Echo Classification: Statistics of Echo Fluctuations

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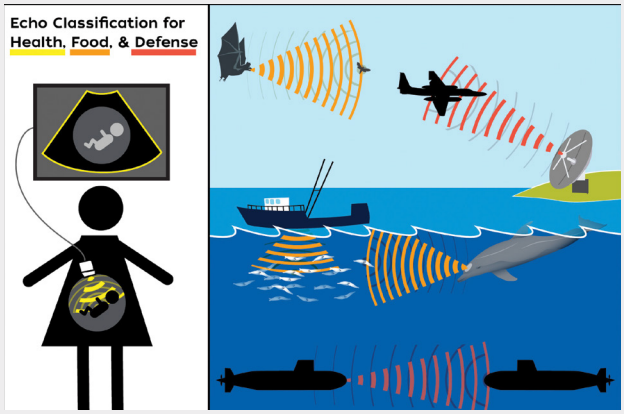
Widespread Use of Echo Classification

Everyone has seen images of unborn babies from medical ultrasound and weather maps of incoming storm clouds from radar. What these technologies have in common is that they involve the classification of echoes received from sensor systems that send out a signal and receive echoes from objects of interest. In each case, echoes are classified into meaningful information, much like how a sonar operator listens for echoes from enemy submarines.

The use of sending a signal and then receiving its echo is widespread and includes both man-made and biological sources (**Figure 1**). For example, many animals, such as dolphins, bats, and other mammals, generate and receive sounds through various anatomical mechanisms to sense objects around them. Moreover, going beyond acoustics, radars and lasers generate an electromagnetic signal rather than an acoustic one.

In all cases, whether the signals are acoustic or electromagnetic, the echoes can be classified through various quantities: the amplitude and time of return of the echo, the image created by multiple echoes as the sensor system scans an area, and the characteristics of the fluctuations of the echo across these multiple transmissions. Classification using the fluctuations is the subject of this article. These fluctuations are, in essence, the "texture" of an image formed from the echoes.

Figure 1. *Echo classification has applications from biomedicine to land and sea. Copyright © 2021 Timothy K. Stanton, all rights reserved.*



Echo Classification Serving Many Needs

Echo classification is exploited across a wide range of societal and ecological needs (**Figure 1**). All applications use echoes to classify objects of interest that cannot easily be seen. Uses of echo classification include

(1) Health. Through use of medical ultrasound devices, echoes are processed to produce images of the interior of the human body (Ketterling and Silverman, 2017; Ruoss et al., 2020). These images can be used to assess how much a fetus has grown or to detect the presence of a tumor.

(2) Food for humans. Acoustic echoes from scientific echosounders are used to produce images of fish schools in the ocean (Stanton, 2012; Warren, 2012). The images help fisheries managers monitor the population of the fish, with the goal of maintaining a sustainable source of food.

(3) Food as prey for animals. In the animal kingdom, echoes from the sounds generated by echo-locating mammals are used to navigate and hunt prey (Simmons, 2017; Tyack, 2017). For example, echoes are used by dolphins to hunt for small fish and squid in the ocean and by many bats to hunt for insects in the air.

(4) Defense. The echoes from sonars (underwater) and radars (in air) are used to detect and classify enemy targets such as submarines and aircraft, respectively (Le Chevalier, 2002; Kuperman and Lynch, 2004). A key aspect is discriminating between the echoes from these targets and from other unwanted sources ("clutter") such as the seafloor (sonar) or

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trees (radar) that will interfere with the process of detecting the target of interest.

Beyond detection and imaging, the fluctuations of echoes between successive transmissions are commonly exploited in classification applications. The statistics of these fluctuations are based on multiple transmissions as the sensor system scans an area. Through modeling, the statistics can be classified in terms of important properties of the scatterers, such as type of scatterer and its numerical density. For example, a large fluctuation in a sonar echo could be from a large fish feeding on an aggregation of smaller marine organisms such as zooplankton. Or a change in the degree of fluctuations in the echoes from a medical ultrasound device could represent the presence of cancerous tissue.

Key elements and applications of echo statistics are briefly summarized. A comprehensive treatment of the subject is given in the tutorial by Stanton et al. (2018). Also, although the material in this article and in the tutorial in 2018 was inspired by the authors' own research in aquatic applications, the diverse examples presented in each publication demonstrate the ubiquity and broad range of usefulness of echo statistics.

