Applying Utility Theory to Improve Autonomous Underwater Vehicle Mission Playload Planning and Replanning

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Abstract. This work presents a method by which utility theory can be applied to the payload decision making processes of autonomous underwater vehicles (AUV) for mission planning and replanning purposes. Such an application allows AUVs to determine the 'best' payload to use for a specific mission without operator intervention, thus improving AUV reliability while the vehicle is out of communication range from the operator. Because 'best' is subjective, focusing on relevant payload attributes and tailoring these functions to individual operator preferences ensures a unique vehicle makes decisions that align with a unique operator's preferences. The creation of these functions is an iterative process that involves interviewing an individual operator to determine the form and weight of that operator's preferences based upon theoretical payload attributes, followed by the testing of the resulting equation using actual payload attributes. Contained in this paper are example utility functions that take into consideration three attributes each for describing the decision making preferences for three AUV operators when determining the appropriate side scan sonar to use to perform a specific seabed imagining mission. These three functions were tested and determined to produce results that align with the individual operators' preferences, thus validating the appropriateness of these equations for these operators on this mission.

Keywords: Autonomous underwater vehicle · AUV
Unmanned underwater vehicle · UUV · Decision theory · Utility theory
Planning

1 Introduction

Militaries, commercial vendors, and research organizations are increasingly relying on unmanned vehicles to perform missions that are dull, dirty, dangerous, or otherwise cost prohibitive. These vehicles perform missions in the air, on land, on water, and undersea. Whereas surface and air vehicles can readily communicate with external information sources, such as human operators or satellites, undersea vehicles have limited communication capabilities, due to the electromagnetic signal-attenuating properties of water [1]. As a result, underwater vehicles not otherwise tethered to an operator must be capable of autonomous decision making.

Y. Zhou and T. Kunz (Eds.): AdHocNets 2017, LNICST 223, pp. 24–33, 2018.
https://doi.org/10.1007/978-3-319-74439-1_3

To program an AUV with a mission, a human operator inputs parameters into the vehicle's controller, prior to launch. These parameters may include: type of mission, actions to be performed, payloads to be used, and mission location, among others. The vehicle uses this input to plan and continuously replan the mission as the missions progresses. The vehicles are, however, unable to plan or replan in a manner that violates these operator-provided inputs. In the event the specified payload fails during a mission, therefore, the AUV is generally unable to replan a mission around an alternate payload. When these payload failures occur, the AUV instead aborts that portion of the mission and either moves to another, pre-defined mission or returns to the surface of the water to await further instruction from a human operator.

Aborted missions create sunk cost or otherwise fail to capitalize on the benefits of the original mission. To minimize the occurrence of these aborted missions, this paper presents a method for allowing the vehicle, rather than the operator, to decide what payload to use for a given mission using mission-specific utility functions tailored to the unique operator, based upon previously-established decision making preferences of that operator.

2 Related Work

Work in the area of mission planning and replanning around a degraded payload has been conducted by researchers at Heriot-Watt University [1, 2]. One of the most comprehensive of these published works is Pedro Patron's 2010 doctoral thesis, from which many other works followed [3]. Much of Patron's work and the work of his coauthors focuses on semantic-based goal-oriented mission replanning around a degraded payload, specifically, a side looking sonar with one of two transducers failed [1–4]. In various published works, Patron and his coauthors propose approaching mission planning around a completely failed payload by searching for redundant components or platforms, however, no significant work has been published using this approach [3].

3 Approach

The focus and approach of this paper is the use of known attributes of possible mission payloads, operator-defined missions, and previously-defined operator preferences to create a set of utility functions that can order, from most preferred to least preferred, alternate payloads for a series of AUV missions. Because 'best' is subjective, these sets of equations will be tailored to individual operators so that a given AUV makes the 'best' decision for its operator. To accomplish this, an operator is interviewed to determine the form of his preferences for a specific attribute of a payload. He is then interviewed to determine the weight of his preferences for various attributes relative to others. Combined, these interviews allow for the creation of a utility function for a specific mission. The validity of this function is tested by asking the operator to rank example payloads, while also having the function calculate the ranks of these payloads. If the operator and equation do not provide the same results, the process is repeated, until the results match. Once the equation and operator provide the same results, the equation is sufficient at replicating operator decision making preferences for that mission.

