Biomimetic Echolocation with Application to Radar and Sonar Sensing

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Abstract

Nature provides a number of examples where acoustic echolocation is the primary sensing modality, the most well-known of these being the bat, whale and dolphin. All demonstrate a remarkable ability to "see with sound". Using echolocation they navigate, locate and capture prey. As species, they have not only survived but have thrived in all their individual environments, often solely reliant on echolocation. All of these creatures are inherently cognitive. They all maintain a perception of their environment through the nervous system that allows them to take actions. In this paper we focus on the bat as an example of a cognitive system exploiting a memory-driven perception-action cycle, enabling it to navigate and interact with its environment. The key conceptual components of cognition and how it could be applied to man-made echoic sensors is introduced. This is followed by a description of how echoic flow fields, a bio-inspired technique that bats have been shown to use, fit guidance and control problems. We then go on to explain how bats are able to reliably distinguish between different targets. A combination of the theory and examples is used to demonstrate the vast potential for advancing the capability of made in man-made systems by adopting aspects of natural echolocating cognitive dynamic systems.

Introduction

Bats provide an informative case study representing an extremely capable echoic cognitive-dynamic system. Specifically, they have been shown to navigate in a manner that is consistent with a description based on an echoic form of flow field theory. These "echoic flow fields" inherently embrace cognition through sensor "perceptions" linked directly to maneuver "actions". Further, nectar-feeding bats are able to discriminate nectar rich flowers from a variety of alternatives. Feeding by the bat results in pollination of the flower, and hence reproduction of the plant species. Consequently, co-evolution has resulted in flowers that are easily identified because elements of their structure preferentially reflect the incident acoustic waves.

Together echoic flow and scene perception play a key role in the autonomous ability of the bat to navigate and feed. Thus, an understanding of the sensing modalities and cognitive processing methodologies used by the bat could have immense and profound implications for future radar and sonar sensing leading to a plethora of new capabilities and applications.

Radar and sonar systems have become indispensable tools for remote sensing, supporting numerous military and civil applications. Indeed, in recent years their utility has been greatly enhanced with the advent of electronic scanning arrays, high-resolution imaging, and space-time techniques for the detection of slow moving targets in dense clutter. New applications are constantly emerging, such as vehicular radar. In the near future it is likely that all newly manufactured cars will carry multiple, highly capable radar systems.

Three main drivers have fuelled radar sensor development in recent years:

(i) Increased signal to interference ratio

(ii) Adaptive beam-forming and sidelobe reduction

(iii) Improved spatial resolution

In different ways each of these has contributed to systems that have increasing sensitivity. As a result, modern radar systems, especially those that produce high-resolution imagery, receive echoes from all objects that are illuminated. Consequently, much more emphasis has to be placed on being able to discriminate between different objects as opposed to merely declaring the presence or absence of, say, an aircraft in the sky. This trend of increasing radar sensitivity is continuing.

Discrimination has the potential to radically transform radar and sonar from being a relatively simple observer of the world to being a sensor system that autonomously perceives and therefore can also decide and act. There has been much research devoted to discrimination and classification in the form of Automatic (or Aided) Target recognition (ATR). However, ATR remains a challenging and largely unsolved problem. Echo "signatures" are complex, exhibit much variability, and reliable interpretation of them has so far proven elusive.

For these reasons ATR remains largely the domain of the research community. Most approaches to radar target classification are linear, in that they sequentially process received echo data until some classification label can be assigned. The resulting performance is inconsistent even under ideal target observation conditions occurring within the context of laboratory or laboratory-like conditions (e.g. targets on a turntable or in an anechoic measurement chamber). Perhaps the best performing ATR systems are those that use 'signature information' such as jet engine modulation (JEM) templates or those able to provide a count of the helicopter rotor blades and their rotation rates [1].

More generally though, these linear approaches bear little resemblance to mammalian cognitive processes. Bats readily discriminate using echolocation to select sources of food. They are constantly probing their surroundings with "calls", interpreting the reflected echoes (perception) to decide if a food source is present and then capturing and consuming the prey item (action). The process is adaptive and can be repeated with variation until a successful outcome is achieved.

Autonomous guidance and control via radar and sonar sensing is a highly sought-after capability with an enormous range of applications. For example, increasing traffic densities lead to an increasing and unacceptably high rate of road fatalities. It follows that technology able to prevent collisions, perhaps ultimately taking over the role of the driver, is of great interest. Radar has the potential to be a key component of such systems because of its proven ability to measure range and range rate in a simple inexpensive, discrete package regardless of time of day or prevailing weather. Processing echo information to enable autonomous collision avoidance is thus a very desirable objective and one that bats seem to have mastered.

Bats use echolocation for navigation, and nimbly avoid collision with obstacles as well as with one another. They have evolved to feed at dusk and into the dark when many other animals, including some predators, are unable to fully function. All of this is achieved with a remarkable degree of agility and few if any collisions in highly-populated, intersecting “three-dimensional highways” [2]. It is echolocation that enables the bat to carry out these complex orientation tasks and to perform discrimination in complete darkness. The ability to navigate using radar or sonar seems tantalizingly close, especially as the technology exists that can match and even exceed the range of parameters used by bats. However, this requires the radar or sonar system to acquire a sufficient awareness of its surroundings (perception) for self-decision making, followed by application of motor forces to maneuver safely thorough those surroundings (action).

Cognition plays a direct and fundamental role in the abilities of bats. Radar and sonar systems also have to be able to “understand” their surroundings to a level that enables them to move about and interact with their sensed environments. This demands an ability to perceive, discriminate, make decisions and provide stimuli enabling action. Incorporating a cognitive approach into synthetic sensors systems has the potential to revolutionize their role in existing and new applications.

Cognition and Sensing

The heart of cognition is the “*perception-action*” cycle that both informs and is informed by memory [3]. It may be autonomic or take higher forms. Cognition, as a topic of study in its own right, is extraordinarily complex and has been the subject of substantial research by many communities. For example, over the past 30 years there have been many laudable attempts to produce cognitive architectures within the artificial intelligence community [4]. These attempts to capture the essence of the cognitive process are also based largely on a biomimetic approach. In the work presented here we draw heavily on the formulation presented by Haykin in [3] in which a memory driven perception-action cycle is first presented and applied to radar.

Cognition requires stimulation by sensors or by memories originally obtained by sensory input. In the human this is via hearing, touch, smell, vision and taste. The nervous system converts sensed stimuli into a “*perception*” of the world. This perception is sufficiently accurate for us to move around and to manipulate our world. In other words, we are able to take informed "*action*" by interpreting our sensory perception of the world and making behavioral decisions. Subsequently, the nervous system sends signals that activate our muscles thus enabling the desired action to take place.