The Echo Classification Process and Statistics of Echo Fluctuations

A principal method for classifying echoes involves analyzing the time it takes for an echo to return to the transmitter as well as the amplitude of the echo. The measure of time is related to the distance between the transmitter and the object that causes the echo. For example, if a ship is using sonar to help navigate in the dark, it is useful to know the distance to an iceberg. To determine the type of object that is causing the echo, the amplitude (a measure of its "strength") of the echo is measured. The amplitude is related to the size and material properties of the object. Back to the iceberg, if there is a loud echo measured by the sonar that comes back quickly, then it may be time to steer the ship in another direction!

There are many ambiguities in using the echo amplitude to classify the object because echoes may be the same or similar for completely different scenarios. For example, the echo from a single large object may be mistaken as the echo from many small, closely spaced objects of similar material properties. Or the echo from a large object with material properties similar to those of the surrounding medium may be confused with the echo from a small object with material properties with a strong contrast relative to that of the surrounding medium.

There are a variety of methods to eliminate such ambiguities. One method involves analyzing how the echo amplitude varies through repeated transmissions as the sensor system scans an area. For example, does the echo remain approximately the same value or does it vary by a large amount across many transmissions? Is the echo generally small most of the time but with occasional large values? Qualitatively, the variability of echoes within an acoustic image or "echogram" of an area is analogous to texture in a photograph of an object. The degree to which the image is grainy or smooth will provide information about the type of object causing the echo. For example, the shiny image of a smooth metallic spoon has a dramatically different texture than that of a wooden spoon of the same size. In this case, the texture of the image provides information about the material properties and smoothness of the object. The challenge for all cases lies in extracting information from the data for quantitative classification.

Physics of Scattering

To quantitatively understand and exploit these variations or texture for classification, the physics of the scattering must first be understood. The scattering of the objects can be modeled in terms of their size, shape, orientation, and material properties as well as their spatial distribution. The echoes will also depend on properties of the sensor system, including the frequency, beamwidth, and duration of the transmitted pulse. The key scattering and sensor properties can be accounted for in a physics-based model of an echo. Specifically, the echo magnitude $\tilde{a}$ from an aggregation of N scatterers is given in Stanton et al. (2018) by

$$\tilde{a} = \left| \sum_{i=1}^{N} \tilde{a}_i e^{j\Delta_i} \right| \tag{1}$$

where the magnitude of the echo voltage from the ith scatterer as received through the sensor system is

$$\tilde{a}_i = \left| f_{bs}^{(i)} \right| b(\theta_i, \phi_i) \tag{2}$$

These two equations correspond to Eqs. 6 and 7, respectively, in Stanton et al. (2018) but with a change in notation. The term $f_{bs}^{(i)}$ is the backscattering amplitude of the ith scatterer, $b(\theta_i, \phi_i)$ is the beampattern function of the sensor system as evaluated at the location of the ith scatterer in the beam, (θ_i, ϕ_i) are the spherical polar angular coordinates of the scatterer in the beam, Δ_i is the total phase shift associated with the ith scatterer (phase associated with scattering properties, the distance between the sensor and scatterer, and the beamformer) and $j = \sqrt{-1}$. The term $f_{bs}^{(i)}$ represents the efficiency with which the object scatters a signal and its magnitude is equal to the square root of the differential backscattering cross section. The phase shift term Δ_i is the source of interference between different scatterers, which contributes significantly to echo fluctuations.

Equations 1 and 2 are for acoustic and electromagnetic waves that have a long duration and are at a constant single frequency, scatterers that are within a narrow range of distances from the sensor system, assume a direct path between the sensor system and scatterer (no boundaries or variations in environmental properties), and are for first-order scattering only. Constants of the system, such as system gain, have been suppressed for convenience. These simple equations describe scalar waves where shear waves (acoustic) and polarization effects (electromagnetic) are not accounted for. Details of these equations are in Stanton et al. (2018), where more complex and realistic scenarios are also described.