4 Mission Definition

To provide the vehicle with the flexibility to plan a mission around a payload or replan a mission around a failed payload, the AUV must be programmed with a mission goal or end state, rather than a specific payload and associated payload action. By applying a goal-specific utility function to that mission, the vehicle will then be able to determine which payload will best allow it to meet that goal. How well a payload performs an action to accomplish a mission goal depends on what that goal is. As such, each goal will have a unique utility function taking into consideration a unique combination of attributes—or technical specifications—that are relevant for that goal. The vehicle can be programmed with a series of these utility functions. After an operator has defined the mission goal, the vehicle can then select the proper function for the decision to be made, apply the function, and calculate the highest-rated payload for mission performance. For multi-attribute utility theory with mutual preferential independence, the general form of a utility function is:

$$\left(\mathrm{x}_1, \ldots, \mathrm{x}_n\right) = \sum_{i=1}^{n} \mathrm{k}_i * \mathrm{u}_i\left(\mathrm{x}_i\right) \tag{1}$$

where k_i is a scaling constant and $\mathrm{u}_i\left(\mathrm{x}_i\right)$ is a function of each attribute i [5]. To determine the form of each $\mathrm{u}_i\left(\mathrm{x}_i\right)$, utilities of 0 to 1 (i.e. least useful to most useful) are assigned for the range of possible attribute values. The utility mid-value point (i.e. the amount of an attribute where utility equals 0.5) is identified, based upon the preference of the operator for whom the function is being developed. This process is repeated for mid-value points for the upper and lower halves, quarters, eighths, and so on until a sufficient amount of precision is captured such that a trendline can be fitted through these mid-value points, the equation of which, $\mathrm{u}_i\left(\mathrm{x}_i\right)$, is the normalized utility function for that attribute. This process is repeated for all attributes, providing the basis for a utility function.

Next, a value for each k_i must be determined. To do this, a set of i equations is needed to solve for all constants. For the first equation, the rules of additive value due to mutual preferential independence provide that the sum of all values of k equals 1. Two attribute profiles for hypothetical payloads are then compared. The value of one attribute in one profile is manipulated until indifference (i.e. the point at which improving one profile or another is equally valued) is identified. This process is repeated until the set of functions can be solved for all values of k [5].

Once all equations for $\mathrm{u}_i\left(\mathrm{x}_i\right)$ and all values for k_i are known, the goal-specific mission utility function is created. By entering attribute values for the payloads under consideration into this equation, the utilities for those payloads can then be calculated. The payload with the highest utility is 'best' and the vehicle can plan or replan the mission around this payload.

5 Results

Although a complete set of equations for all possible missions spanning all applicable attributes would be required to allow a vehicle to autonomously plan and replan all possible missions around all available payloads for one operator, this paper establishes one utility function for one mission goal based upon three attributes to demonstrate the viability of applying utility theory to AUV decision making. The process is repeated for a total of three operators to show that different operators have different preferences.

5.1 General Form of a Utility Function

To create an example utility function, a goal must be defined, such as: imaging a given area of the flat ocean floor via survey to locate an object the size of a small automobile using side scan sonar, while traveling at 4 knots and maintaining an elevation of 100 m. Next, relevant attributes that influence the decision are considered, such as sonar frequency, transmit bandwidth, and ping rate [6, 7]. Assuming a scenario in which all sonars are otherwise equal, the general form of the overarching utility function will take the form:

$$u = \left[k_F * u_F(F)\right] + \left[k_P * u_P(P)\right] + \left[k_B * u_B(B)\right] \tag{2}$$