The notion of perception and action may be embedded within a system. Consider, as an example, the reflex reactions of animals and radar closed-loop tracking. These are termed "*autonomic*", implying an automatic response rather than requiring contemplative thought. Conversely, perception and action can be external. Detecting an obstacle and deciding whether to walk around it to the left or right requires cognition at a higher level, necessitating informed decision-making (perhaps the route to the left is twice as long as the one to the right).

Closely coupled with perception are "*recognition*" and "*categorization*". Recognition and categorization operate on the output of a perceptual system and lead to the "*understanding*" of an environment or scene. Recognition and categorization are both informed by and assist in the creation of "*memories*". Memories might be derived from recent experiences, such as from a previous observation (e.g. a coherent processing interval in radar), or from earlier experiences derived from a similar situation. Both require effective creation and application of memories. Hence prior knowledge is an important resource and component of a cognitive sensing system.

"*Attention*" is closely related to perception and may be thought of as the requirement to allocate and direct the sensing resources towards relevant information. "*Decision-making*" implies the establishment of choices and the selection of one appropriate to a desired goal. In a radar system this process could entail, for example, changing sensor parameters to maintain a desired quality of track. The basis for determining the set of possible choices, resolving possible conflicts, and selecting the best choice varies in complexity depending on the task. In some cases this process may be enabled by the architecture whilst for others it is embedded within it.

Perception clearly plays a fundamental role in situational awareness and leads to "*prediction*". Perceptual information about entities and events combined from many sources takes the form of behavioral patterns that can be extracted and extrapolated into a prediction of the future. Prediction implies some form of a model of the environment and the effect actions may have on it (e.g. expected social norms). Such prediction enables generation of *"plans"* usually according to prescribed policies for carrying out tasks such as the order in which different targets might be interrogated or the deployment of resources in an electronically scanned radar system. Over longer timescales cognitive sensing performance will also benefit from concepts such as "*reasoning*", "*reflection*", and "*learning*" that facilitate adjustments to the underlying policies.

The application of cognitive-dynamic systems to radar and sonar sensing is in its infancy and whilst the above describes key components of a cognitive system it is beyond the scope of this article to address them all. Here, we examine two connected tasks, discrimination and autonomous guidance using the bat as inspiration for synthesizing man-made counterparts.

Biomimetic guidance and control – Echoic flow fields

Bats provide an excellent example of a natural echolocating cognitive system. They sense the environment by transmitting "calls" collimated in a beam which can be directed into the surrounding open space. Echoes are processed on reception in both ears. Bats are able to perceive their environment such that they can navigate, avoid collisions, select targets and make decisions critical to their survival. They do this by adapting to the characteristics of the environment and continuously changing their echolocation sensing parameters such as the form of the call (frequency and depth and rate of modulation), call duration, the rate at which calls are transmitted, call amplitude and the direction in which the call is transmitted [e.g. 5, 6]. This section explores methods and strategies for collision-free guidance and orientation based on exploiting echoic flow fields.

Flow fields were first conceived by Gibson [7] and subsequently developed by Lee and co-workers [e.g. 8]. Flow field theory seeks to explain how humans and other members of the animal kingdom are able to navigate complex environments without having to compute and re-compute the position of all objects and obstacles along with the position of self. Flow fields naturally occur in many domains but most research attention has been on vision in the form of optical flow, see [9] and references therein. Optical flow represents the relative movement between a point of observation and objects in an illuminated environment as the ratio of light intensity to changes in light intensity. A human walking towards a doorway will exploit observed changes in the global pattern of scattered light. The instantaneous time to reach the doorway is automatically sensed and the nervous system controls the approach to, and transit through, the doorway.

Flow fields are a direct measure of the time for objects in relative motion to come together or, more generally, for a gap to be closed. The closure of a gap includes, for example, the closure of the angle between a current or reference direction of travel and a desired direction of travel. Distance and angle gaps can be combined enabling the computation of three-dimension flow fields. The derivative of a flow field determines how the gap will be closed. Holding the derivative at a constant value fixes the form of the resulting trajectory. A range of trajectory types can be chosen by selecting the value of the constant thus enabling different types of task to be carried out. Crucially, the sensed flow field (perception) can be used to directly compute the desired trajectory (action) consistent with [10]. In the case of humans a neuronal response stimulates muscles in the required way. Therefore measurement of gap closure times in both distance and angle (azimuth and elevation) provides a powerful basis for enabling autonomous behaviors in synthetic systems. The flow field or gap closure time is usually denoted with the parameter τ and this convention will be adopted here.

Bats have been shown [10] to perform tasks such as intercepting prey on the wing or maneuvering to a landing site in a manner that is consistent with exploitation of flow fields. Lee uses the term acoustic flow whereas here the term Echoic Flow (EF) is employed to specifically denote an active sensing system where acoustic or electro-magnetic signals are transmitted and received. In [4] it is concluded that bats use EF as a method enabling controlled landings and feeding on the wing. The behavior of the bat was found to be consistent with computation of τ and its derivative in both range and angle. Bats employ a strategy whereby the values of the derivatives of range and angle τ take a specific value. Radar and sonar systems inherently measure distance and angle using echolocation and thus lend themselves well to the measurement of 3-D flow fields. The flow field, τ, associated with radial range is given by:

$$\tau_r = r/\dot{r} \tag{1}$$

where r is the range to a detected object and $\dot{r}$ is the change in range of the object between the current and previous measurements. Strictly τ_r, r and $\dot{r}$ are all functions of time, t, however, here the '(t)' has been omitted for clarity in the equations.

τ_r is a direct measure of the time to collision or time to close the range gap and has units of time. For example, if a radar sensor system is moving directly towards a stationary object with a velocity of 3 ms^{-1} and the object is located at a distance of 6 m, the gap closure time is 2 s.