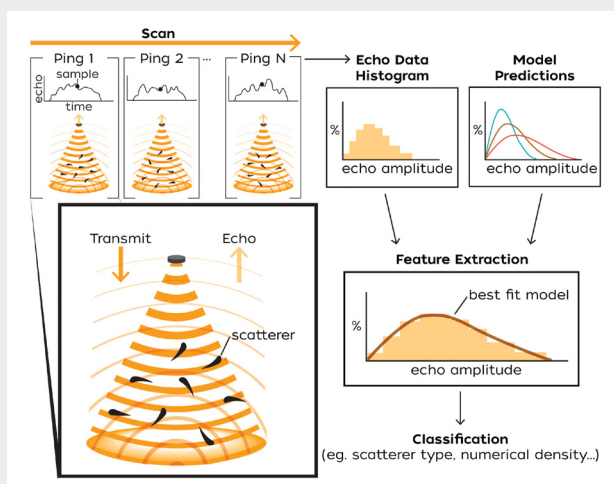
Each of the following three terms in Eqs. 1 and 2 are considered in this analysis to be random variables: $f_{bs}^{(i)}$ varies with random orientation and size, shape, and material properties of the scatterers; b varies with the scatterers' random angular location (θ_i, ϕ_i) in the beam; and Δ_i varies with scatterer properties and random range. For simplicity, the number of scatterers (N) in each transmission is held fixed, although that term can also be randomized to simulate a non-uniform distribution of scatterers. Because the above three terms are random variables, the echo $\tilde{a}$ is also a random variable.

In addition, as the sensor system scans an area, different scatterers are "seen" by the system from transmission to transmission. Because naturally occurring objects are generally randomly distributed, the echo will correspondingly vary randomly from transmission to transmission according to the complex combination of the scattering, the random location in the beam, and the interference processes that vary across transmissions. This random variability can be accounted for in Eqs. 1 and 2 through randomizing the three parameters: $f_{bs}^{(i)}$, $b(\theta_i, \phi_i)$, and Δ_i. An ensemble of statistically independent realizations of $\tilde{a}$ is calculated through the summation in Eq. 1 for a statistically independent set of values of each of the three terms. The probability density function (PDF) of the echoes is formed from the ensemble of the echoes and represents the probability of occurrence of each echo value. This PDF is considered a "physics-based" model because the scatterer properties and sensor properties are explicit in the formulation. Its shape and mean value vary with those properties.

Connecting Theory with Experiment

Experimentally, a set of observed echoes from many transmissions can be described by a histogram of its values (**Figure 2**). As with its theoretical counterpart, the shape of the histogram gives clues to the types of scatterers, how many there are, and how they are distributed. Through

Figure 2. *As a sensor system scans across an aggregation of scatterers, the echo variability from multiple transmissions (sometimes called "pings") is summarized in an echo histogram that is, in turn, compared with model predictions. Parameters of the best fit model are then related to key properties of the scatterers such as their type and numerical density.* ***Bottom left:*** *an expanded view of one of the pings illustrating the transmitted signal, the various scatterers (**black symbols**), and the returning echo from the scatterers.* ***Top left:*** *data are sampled at a single point in the echo time series, which is referred to as "first-order statistics." Adapted from Stanton et al., 2018, license by Creative Commons.*



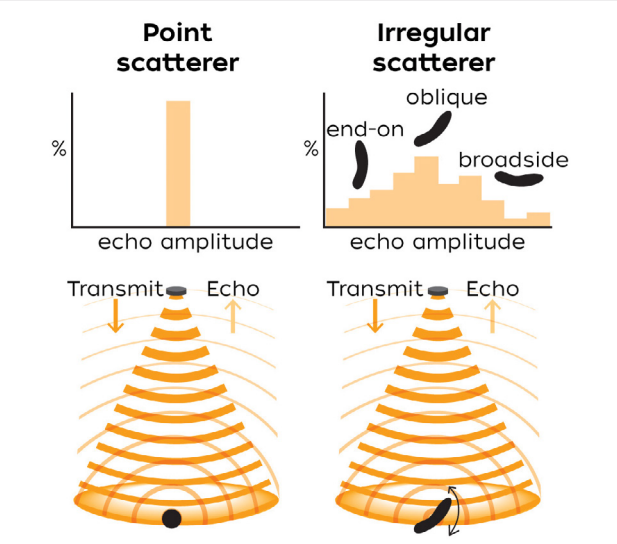


Figure 3. *The echo fluctuations depend on the type of scatterer.* ***Left:*** *for a simple small ("point") scatterer, the echoes are constant from ping to ping, as indicated by the single value in the echo histogram.* ***Right:*** *for elongated irregular scatterers whose orientation changes from ping to ping, the fluctuations are significant, as indicated by the broad range of values in the echo histogram. Adapted from Stanton et al., 2018, license by Creative Commons.*