5.2 Operator-Specific Utility Function

For this paper, three AUV operators were interviewed to determine their payload decision making preferences. Operator 1 has project engineer experience with the U.S. Navy's Salvage and Diving Command. Operator 2 has technical engineering experience with the U.S. Naval Sea Systems Command. Operator 3 has project management experience with a commercial vehicle operation company. The operators were presented with the abovementioned assumptions and attributes under consideration, with all other attributes behind held constant. Given these assumptions and using the technical specifications of commercially available sonars to approximately bound the equations, attribute-specific utility functions for Operator 1 were plotted as shown in Figs. 1, 2, and 3:

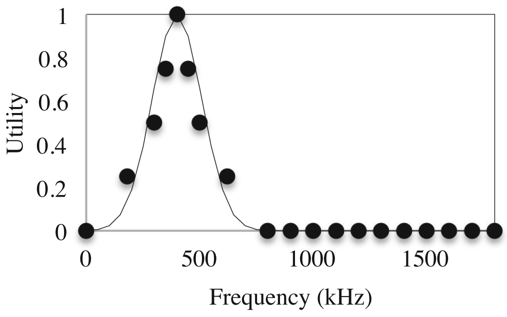

Fig. 1. Operator 1 frequency utility as a function of frequency (kHz).

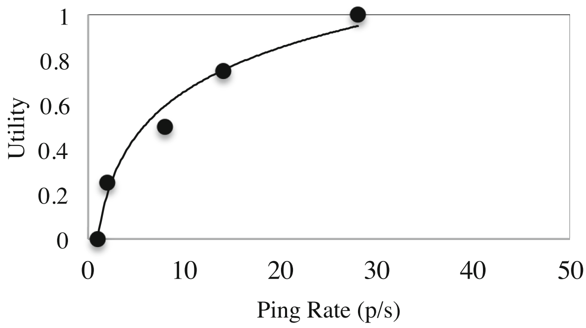

Fig. 2. Operator 1 ping rate utility as a function of ping rate (ping/s).

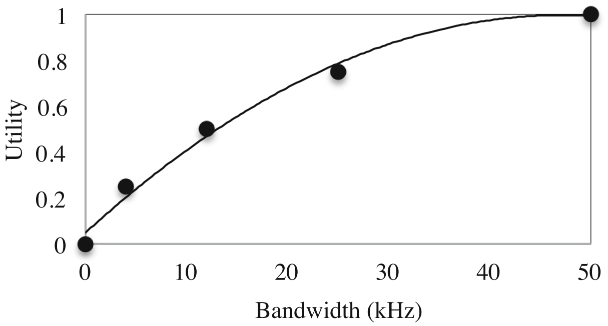

Fig. 3. Operator 1 bandwidth utility as a function of bandwidth (B).

The equations for the trendlines fitted through these plots are:

$$u_F = e^{\frac{-(F-400)^2}{24,000}} \tag{3}$$

$$u_P = \begin{cases} -0.0004B^2 + 0.04B + 0.05 & \text{for } B \leq 20 \\ 1 & \text{for } B > 20 \end{cases} \tag{4}$$

$$u_B = 0.28 \ln P + 0.004 \tag{5}$$

For Operator 2, these functions are represented by Figs. 4, 5, and 6:

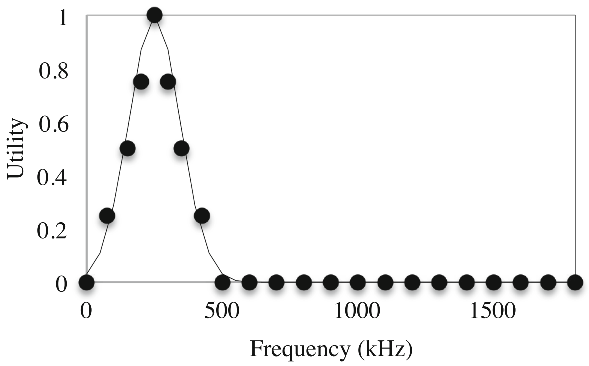

Fig. 4. Operator 2 frequency utility as a function of frequency (kHz).