The time derivative of τ, denoted $\dot{\tau}$, is a dimensionless quantity that is related to the velocity and acceleration as the system approaches a target. $\dot{\tau}$ depends on range, range rate and acceleration according to

$$\dot{\tau}_r = \frac{\partial \tau_r}{\partial t} = 1 - \frac{r\ddot{r}}{\dot{r}^2} = 1 - \tau_r \frac{\ddot{r}}{\dot{r}} \tag{2}$$

Equation (2) is a second order differential equation and can be solved for cases where $\dot{\tau}$ takes a constant value, k, to give the expression in (3a) that describes the change in range as a function of time and the initial range and echoic flow. Differentiating (3a) with respect to time gives (3b) that describes the progression of range-rate, or speed. A further differentiation gives (3c) that describes the progression of acceleration. Equations (3a) to (3c) are the equations of motion for the system [10],

$$r = r_0(1 + kt/\tau_0)^{\frac{1}{k}} \tag{3a}$$
$$\dot{r} = \dot{r}_0(1 + kt/\tau_0)^{\frac{1}{k}-1} \tag{3b}$$
$$\ddot{r} = (\dot{r}_2^0/r_0)(1 - k)(1 + kt/\tau_0)^{\frac{1}{k}-2} \tag{3c}$$

where r_0 and $\dot{r}_0$ are the range and velocity at time $t = 0$ s and $\tau_0 = r_0/\dot{r}_0$ is the initial echoic flow. The convention is that the initial range is negative while the velocity is positive, i.e. the gap between radar platform and target is closing. These are the basic equations of EF and, as shown here, enable the sensed flow field to generate changes to velocity and acceleration such that a desired trajectory is followed. Note that the range, r, in (3) could be replaced with any sensor measurable parameter permitting its control by echoic flow.

Figure 1 shows the equation of motion curves, for constant values of $\dot{\tau}_r = k$ and initial conditions of $r_0 = -10$ m and $\dot{r}_0 = 1$ ms^{-1}. In this example, the radar is part of a vehicle approaching the object head-on. Unless braking is applied the vehicle and object will collide. Figure 1 shows five regions of behavior types.

1. $k = 1$. There is no change in acceleration with time and the platform collides with the target after 10 s at the same speed as when the target was first detected. The collision is “hard”.
2. $0.5 < k < 1$. The trajectory is consistent with “a late braking strategy” (such as one might be used by a runner in baseball). This still results in a collision as the sensor platform vehicle still has positive velocity. However, the initial braking acceleration (with negative value) is insufficient to stop the system at the object location. As the sensor platform approaches the target the braking increases (theoretically to an infinite amount) at the instant the vehicle and object collide. Infinite braking would mean there is no actual collision with the target, since the velocity will become zero at zero gap. However, no real system (or baseball runner) can actually have a negative infinite acceleration, so in practice the platform will crash into the target with a positive velocity and the collision can still be hard, depending on the value of k.

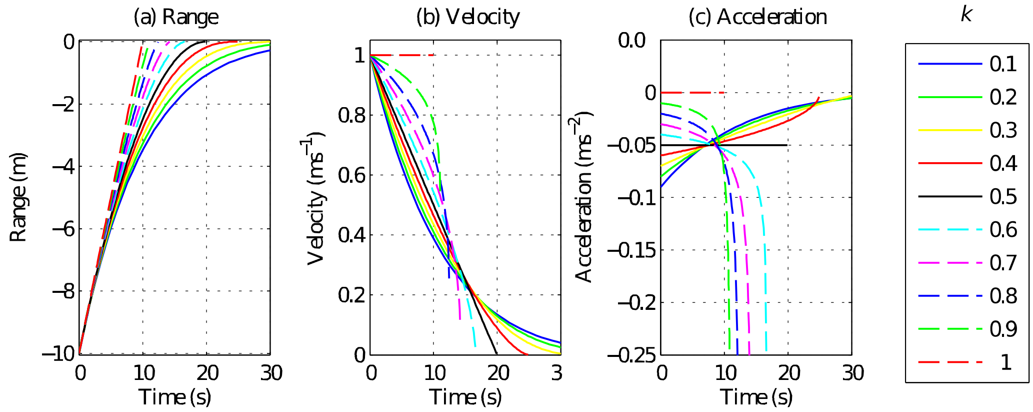

Figure. 1: The variation, over time, of (a) range, (b) velocity and (c) acceleration as the sensor system approaches a target. Note the accelerations are negative indicating braking. The curves are calculated using (3).

3. $0 < k < 0.5$. This is an example of an early braking strategy (such as one might be used by the driver of a passenger vehicle). The initial braking is larger than necessary to bring the sensor platform to a halt and thus the braking has to be

gradually reduced as the object is approached. When the object is reached the velocity and braking will be zero resulting in a soft collision or no collision at all. This case is particularly valuable since its end conditions are favourable for many applications such as parking, docking and aircraft landing.

4. $k = 0.5$. Here, a constant braking is applied such that the velocity decreases linearly until the platform comes to rest at the target location.
5. $k > 1$. Here, the sensor system accelerates towards the target. If k is close to 1 then the acceleration comes only when the platform is close to the target. While if $k \gg 1$ the acceleration begins immediately. The resulting collision tends towards the catastrophic.

To illustrate the application of echoic flow to autonomous guidance, a simulation of a robotic vehicle equipped with a monostatic radar system located inside a corridor is used. The “corridor” was formed from of a series of closely spaced point scatterers (as shown in red in Figure 2) each of which provides a scaled and delayed reflection of the signal incident upon it. The parameters of the radar system are shown in Table 1. The antenna transmits and receives two beams with 15° beamwidths angled at ±45° from the direction of travel. The initial heading angle is 45° to the left of the *y*-axis. To control the platform τ_r for each beam is computed and a decision is made to steer away from the beam with the small EF, i.e. only a single steering control instruction is used.

Table I: Parameters of the autonomous navigation simulation.

Parameter	Value	Unit
Number of beams	2	N/A
Optimum beam angles	± 45	° (degree)
Beamwidth	15	° (degree)
PRF	10	Hz
Platform speed	1	ms^{-1}
Platform turn angle	30	° (degree)
Display update interval	1	s

