Development of dynamic safety envelopes for autonomous remotely operated underwater vehicles

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ABSTRACT: This paper describes the implementation of dynamic safety envelopes for autonomous remotely operated vehicles (AROVs). A safety envelope is defined as a three-dimensional spatial area around the AROV, which forms a virtual protective barrier against collision with known and unknown obstacles in the subsea environment. The Octree method is used to setup the cuboidal shape of the proposed safety envelope. A fuzzy inference system (FIS) is modeled to derive the size of the dynamic safety envelope. The three inputs of the proposed FIS are vehicle velocity, probability of acoustic sensor failure and time to collision risk indicator. A user interface allows for verification and visualization of the resulting dynamic safety envelope during live laboratory tests. The results show that similar to vehicular envelopes in other industries, dynamic safety envelopes can be implemented on AROVs. The proposed dynamic safety envelope may be used to model the behavior of AROVs when confronted with different collision scenarios.

1 INTRODUCTION

Globally, numerous research initiatives are investigating the use of autonomous remotely operated underwater vehicles to perform subsea inspection, maintenance, and repair (IMR) operations (Jamieson et al. 2012, Furuholmen et al. 2013, Mai et al. 2016, Gancet et al. 2016, Schjølberg et al. 2016). Autonomous remotely operatedc underwater (AROVs) are tethered/untethered underwater vehicles, which can independently control manipulator functions, permit shared control between the vehicle and the human operator. AROVs can navigate autonomously, perform self-diagnostics, and be equipped with remotely operated tool systems requiring limited operator control (Hegde et al. 2015). However, the introduction of autonomy in subsea IMR operations may also result in emerging risk factors. One such risk factor is the risk of collision posed by the use of AROVs (Hegde et al. 2016, Utne and Schjølberg 2014). Delayed IMR operations, loss of vehicle, loss of structural integrity may be some of the severe consequences of AROV collisions with the subsea structures, other AROVs and the seabed. Safeguarding the functions of subsea infrastructure and the AROVs is vital to ensure safe and cost efficient autonomous subsea IMR operations.

Studies to identify, assess, and avoid collision risk of vehicles are paramount for all vehicular systems. In the early 1970s, an increase in maritime traffic and need for safe envelopes around the marine vessel was highlighted by Fujii and Tanaka (1971). Influenced by the collision avoidance procedures in the aviation industry, Goodwin (1975) coined the term "*ship domain*". Goodwin (1975) defined "*ship domain*" as the "*sea around the ship, which the navigator would like to keep free, with respect to other ships and fixed objects*". Over the years, the size, shape, and the area covered by the ship domain has evolved continuously (Pietrzykowski and Uriasz 2009, Tam et al. 2009, Lewison 1978, Davis et al. 1980). Currently, in the automotive, maritime (surface vehicles), aviation and space industries, different forms of vehicular safety envelopes are utilized during operations. The primary aim of these vehicular envelopes is to suggest or autonomously modify the behavior of the vehicle when obstacles are detected inside the vehicular safety envelope.

Hegde et al. (2017) utilize the Octree method to design a static safety envelope for AROVs. The term safety envelope can be defined as *a 3D spatial area around the underwater vehicle forming a virtual protective barrier (in space and time) against collision with known and unknown obstacles in the subsea environment, influencing the behavior of the AROV* (Hegde et al. 2017). In a static safety envelope, the size of the envelope is constant and does not change during live IMR operations. This approach is valid when the AROV is in close proximity to the subsea equipment. However, when the AROV is moving from one location to another, a dynamic safety envelope may assist the AROV and the human operator to adapt and react to different collision scenarios. In addition, a dynamic envelope can reduce the need to detect obstacles by decreasing the area of the envelope. This can result in decreased data processing requirements for the on-board collision detection module. At this time, such dynamic vehicular envelopes do not exist for AROVs (Hegde et al. 2015).

The objective of this paper is to develop dynamic safety envelopes for AROVs, i.e., the size of the safety envelope changes depending on operational parameters of the AROV.

This paper is organized as follows: Section 2 presents the design of safety envelope. The elements of the proposed fuzzy inference system is described in Section 3. Section 4 describes the laboratory setup used to test the dynamic safety envelope. The results from the laboratory tests are presented in Section 5. The findings are discussed in Section 6. Section 7 presents the conclusions and future work possibilities.