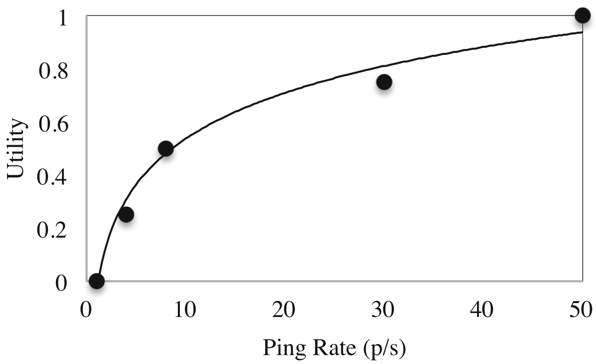

Fig. 5. Operator 2 ping rate utility as a function of ping rate (ping/s).

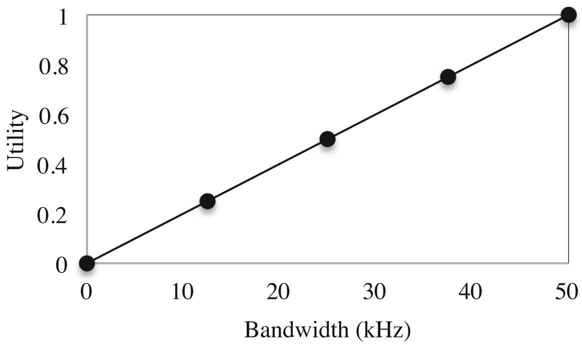

Fig. 6. Operator 2 bandwidth utility as a function of bandwidth (B).

And:

$$u_F = e^{\frac{-(F-250)^2}{18,000}} \tag{6}$$

$$u_P = 0.25 \ln P - .04 \tag{7}$$

$$u_B = 0.02B \tag{8}$$

For Operator 3, these plots and functions are depicted in Figs. 7, 8, and 9:

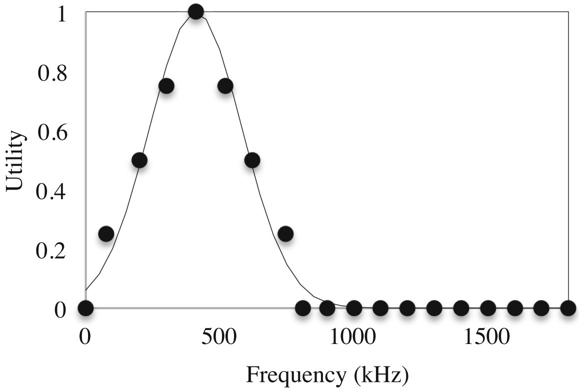

Fig. 7. Operator 3 frequency utility as a function of frequency (kHz).

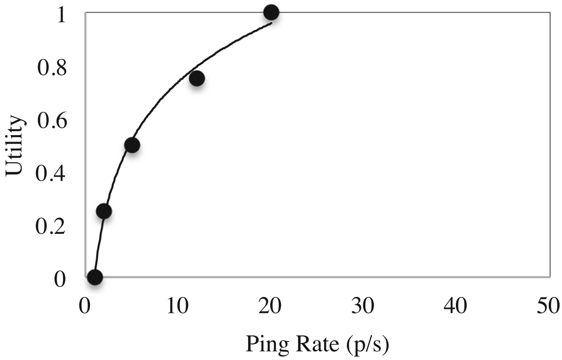

Fig. 8. Operator 3 ping rate utility as a function of ping rate (ping/s).

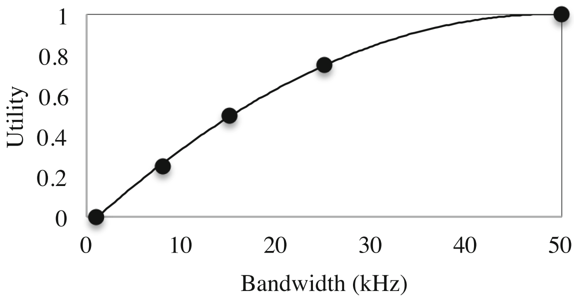

Fig. 9. Operator 3 bandwidth utility as a function of bandwidth (B).