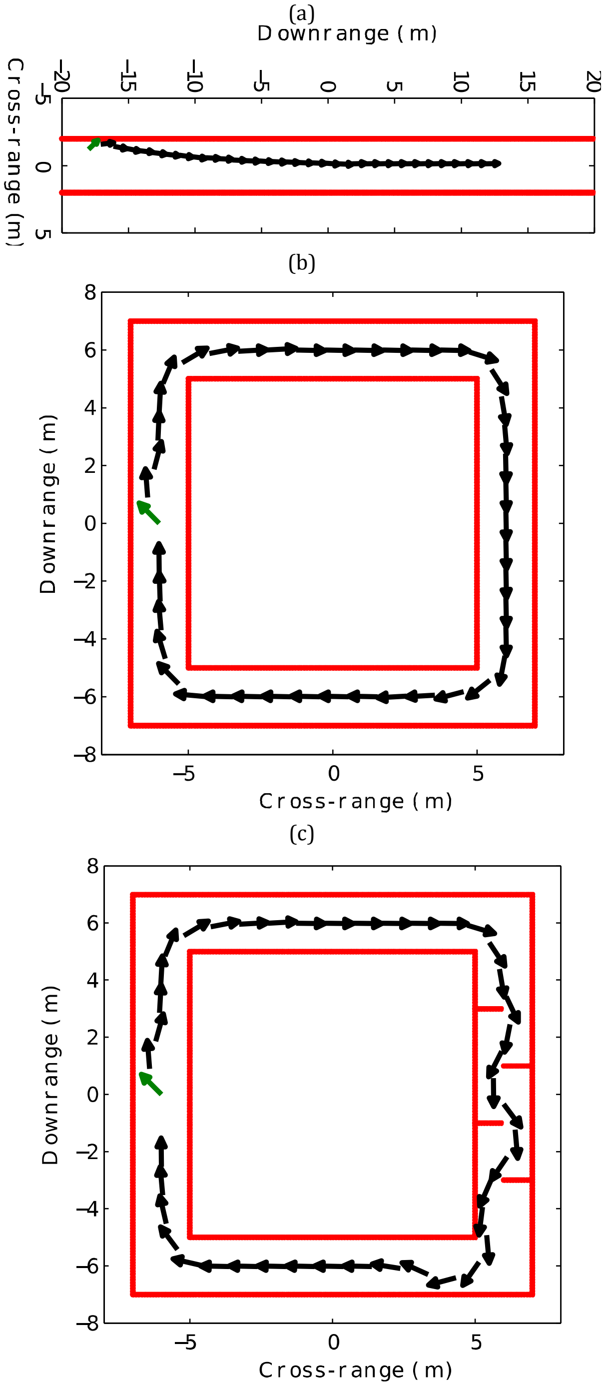

Figure 2 Cognitive guidance and control using echoic flow for (a) a straight corridor, (b) a closed loop and (c) a closed loop with obstacles. Arrows indicate location and forward direction; green arrow indicates starting location & direction.

Figure 2a shows that a stable condition for the control rule is reached when the EF is balanced in both beams; this causes the platform to navigate to the center as it progresses along the corridor. Figure 2b shows results for a continuous square corridor.

The control rule successfully steers the platform to navigate the loop. Although a notional steady state is reached after the second corner is passed, the robotic vehicle doesn't follow exactly the same trajectory on future circuits due to slight difference in orientation producing a slightly different perception-action combination. The final configuration, Figure 3(c), is a continuous square corridor with obstacles. While the platform is able to successfully navigate around the obstacles, it does deviate from the steady state condition in their aftermath. Nevertheless the platform avoids the wall and proceeds without collision around the entirety of the corridor using just a single instruction.

Flow fields can be coupled together, that is to say they can be linked such that action based on one field can be directly associated with another. The coupling can be expressed by a simple linear relationship

$$\tau_\chi = m\tau_\gamma \tag{4}$$

where τ_χ is the time to close a gap between the current value and a desired value of a parameter χ. In other words the parameter χ can represent, range, angle or even echo power. Equation (4) couples the flow fields of χ and γ such that both gaps must close at the same moment in time, but that the gap in χ closes m times faster than that in γ. This allows the simple example above to be easily extended to three-dimensional trajectories.

A cognitive radar system can measure range, r, and angle, θ, accurately and through (4) couples the flow fields as $\tau_r = m\tau_\theta$ so that the range and angle gaps close at the same time. Consider the example of a radar sensor (on a vehicle) intercepting a moving target following a non-ballistic, or irregular trajectory. The radar sensor measures the range, r, and angle, θ, to the target on a pulse-by-pulse basis. Over two pulses the radar is therefore able to perceive the flow field for the parameters as

$$\tau_\chi = \chi_n/(\chi_n - \chi_{n-1}) \tag{5}$$

where χ is either r or θ and n is the pulse number.

Replacing r with χ in (2), to indicate application of the equation to a general parameter, and re-arranging gives an expression for the acceleration

$$\ddot{\chi} = \dot{\chi}^2\left(1 - \dot{\tau}_\chi\right)/\chi \tag{6}$$

This is the acceleration required, based on the current time to collision, to close the gap in the parameter χ. During the action phase of the cycle the radar sets the linear and angular accelerations of the platform to the values obtained from (6). This is repeated every pulse from the second pulse allowing control of the platform velocity and heading direction.

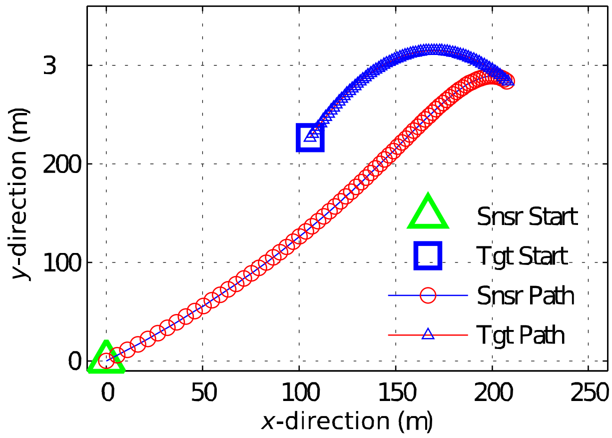

Figure 3. Interception of a moving target. The guidance and control of the sensor platform is achieved using the echoic flow measured in the x and y directions and the two flow fields are coupled.

Figure 3 shows a platform being guided by a radar that processes echoic flow intercepting an accelerating target. The radar is capable of perceiving the flow in the *x* and *y* directions based on its measurements of range and angle. The decision to use the *x* and *y* directions rather than range and angle is for ease of simulation implementation and not to suggest they are preferable. The two fields are coupled and through (4) and (6) updates to the platform acceleration can be calculated from each radar pulse to guide the platform to the target. The initial velocity of the sensor is 20 ms^{-1} with a heading angle of 45°, measured from the *y* direction. The acceleration is set to 0 ms^{-2} and is along the heading direction. The target location is 250 m from initial platform position and the angle between the line of sight (LOS) and the heading direction is 20°. The target will be assumed to have an initial velocity of $\boldsymbol{v}_{\mathrm{tgt}} = 10 \times [\sin 20 \quad \cos 20]^{\mathrm{T}}$ ms^{-1} and an acceleration of $\boldsymbol{a}_{tgt} = -0.5 \times [0 \quad 1]^{\mathrm{T}}$ ms^{-2}. At the end of the simulation, the final target velocity was $[3.4 \quad -5.6]^{\mathrm{T}}$ ms^{-1} while the platform final velocity vector was $[3.6 \quad -5.5]^{\mathrm{T}}$ ms^{-1}. The absolute error between the two velocities is small, just 0.2 ms^{-1}.