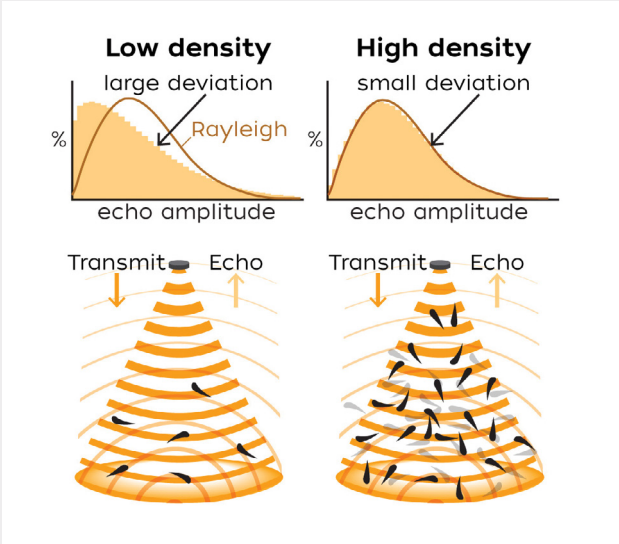


Figure 4. *The echo fluctuations also vary with numerical density of the scatterers.* ***Left:*** *for low densities, the echo histogram deviates strongly from the Rayleigh distribution (**smooth curve**) and depends on density.* ***Right:*** *for high densities, the echo histogram tends to the Rayleigh distribution and there is little deviation from the Rayleigh curve. Copyright © 2021 Timothy K. Stanton, all rights reserved.*

fitting the physics-based PDF model to the data histogram, the parameters of the best fit PDF can be used to infer meaningful characteristics of the scatterers, such as their type [related to $f_{bs}^{(i)}$] and numerical density (related to N). The accuracy of the inferences depends on the accuracy of the model, presence of noise, and goodness of fit between the model and data. Also, to be clear, the echo statistics described here concerns the variability of the echo from transmission to transmission. The characteristics of this variability are exploited to classify the echo in terms of the meaningful properties of the scatterers. The echo statistics here are not to be confused with goodness-of-fit statistics, such as a chi-square test.

Causes of Echo Fluctuations

As discussed, there are many causes of echo fluctuations, including those associated with the (1) type of scatterer (**Figure 3**); (2) numerical density (**Figure 4**); (3) patchiness (such as variability in numerical density); (4) sensor parameters (beamwidth, signal type); and (5) environment (presence of boundaries, variation in medium type).

For the simplest case of a single point scatterer fixed in the sensor beam, the echo remains constant through repeated transmissions (**Figure 3**). This scatterer could be, for example, an underwater spherical bubble (sonar) or a scatterer of any shape (sonar, medical ultrasound, or radar) whose dimensions are much smaller than a wavelength. For a scatterer with a realistic shape, such as elongated with an irregular boundary, the echo will vary as the scatterer changes orientation (**Figure 3**). This scatterer could be, for example, a fish or submarine (sonar) or aircraft (radar) whose dimensions are much greater than a wavelength. Because of the elongated shape, the echo is generally the loudest for broadside incidence, weakest for end-on incidence, and at intermediate levels for oblique angles. Irregularities will further complicate the variability in echoes because destructive interference from the various portions of the object's boundary will reduce the echoes, even at broadside incidence.

When there are multiple scatterers present, interference between the echoes from the individuals will cause fluctuations through repeated transmissions. For example,

as the sensor beam is scanned across the aggregation of scatterers, there will be some echoes in which the interference is constructive and the echoes are relatively large. Other echoes will be small due to destructive interference. For a dense aggregation of scatterers, the echo histogram will tend to be distributed according to the Rayleigh PDF, which corresponds to the echo variability in the limit of a large number of randomly distributed scatterers. However, the histogram will deviate significantly from the Rayleigh distribution under a number of conditions, including for the case when the density of the scatterers is lower (**Figure 4**). Also, in some applications, all echo histograms are plotted on a log-log scale (whereas the histograms in **Figure 4** are on a lin-lin scale). On a log-log scale, the "tail" of an echo histogram (that is, the portion of the histogram associated with the highest echo values), can readily be seen as significantly higher than that of the Rayleigh curve when the scatterer density is low.