And:

$$u_F = e^{\dfrac{-(F-410)^2}{60,000}} \tag{9}$$

$$u_P = \begin{cases} -0.0004B^2 + 0.05B + 0.04 & \text{for } B \leq 20 \\ 1 & \text{for } B > 20 \end{cases} \tag{10}$$

$$u_B = 0.31 \ln P + 0.003 \tag{11}$$

Once attribute-specific utility functions are established, additional interviews of the operators 1, 2, and 3, reveal the weights for each attribute utility to be shown in Eqs. 12, 13, and 14, respectively:

$$u_{Operator\,1} = 0.73u_F + 0.13u_P + 0.14u_B \tag{12}$$

$$u_{Operator\,2} = 0.85u_F + 0.07u_P + 0.08u_B \tag{13}$$

$$u_{Operator\,3} = 0.71u_F + 0.15u_P + 0.14u_B \tag{14}$$

Of note, operators 1 and 3 have similar project management backgrounds and produced similar utility functions, both in weight and form. Operator 2, however, has a stronger technical background and placed more emphasis than the other operators on the technical impact of frequency on resolution.

To test the validity of these equations for these operators, the theoretical sonars depicted in Table 1 were passed through Eqs. 12, 13, and 14.

Table 1. Theoretical sonars

Sonar	Frequency (kHz)	Ping rate (ping/s)	Bandwidth (kHz)
1	300	5	50
2	410	10	50
3	500	20	10

A ranking of most preferred to least preferred of these theoretical sonars was calculated for each operator using the above equations. Concurrently, these theoretical sonars were presented to the operators, who then ranked these sonars. The equation rankings and operator rankings from most preferred to least preferred are listed in Tables 2, 3, and 4, with calculated utility listed in parentheses next to each equation ranking:

Table 2. Operator 1 rankings of theoretical sonars.

	First preference	Second preference	Third preference
Equation ranking	Sonar 2 (0.75)	Sonar 1 (0.94)	Sonar 3 (0.65)
Operator ranking	Sonar 2	Sonar 1	Sonar 3

Table 3. Operator 2 rankings of theoretical sonars.

	First preference	Second preference	Third preference
Equation ranking	Sonar 1 (0.85)	Sonar 2 (0.33)	Sonar 3 (0.09)
Operator ranking	Sonar 1	Sonar 2	Sonar 3

Table 4. Operator 3 rankings of theoretical sonars.

	First preference	Second preference	Third preference
Equation ranking	Sonar 2 (0.87)	Sonar 1 (0.96)	Sonar 3 (0.81)
Operator ranking	Sonar 2	Sonar 3	Sonar 1

The equations for Operators 1 and 2 produced test results that matched the operator rankings on the first iteration. The equation for Operator 3, however, did not initially provide results that matched operator ranking. After presenting Operator 3 with the calculated utilities for the three sonars—specifically, how similarly-ranked sonars 2 and 3 were, Operator 3 conceded that he equally or nearly-equally preferred the equation ranking and his original ranking and agreed to the equation rankings. Because these two sets of rankings—from the equations and from the operators—eventually matched, these equations are reasonable bases on which to build more complete utility functions of side scan sonars for this mission.

6 Discussion, Conclusion, and Future Work

By applying utility theory to the decision making processes of AUVs in mission planning and replanning around failed payloads, AUVs can more robustly make decisions without real-time assistance from human operators. Instead, operator preference, as defined prior to mission performance, will influence these decisions. By taking into account multiple applicable attributes and multiple applicable types of missions, the vehicles can be programmed to handle a variety of alternate payload decisions, thus improving the likelihood that the mission goal is met. As the examples presented in this paper demonstrate, different operators will have different preferences. As such, the equations must be tailored to specific operators.

To transition this work from the theoretical to the practical, future efforts should include reconfiguring the logic of a vehicle controller to accept mission goals, rather than specific mission payloads and associated activities, as well as allowing the vehicle to calculate the utility of each payload for meeting mission goals, as defined by the equations created by the process outlined in this paper. Such modifications would allow the vehicle to initially plan the mission around the 'best' payload available and replan the mission around the next 'best' payload, in the event the initially-selected payload fails.

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