This example of guidance and control demonstrates how, when the right perception is taken from the radar data, i.e. echoic flow, actions can be decided on easily. Here, the action is to correctly set the vector acceleration such that the target is intercepted and its heading and speed are matched. The acceleration is calculated (action decided on) using (6), with the distances to the target in the x and y directions substitutd in for χ, and (4) resulting in a deterministic implementation of the perception-action cycle. The cycle is normally considered to act in the presence of memory; here we might consider the memory to be the fixed value of $\dot{\tau}$ required in (6) and the value of m from (4). The system remembers which value of $\dot{\tau}$ and m to use, 0.5 and 2.14, respectively, in the example, to obtain a desired approach trajectory.

Echoic flow based cognitive guidance and control has many applications in the real world. One example would be a landing aid for a helicopter approaching the helipad on a ship. The ship is moving in the sea, so even if the helicopter remained stationary, the range would vary. If the helicopter is decending, equation (6) provides a deterministic implementation of the perception-action cycle in which the required action—braking ($\ddot{r}$, substituted in for $\ddot{\chi}$ in (6))—can be determined based on the perception or measurement of echoic flow. Since the echoic flow perception is time varying, the motion of the helipad merely changes the instantaneous estimation of the flow and the braking action automatically adjusts susch that the landing type, determined by the control constant, k, will still occur. As a more sophisticated example, if the target in Figure 3 were considered to be a space in a line of moving traffic then it is clear that echoic flow could be used to allow a self guiding car to merg in. Clearly echoic flow has many potential applications and is a demonstration of the power of cognition coupled with radar sensing.

Biomimetic discrimination

Echoic flow offers a powerful method for guidance and path planning, however, it is only one aspect of the bat's cognitive process; another equally significant cognitive ability is the bat's ability to distinguishing legitimate sources of nourishment from other objects. In other words, the bat is able to recognise desirable objects from their acoustic signatures, a capability that is highly desirable in radar and sonar systems.

By visiting flowers for nectar, the bat is responsible for pollen transfer between different individual plants and hence plays a key role in plant pollination. In other words, although the short-term interest of the bat is solely efficient feeding, it is in the long-term interest of both the bat and plant species for pollination to take place successfully. Because of this, it has been hypothesised that co-evolution of bat and plant may have contributed to forming the shape and structure of bat-pollinated flowers in order to ease classification by bats [11-16]. Thus the ingredients for successful classification are in-built and this makes an ideal study case for deducing techniques applicable to synthetic echoic sensing. Recognition of flowers by bats is a demanding task, but nectar-feeding bats succeed in foraging using echolocation alone [e.g. 10, 11].

As a result of co-evolution, plants will have developed to provide clues in the echo responses obtained by the bat. In particular, bats have to distinguish between good flowers, wilting flowers and buds as well as timing their feed for maximum effect (efficient eating and energy consumption). It would seem likely, therefore, that characteristics indicating the difference between these flower states are embedded in echoes of the bat's cry to facilitate discrimination. In this research the floral echoes are examined to evaluate their dominant features and better understand how the bat might utilize them. Ultimately, this knowledge may inform on how to interpret the target information available in manmade synthetic aperture radar and sonar images.

The "*Rhytidophyllum auriculatum hook"* is a bat-pollinated plant that grows in the Caribbean region and produces small flowers whose nectar is extremely attractive to bats (Figure 4).

Figure 4. The "Rhytidophyllum auriculatum hook" is a bat-pollinated plant that grows in the Caribbean region. The photo on the right shows a flower corolla taken from the plant grown at University of Bristol with its main components. The flower corolla was around 1 cm long.

Echoes from this plant are ideal for investigating the information sensed by the bats, as well as the relationship between the echo and the maturity status of the *Rhytidophyllum auriculatum* plant. Two datasets containing High Range Resolution Profiles (HRRPs) of an open flower and a bud of *Rhytidophyllum auriculatum* are compared. Of course we cannot be certain the bat processes received echoes as HRRPs but it biological analysis has proposed bats to be sensitive to target range and the range differences between parts of a target [14].

The bat has to be able to discriminate between nectar-bearing open flowers and closed buds. Although the form of the bat's neural signal processing is largely unknown, we expect the HRRPs of the bud to therefore be significantly different from those of open flowers. Closed buds are physically smaller than open flowers. Consequently the amount of energy they reflect is lower than for open flowers. Thus overall echo strength can be one factor in helping the bat distinguish between open flowers and closed buds.

HRRP data was collected at the School of Biological Sciences at the University of Bristol in 2009. Flowers were impaled on a thin metallic pin (1.5 mm diameter) placed at the center of a horizontal turntable. The turntable was set so that HRRPs could be measured at 1° angular intervals. The *Rhytidophyllum auriculatum* plant was ensonified using a custom-built loudspeaker emitting pulses over which the frequency was linearly decreased from 200 kHz to 50 kHz. The resulting HRRPs have a range resolution of approximately 1.5 mm. This was experimentally measured as the width of the main lobe of the cross-correlation function between the transmitted chirp and the echo generated by a metallic flat plate. Facsimiles of bats' calls were digitally encoded, amplified with a Piezo Driver/Amplifier Series, Treck, PZD 350 M/S and emitted through an ultrasound loudspeaker. Echoes were recorded with an ultrasound microphone and digitised at a sampling rate of 500 kHz. A measurement of the background was removed from the echoes before subtracting the data mean value. The Hilbert transform of each echo was then cross-correlated with that of the transmitted waveform to generate the HRRPs. A much more detailed description of the experimental facility can be found in [17].

Figure 5a shows the HRRPs plotted as a function of orientation angle for an open *Rhytidophyllum auriculatum* flower. The complex structure of the scattering from the corolla is visible over the entire angular range. There are discernable regions of both high and low reflectivity that persist over large angles. Whilst complex, the HRRPs are far from random, but a route to correct recognition is not obvious.

The flower is broadly bell-shaped. This results in a relatively large echo being reflected over the wide range of angles, making them easier to detect against the background. The petals contribute significantly to the amount of reflected energy. Indeed, the petals are themselves visible over a wide angular window that spans at least ±90°.