There are broadly similar effects as illustrated in **Figure 4** when there are changes in the beamwidth and pulse duration of the sensor system. When either of those quantities becomes smaller, there are fewer scatterers causing an echo for a given transmission, resulting in deviations from the Rayleigh distribution. And once there are variabilities in the acoustic properties of the medium, such as changes in density and/or the presence of boundaries, more variability in the echo is introduced. Details of these effects for a wide variety of conditions are given in Stanton et al. (2018).

What Type of Information Can be Obtained from Echo Statistics?

Statistical analyses of echoes are especially useful in discriminating between one type of scatterer and another. In medical ultrasound, one can potentially discriminate between cancerous tissue and normal tissue. In defense applications, one can potentially distinguish between an enemy submarine and a school of fish. As part of these discrimination techniques, echo statistics can be used to identify types of scatterers, at least in terms of their gross physical features. For example, objects that are spherical will cause echoes that vary differently from objects that are elongated (**Figure 3**).

The numerical density of the objects can also be estimated from the echo variability. This is due to the fact that echoes from dense aggregations of scatterers, where all echoes overlap, will have different statistics from those involving sparse aggregations (**Figure 4**). This is useful for a wide range of applications, including the assessment of fish stocks for the management of food resources and estimating the density of scatterers within tissue. Furthermore, if two different types of scatterers are known to occur with different numerical densities, then those differences can be used to discriminate between them.

Physics-Based Echo Statistics Versus Generic Approaches

As discussed, a model can be used to interpret the statistics of echoes for classification (**Figure 2**). There is a wide range of models that can be divided into two broad categories: (1) physics-based models and (2) generic statistical functions. With the physics-based models, the scattering process that gives rise to the echo is formulated from fundamental physical principles (e.g., Eqs. 1 and 2) (Stanton et al., 2018). Through randomization of various parameters associated with the scatterer and the environment, parameters of the echo variability can be expressed explicitly in terms of those physical quantities and of the sensor system itself.

When generic statistical functions are used, a function that is generally not derived from physical principles is fit to experimental data and the echoes are classified in terms of the best fit parameters of that distribution. Classification is commonly verified by comparisons with controlled experimental (that is, empirically based) data rather than through physics-based modeling. There are many different types of functions used in this approach, including variations of the K-distribution (Jakeman and Ridley, 2006; Destrempes and Cloutier, 2010). The K-distribution is based on a Rayleigh PDF but with a randomized mean square that is used to account for the echoes from a nonuniform spatial distribution of scatterers.

There are both advantages and disadvantages to each of the above two approaches. Because the physics-based approach is explicitly connected to the physical parameters of the object, quantitative information such as numerical density can potentially be extracted from the data. However, the analysis requires detailed knowledge of the environment and other physical information concerning the object, such as its shape. Conversely, if the shape is of interest, then that can be inferred if other information, such as the numerical density is

known. Because the generic function is not connected to the physical parameters of the object and environment, related quantitative information cannot directly be extracted. However, if the function is applied under controlled conditions (such as with the same known types of scatterers and environment), then deviations in the parameters of the generic function can be used in classification and discrimination.

Sonar Applications

Assessing Fish Abundance

Fishes and the generally much smaller organisms, zooplankton, are prevalent throughout the world's oceans. These two types of organisms are a major source of protein, both for larger organisms such as whales and for humans. Given the breadth of the importance of fishes and zooplankton, scientific echosounders are routinely used to assess their abundance and study their behavior (Stanton, 2012).

A common method used to estimate the abundance of fish and zooplankton is to relate the energy of the echoes from the echosounders to the number of organisms. However, it is commonly the case where an occasional large fish is feeding on a dense aggregation of zooplankton. In this case, the occasional echo from the fish can get washed away in the calculation of echo energy and therefore will not be counted. This issue can be addressed through use of echo statistics, where the presence of a dense aggregation of zooplankton forms the "background" or "baseline" echo and the occasional large fish shows up as a "blip" above the background echoes (Stanton and Clay, 1986; Lee and Stanton, 2015). By using a statistical analysis, the two types of echoes can be separated. The fish echo occurs principally in the tail of the echo histogram, separate and distinct from the zooplankton echo (**Figure 5**). Through modeling of the echoes, the area under the tail can be used to count the fish.