2 DESIGN OF DYNAMIC SAFETY ENVELOPES

An Octree is used to generate the dynamic safety envelopes. Octree is a recursive tree data structure, which consists of spatial cubes named Octants. Each Octant can further be divided into eight child Octants. Figure 1 illustrates the Level 1 and the Level 2 Octree rendering with the AROV in the center of the Octree. In the Level 1 Octree, eight cubes surround the AROV and in the Level 2 Octree sixty four cubes surround the AROV. Each of the cubes are allocated an unique identifier and linked to a safe subsea traffic rule. The subsea traffic rule aims to maximize the horizontal and vertical seperation from the identified obstacle. If an obstacle is detected in one or more Octants, a suitable subsea traffic rule is suggested to the AROV or the human operator.

According to Hornung et al. (2013), there are four main reasons to use the Octree method for robot applications.

1. Octrees can establish virtual spatial grids around the robot, which can be used to check for collisions with the obstacles in all three axis.

2. The resolution of Octrees can be increased or decresed, which can result in detailed obstacle tracking, if required.

3. Measurement data from multiple sensors can be probabilistically represented using Octrees.

4. Both active and passive sensors can be used to check for collisions in known and unknown environments.

AROVs are also exposed to collisions with obstacles. Data from multiple active and passive sensors can be used to detect obstacles in the subsea enviornment. Therefore, use of the Octree method as highligted by Hornung et al. (2013) can also be extended to underwater vehicle applications.

In addition, the size of the of the Octree can increase or decrease the computational load in detecting the obstacle. If the safety envelope is static, the constant computations required may consume battery power by the AROV even when there are no obstacles in the vicinity. A dynamic safety envelope may lead to decrease in the computations required by limiting the collision detection module to an optimized Octree area. The next section explores the use of fuzzy logic to derive the size of the dynamic safety envelope.

3 FUZZY INFERENCE SYSTEM

Fuzzy logic delivers precise outputs from imprecise inputs. Input values are assumed to vary within a given range of values, which resembles real-life scenarios. Figure 2 is adapted from (Zadeh 2002, Zadeh 1996) and describes the overall methodology of a fuzzy inference system (FIS). In a FIS, input and output variables can contain n number of fuzzy sets with shared memberships among other fuzzy sets. This process of converting the crisp input to range values is known as fuzzification. A fuzzy operator is used to connect the antecedent (fuzzy inputs) to a consequent (crisp output) through an if-then logic. Defuzzification is achieved by calculating the membership of input variable fuzzy sets against the output variable fuzzy sets. Defuzzification results in a crisp value that can further be used as input to make decisions. Fuzzy inference systems are useful in two main use cases: first, to model systems that are highly complex and when the systems behavior is vaguely understood; and second, where an approximate, but quicker solution is acceptable.

Scikit Fuzzy, a fuzzy logic module in Python programming language is utilized to set up the proposed FIS (Warner et al. 2017). Figure 2 provides an overview of the proposed FIS, which has three input variables and one output variable.

3.1 *Fuzzification of variables*

Three input variables (operational performance indicators of the vehicle) are identified to influence the output variable i.e., the size of the safety envelope. This means that it is assumed that the vehicle performance influence the safe operation. This subsection describes the fuzzification of the input and output variables.

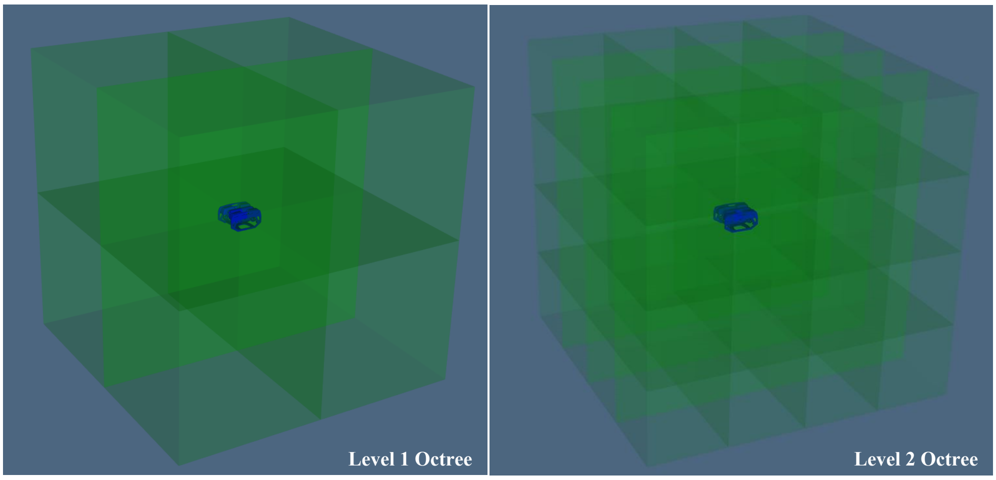

Figure 1: Rendering of static safety envelope for AROVs as proposed by Hegde et al. (2017)