Figure 5b shows HRRPs when the *Rhytidophyllum auriculatum* bud was ensonified. The structure of the HRRPs of the bud is very different from that of the open flower. Again, scattering is present over all angles but the level of complexity in the HRRP's is reduced giving them a more sparse appearance. The image suggests only one or two discrete scatterers are now contributing to the HRRPs. At an angle of 0° (when the sensor directly faces the bud), the scattering is weaker than at any other angles. This is due to the ensonified surface now being smaller that at any other angles and sloping away from the direction of the sensor. There is also scattering caused by the sepals that cover the back of the corolla. This is visible at around 21.5 cm and exists over all angles between $\pm 90°$.

These results illustrate that specific parts of the flower contribute to the overall information sensed by the bat. The HRRP responses for the open and closed flower show how information is modified as the flower changes appearance both in terms of the total reflected signal as well as the detailed structures shown in the HRRPs.

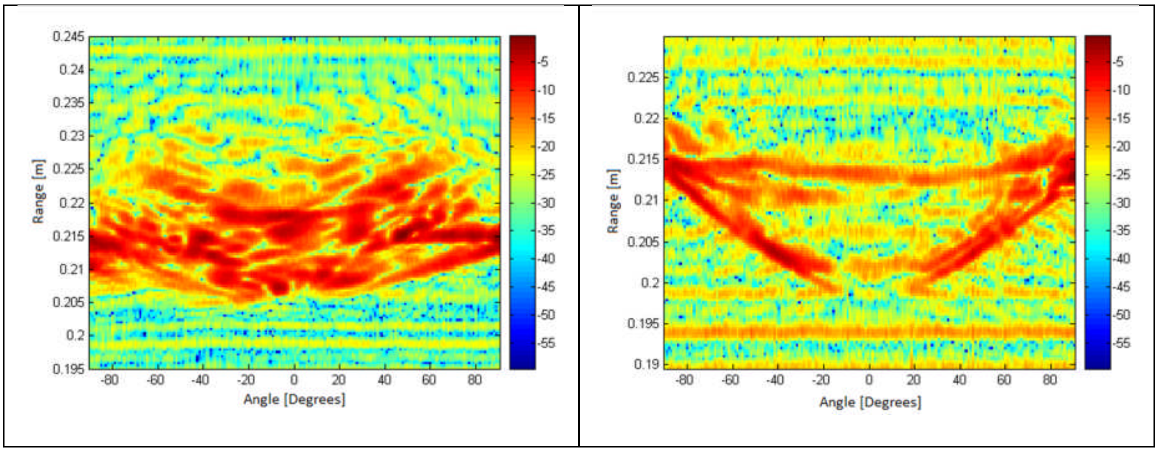

Figure 5. Magnitude of the HRRPs of a) a Rhytidophyllum auriculatum open flower and b) a Rhytidophyllum auriculatum bud. The structure of the bud is very different from that of the open flower. This may be thought as the flowers way to attract the bat attention. The color scale indicates the echo strength in [dB] normalised to the maximum echo value.

However, the bat has a much more complex task in approaching and selecting flowers suitable for feeding. It has to do this in an area of highly dense scattering caused by many *Rhytidophyllum auriculatum* flowers of different ages as well as other plants not suitable for feeding. The bat has to be able to process echoes to gather the right information for successful feeding [18]. It seems likely that the bat's (echoic flow) flight trajectory in approaching the flower is also a contributory element in extracting information in the recognition of suitable nectar-bearing open flowers. Because the plant species perpetuates through the resulting pollination, the spatial and shape arrangements between individual flowers, buds and Calyxes (i.e. flowers without the corolla) have all evolved to give the bat the necessary information to succeed in the task of flower recognition.

Differences between echo responses from buds, calyxes and open flowers allow the bat to detect and recognise the correct target (the open flower). The bell-shaped flowers act as efficient retro-reflectors over a broad range of angles correspondingly causing a large echo at all angles. This alone helps make them easier to detect. Closed buds and calyxes scatter less energy back towards the bat. These differences between echo strengths are exploited by the bat and help to plan the approach trajectory to the nectarium (the part of the corolla that contains the nectar).

Figures 6a, b and c show HRRPs as a function of azimuth and elevation angle. The measurements were made with the same apparatus described earlier. The vertical-axis is the distance in metres between the artificial bat-head and the centre of rotation of a turntable located at a distance of approximately 20 cm. The horizontal axis is the angle between the horizontal turntable and the bat-head. At 0° the bat-head directly faces the plant. The color coding indicates echo strength and has been normalised to the maximum echo value.

Figure 6a shows, at a 0° depression angle, that the scattering from the two buds located on the left of the open flower (as viewed from the front) is clearly visible at a distance between 16 cm and 18 cm. The bud scattering is present over a large angular window between -80° and 0°. The scattering from the bud located on the same side as the open flower superimposed with echoes from the dead branches is visible between -30° up to +80° at a distance from 16 cm to about 19 cm. The open flower protrudes maximally and hence is visible at the nearer range of about 14 cm. Its reflections are more directional than those of the buds.

In Figure 6b (-25° depression angle) the scattering from the two buds located on the right of the open flower is clearly visible between 16 cm and 18 cm and again is present over a large angular ambit from -80° and 0°. However, the scattering from the two buds on the left hand side is much weakened. This illustrates the strong dependence of the scattering on relative orientation between the bat and the ensonified object. The open flower still protrudes maximally and is visible at a range of about 14 cm. As before, its reflections are more directional than those associated with the buds.

The vertical plane HRRPs are shown in Figure 6c. The Figure shows that scattering from the buds and the dead branches with Calyx is visible at a distance of 16 cm and persists over almost all perspectives. The open flower is visible at a distance of 14 cm and over a smaller angular window between -25° and -10°. This is typical of the comparatively higher directionality of floral echoes in the vertical plane. The bell shape of the flower provides the bat with a strong echo response over a broad range of azimuth and elevation angles. The figures also show the open flower protruding which helps to facilitate separation from buds, calyxes, and background clutter.

Nectar-feeding bats have a remarkable ability to extract information from echoes by exploring a number of vertical and horizontal perspectives. They use a lot of hovering flight which can certainly help them build up a profile of acoustic flow field images across different angular profiles [19]. This aids selection of an appropriate approaching angle into the corolla. Information is exploited in a wide variety of ways. The analysis of HRRPs carried out above suggests that the magnitude of echoes, and the detailed and angular dependent echo structures, might all combine to enable successful recognition.