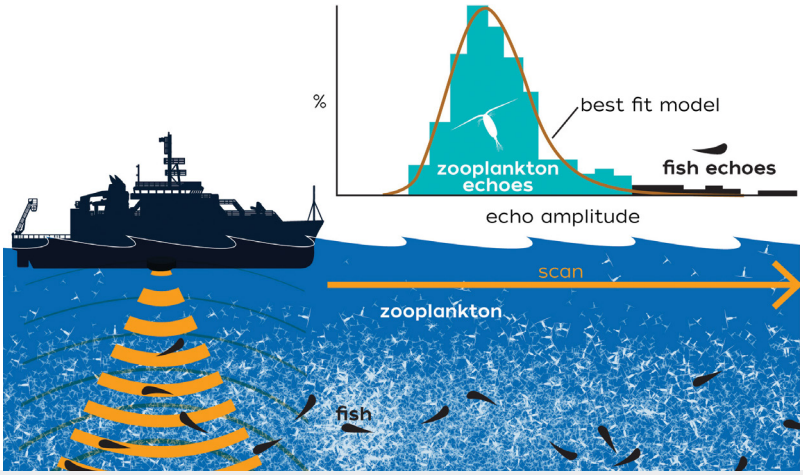
Similar Applications: Submarines and Bats

The above example is conceptually similar to other types of applications: replace the individual fish with a submarine and replace the zooplankton with other various sources of scattering in the ocean such as the rough seafloor and sea surface (**Figure 1**). The echo from the submarine now creates a blip above the background echoes from the seafloor and sea surface. The process of detecting and classifying the submarine within this background clutter is broadly similar to the fish/zooplankton problem. Here, the statistics of the echoes from the submarine and clutter must first be characterized separately and then be used to discriminate between each other. The comparisons continue with terrestrial applications. For example, in the case of a bat echolocating on a moth flying in a forest, the moth creates the echo of interest and the trees and bushes are the background clutter.

Medical Ultrasound

The statistics of echoes from live tissue have been found to be useful in classifying echoes from different types

Figure 5. *Sonar counting of occasional large fish feeding on a dense cloud of small zooplankton. Echoes from the zooplankton comprise most of the histogram (**top right**). The echoes from the occasional large fish appear in the "tail" of the histogram from which they can be counted. Adapted from Stanton, 1985.*



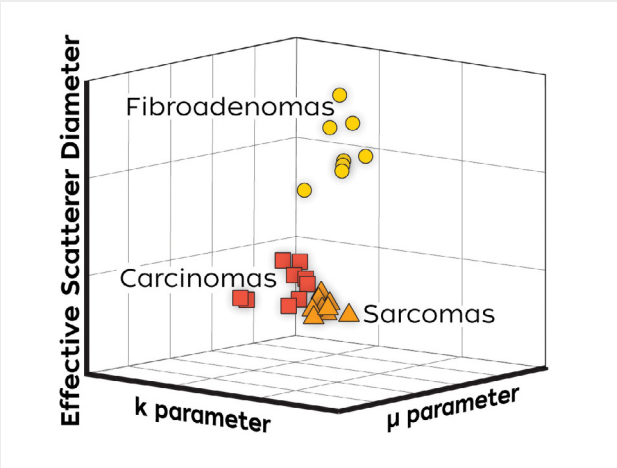


Figure 6. *Medical ultrasound classification of cancerous tissue using echo statistics parameters (k and μ) in combination with acoustically inferred scatterer size (Effective Scatterer Diameter) to classify different types of cancer. The terms k and μ are from the generic statistical function, the homodyned K-distribution, and were determined from a best fit of that function to echo statistics data (i.e., the histogram). Adapted from Oelze and Mamou, 2016, with permission of the IEEE.*

of cancer (Oelze and Mamou, 2016). In this case, the variability in echo level is a function of the variability of the material properties (sound speed and density) of the tissue, and those properties are, in turn, dependent on tissue type. As an aid in discrimination, it has been found to be useful to include an acoustic inference of scatterer size within the tissue. The size is estimated by comparing predictions based on scattering models and the data. This estimate has been combined with two parameters of the echo statistics for classification and discrimination between different types of tissue (**Figure 6**).

