbjednost*.