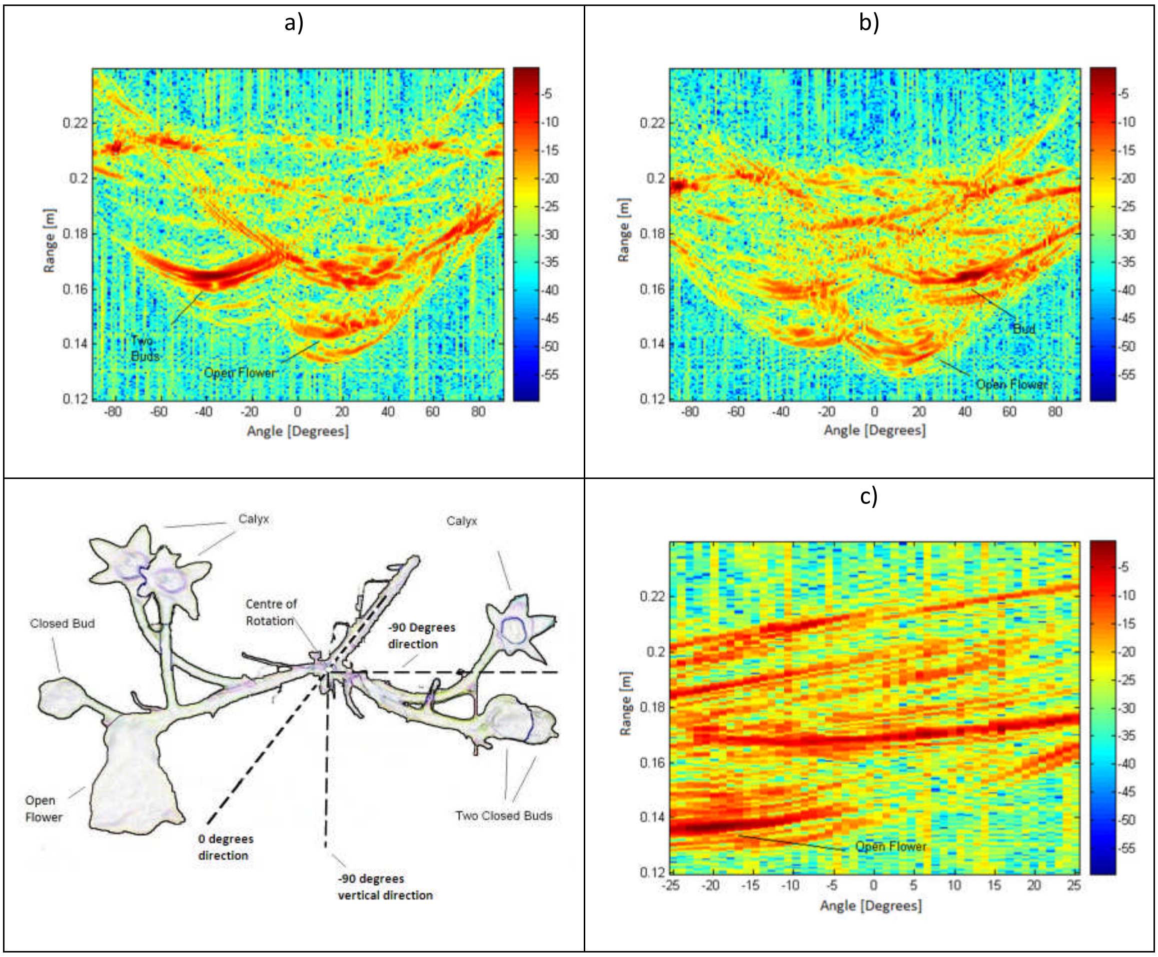

Figure 6. Inflorescence of a R.auriculatum plant composed of an open flower and three buds measured a) horizontally from a vertical angle of 0° b) horizontally from a vertical angle of -25° and c) vertically from a horizontal angle of 0°. The 0° aspect angle corresponds to the artificial bat-head being placed at the same height as the centre of rotation and facing the 0° direction. The image shows the more complex structure and higher directionality of flowers in the horizontal and vertical planes. The flower also protrudes and this facilitates separation from buds, calyxes and the background. The color scale indicates the echo strength in [dB] and it has been normalised to the maximum echo value.

To explore this further in the context of synthetic sensing, HRRPs of a car and a tank are measured in the same way as for the flowers. Figure 7 shows photos of the two (scaled) targets used together with their corresponding HRRPs. The HRRPs were collected over an angular ambit of 180° at 1° intervals. Across this broad range of angles, it is clear the echo responses from the two objects are very different but also exhibit a complexity that makes recognition challenging.

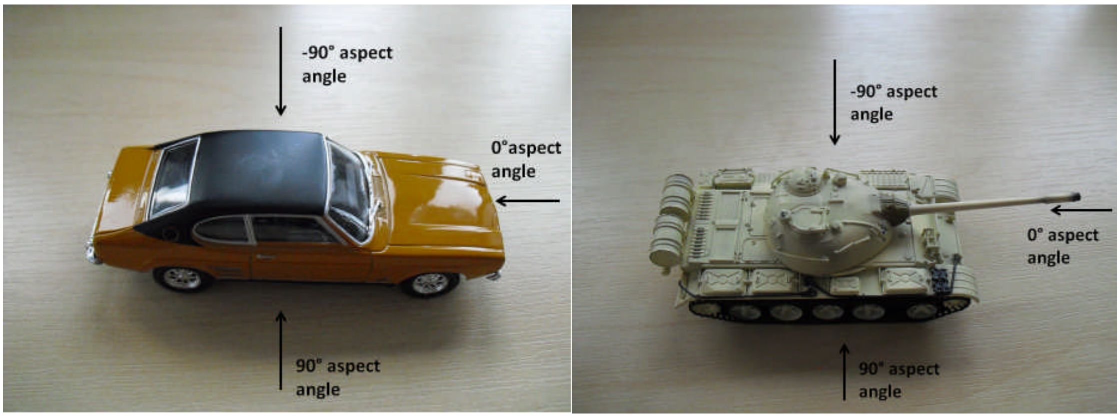

Photo of the scaled Ford car and the scaled T55 tank used for the experiments.