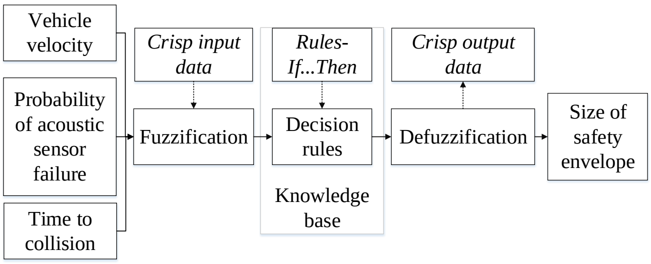

Figure 2: Overview of the proposed fuzzy inference system

3.1.1 *Vehicle velocity*

Considering the kinetic energy of a moving vehicle, the velocity at which the vehicle moves can influence collision detection and avoidance ability of the underwater vehicle. An AROV traveling at high velocity can result in a faster approach to a potential obstacle. This means that the time needed to detect and avoid the collision scenario is inversely related to the velocity of the underwater vehicle. Therefore, vehicle velocity (vv) is used as one of the inputs in the proposed FIS. Three membership functions for the vehicle velocity input are assumed, namely low, medium and high.

The FIS was modeled according to the technical specifications of the Blue Robotics BlueROV2. The maximum achievable velocity of the BlueROV2 vehicle is 1 m/s (Blue Robotics 2017). Figure 3 illustrates the resulting membership functions (MFs) for vehicle velocity input. The three MFs are low, medium and high. The low velocity MF ranges from 0 to 0.4 m/s. The medium velocity MF ranges from 0.2 to 0.8 m/s and high velocity MF ranges from 0.8 to 1 m/s.

3.1.2 *Probability of acoustic sensor failure*

Stovner et al. (2017) demonstrate use of underwater acoustic sensor grid to aid localization capabilities of the AROVs. A grid of acoustic sensors is used to communicate with and track the position of the AROV during IMR operations. However, failure of one or more subsea acoustic sensors may result in inaccurate position, orientation and velocity estimates. Re-

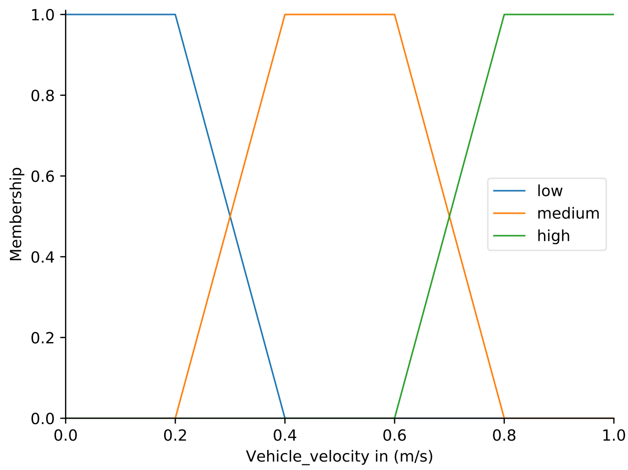

Figure 3: Membership functions for vehicle velocity (m/s)

liable measurements of vehicle position, orientation, and velocity are important to safely navigate in the subsea enviornment. Failure of acoustic sensors may lead to increased risk of collision or loss of the AROV. It is therefore, important that AROVs use the available acoustic sensor information to make informed decisions.

In this paper, the acoustic grid consists of four acoustic transducers on the bed of the pool and two acoustic transducers on the AROV as illustrated in Figure 7. Acoustic transducers placed on bed of the pool can communicate with the transducers on the AROV. This results in an acoustic network with eight possible range (distance) measurements. A minimum of four range values are needed for the acoustic positioning system to be classified as reliable. If there are fewer than four range measurements, the resulting estimates (position, orientation and velocity) are assumed to be unreliable. In such scenarios, the acoustic localization system is categorized as failed i.e., the probability of acoustic sensor failure is 1. Failure is defined as the termination of the ability of a functional unit to provide a required function or operation of a functional unit in any way other than as required (IEC 61508 2009). Therefore, the acoustic sensor voting scheme is $4oo8$ (four out of eight). In a failed state, it is vital that the safety envelope around the AROV increases in size.