Echolocating Mammals: Dolphins and Bats

It is currently impossible to state definitively how dolphins, bats, and other echolocating mammals "process" their echo data. However, studies demonstrate that the mammals are using sound to discriminate among scatterers with different echo signatures to identify their prey (Simmons, 2017; Tyack, 2017). Because it is known that prey with different anatomies have different acoustic signatures, it is reasonable to assume that the mammals are, in some way, using the differences in echo characteristics as a basis for discrimination between those different types of prey. For example, the echoes from moths (a prey of bats) with different anatomies have been shown to possess different modulations from the fluttering of their wings and, hence, different echo statistics (Lee and Moss, 2016). In addition, a Blainville beaked whale has been observed to target (and eat) a type of scatterer (presumed prey) that possessed a particular echo-frequency spectrum (Jones et al., 2008).

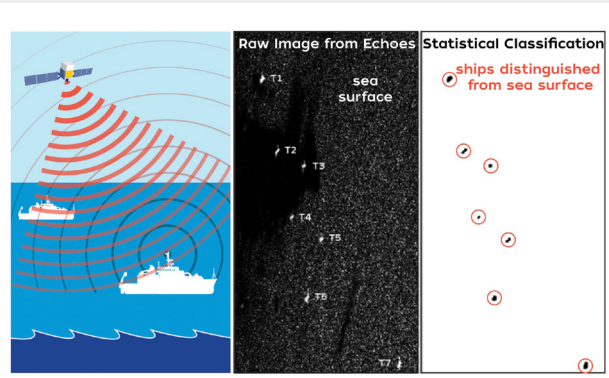
Beyond Acoustics: Radars and Lasers

The principles of echo classification extend well beyond acoustics to important applications involving radars and lasers (Goodman, 1985; Watts and Ward, 2010). After all, whether it be acoustics (a mechanical vibration) or radar/laser (an electromagnetic phenomenon), the signals all travel as a wave that has properties including scattering and interference (Jakeman and Ridley, 2006). For example, radars are routinely used in air traffic control on the ground to track incoming and outgoing aircraft. They are also used on ships to aid in navigation and detect unknown nearby vessels.

Radar Classification of Ships

In one controlled study, a radar mounted on a satellite was used to detect ships and oil rigs on the ocean (Ferrara et al., 2011). The data contained a complex superposition of echoes from the sea surface and the various metallic structures that were on the surface. In some cases, it was difficult to distinguish between (1) the occasional high values of the

Figure 7. *Radar detection and classification of ships using a satellite-deployed radar. Echo statistics parameters are used to separate radar echoes from ships and the sea surface.* ***Center*** *and* ***right:*** *raw and processed echoes, respectively, arranged in an aerial view of the data. T1-T7 are echoes from ships.* ***Center:*** *grainy background echoes are from the sea surface. Adapted from Ferrara et al., 2011, with permission of the IEEE.*



statistically varying echo from the sea surface and (2) the "target" echoes from the ships or rigs. Through understanding the characteristics of the echoes that are specific to each type of scatterer, those differences were exploited using echo statistics to discriminate between the echoes from the ships/rigs and the sea surface (**Figure 7**).

Laser Classification of Tissue Surfaces

The variability of echoes from a laser signal is typically referred to as "speckle." The speckle provides information for the classification of surfaces. In the medical community, lasers have been used for Laser Speckle Contrast Imaging (LSCI) as a metric for classification (Heeman et al., 2019). This imaging exploits the variability of the echo normalized by (i.e., contrasted with) the averaged echo. Current and potential future applications include ophthalmology (retina scans) and dermatology (characterization of burns) as well as diagnosing surfaces of organs during surgery. It is especially useful in the objective characterization of changes in tissue conditions in these applications.

The Future

The information contained in the statistical variability of echoes is being exploited across a wide range of applications, acoustic and electromagnetic. Although some applications have been operational for a long time, others are currently at much earlier stages, such as in medical ultrasound. Potential advancements in the use of echo statistics include operationalizing what is currently being explored in the research phase. In addition, there should be more crossover among different fields on their respective proven techniques, such as methods involving generic statistical functions and those involving physics-based methods.

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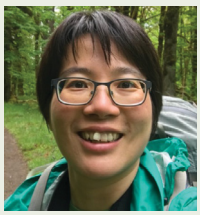

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