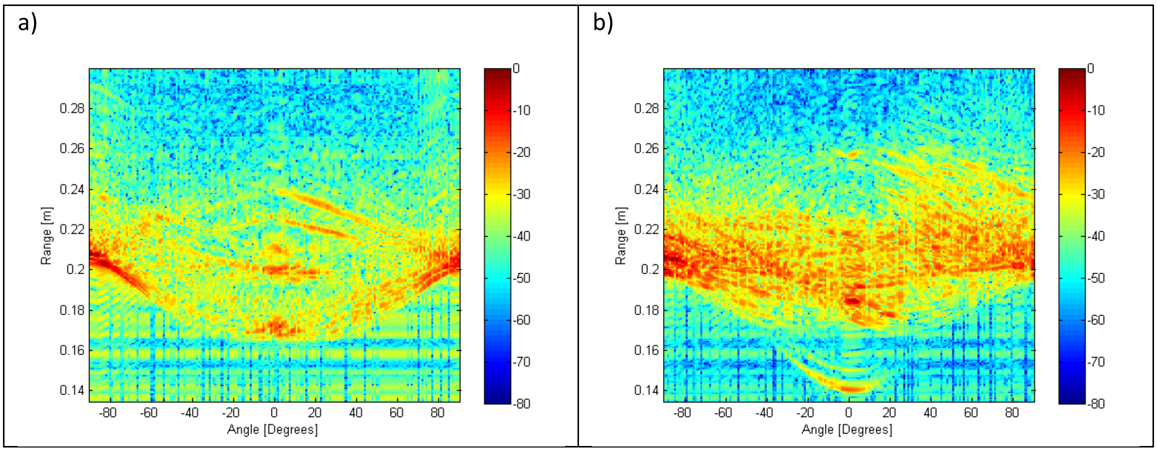

Figure 7. Amplitude of the HRRPs of a) the scaled Ford car and b) the scaled T-55 tank over an angular window between -90° and +90°. The 0° aspect angle corresponds to the artificial bat-head being placed at the same height as the centre of rotation and facing the front side of the target. The color scale indicates the echo strength in [dB], normalised to the maximum echo value.

To examine how recognition might be affected by the relative orientation between the sensor and the target, classification performance discriminating the two targets is computed as a function of look-angle. Classification performance is assessed using a k-NN classifier. In this specific case the N_{train} profiles separated by a constant angular step $s = 30°$ were extracted from each object to train the classifier. These were used to form a training set ***U***. The remaining N_{test} HRRPs in each class were used to form the test set ***W***. Features were extracted from the profiles and used for training. The $N_f = 20$ features were extracted from each HRRP using the Principal Components Algorithm (PCA) similar to [17] to generate the feature based training set ***D*** and test set **E**. Classification performance was assessed as a function of the width of the target sector.

Figure 8 shows a plot of the results as a function of angle for 10°, 15° and 20° sector sizes. Each angle on the *x*-axis corresponds to the first HRRP belonging to the target sector. For example the peformance at 0° for the 10° large sector corresponds to the case when the test set was formed with all HRRPs from 0° to 9°. The training set remained constant.

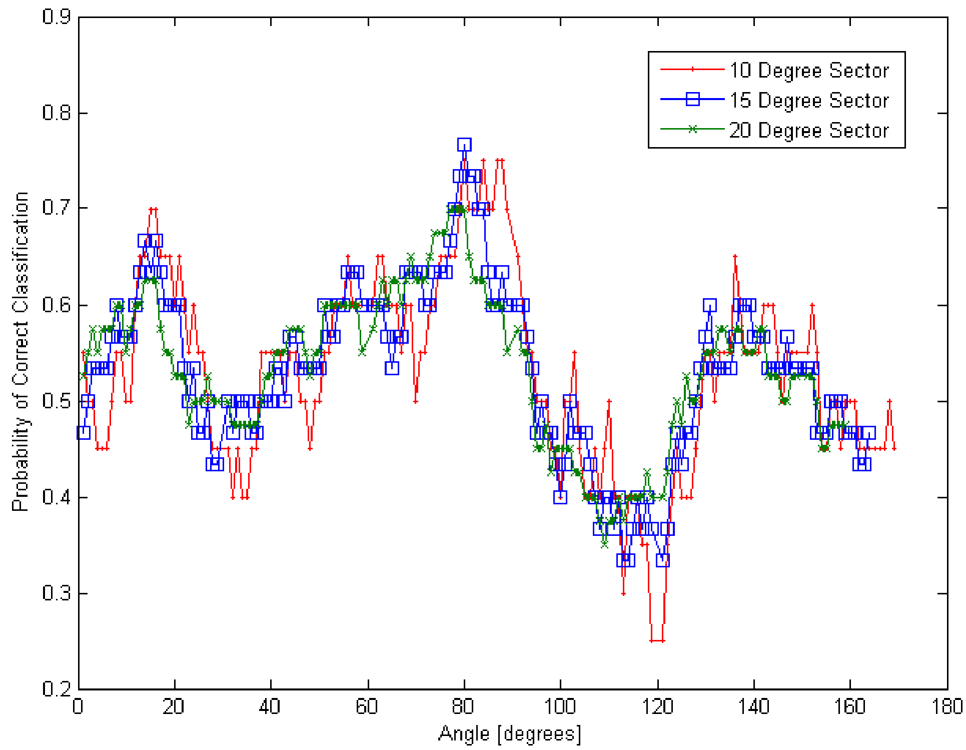

Figure 8: Classification performance as a function of angle for three different sector widths: 10 degrees, 15° and 20°. The image shows there are angles that provide best separation between the two targets. If selectable, these would represent a more optimum choice for target classification.

Figure 8 shows that classification performance can vary significantly as a function of illumination angle with the sector width only having a small influence. Thus there are angles that provide best separation of the two targets that, if selectable, would represent a more optimum choice.

Summary and Conclusions

Echoic flow is an inherently cognitive concept embodying perception linked to action. It provides a powerful yet simple rationale for autonomous guidance and control consistent with behavior observed in natural systems. These properties make it highly suited to many radar and sonar sensing applications. Flow fields are readily computable from radar measurements of range and angle to a target or object. They provide a convenient metric indicating a gap closure time between the radar and an object regardless of the motion of either. By perceiving the environment in this manner the cognitive decision making process is straightforward enabling selection of appropriate actions based on information extracted from the received radar signal.

However, more complete and capable cognitive sensing system requires the ability to recognize and categorize information in any given scenario. A key component is a robust and reliable discrimination function. Bats are able to use coarse information such as echo strength combined with the fine detail provided by (perhaps) HRRPs augmented by observation at multiple different orientations. Exploitation of this approach in synthetic sensors is challenging, but the insights provided through observation and measurement of natural systems is pointing the way to new approaches offering genuine promise.

These are but two ways in which synthetic echolocation sensing can begin to adopt processing approaches that exploit new freedoms offered by a cognitive approach.

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