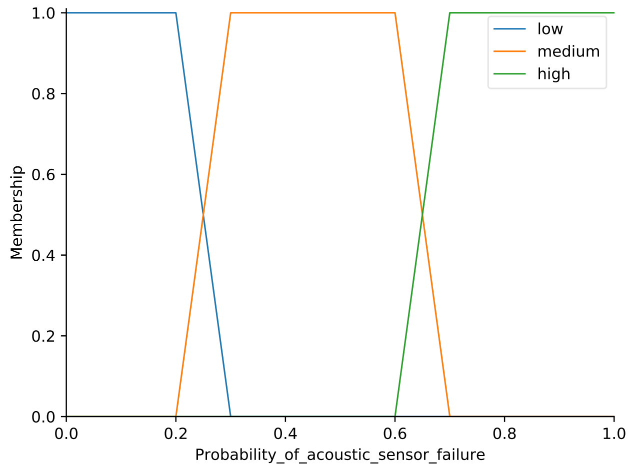

Figure 4: Membership functions for probability of acoustics sensor failure

Figure 4 illustrates the membership functions of the probability of acoustic sensor failure. A trapezoidal membership function (TRAMF) is used to signify that at certain range of input values the membership is unity (1). As shown in Figure 4, the probability of the acoustic sensor failure variable consists of three MFs, namely low, medium and high. The low MF ranges from probability 0 to 0.3. The medium MF ranges from probability 0.2 to 0.7 and the high MF ranges from probability 0.6 to 1.

3.1.3 *Time to collision*

In the automotive and aviation industry, the time remaining for the vehicle to collide with an obstacle is used to suggest collision avoidance maneuvers. The term time to collision (TTC) is used to convey the criticality of the collision scenario. The lower TTC, the greater the risk of collision with the obstacle. In the Traffic Collision Avoidance System (TCAS), the value of TTC is utilized to calculate the criticality of the obstacle (US Department of Transportation and Federal Aviation Administration 2011).

Hegde et al. (2016) apply the TTC as a risk indicator that can indicate risk of collision in a given AROV path. The TTC can be classified as an operational parameter, in that it can change as the vehicle velocity and the distance to the obstacle varies. As AROVs are required to navigate through the subsea infrastructure, they may face many obstacles in their path.The TTC risk indicator can aid in classifying critical obstacles by monitoring continously. TTC is calculated by using Equation 1

$$Time\,to\,collision = \frac{Distance\,to\,obstacle}{Resultant\,velocity\,of\,AROV} \tag{1}$$

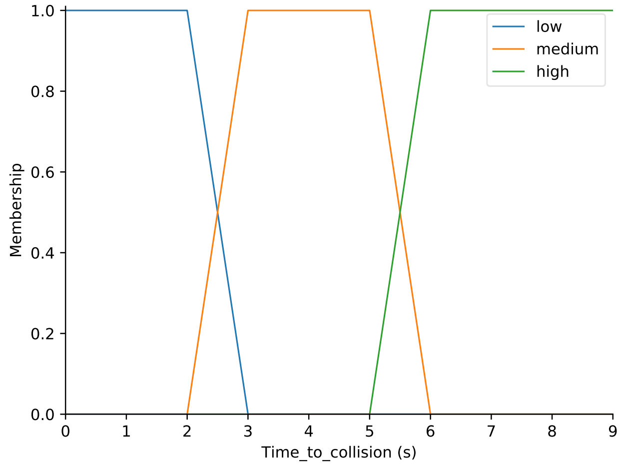

Figure 5: Membership functions for time to collision (s)

A recommended standard for autonomous subsea IMR also highlights the need for monitoring all existing obstacles in the vicinity of the subsea production system (Germanischer Lloyd Aktiengesellschaft 2009). Therefore, the inclusion of the TTC indicator in the proposed FIS allows the AROV to not only monitor the obstacles, but also devise collision avoidance behavior if they are under a threshold value. In the proposed FIS, the threshold values relate to the MFs. Three MFs are determined for the TTC input variable, namely low, medium and high. The low MF of TTC ranges from 0 to 3 s. The medium and high MF range from 2 to 5 and 5 to 10 s respectively.

3.1.4 *Size of safety envelope*

The output variable in the proposed FIS is the size of the safety envelope. The safety envelope is realized in form of a cuboid. Therefore, the FIS output: size of the safety envelope will increase or decrease uniformly along all three axes *North, East and Down*. The size of the safety envelope is proportional to the velocity of the vehicle and probability of acoustic sensor failure (PASF) and inversely proportional to the time to collision input. In short, the safety envelope size increases when vehicle velocity and PASF increase and decreases when TTC value increases. A large safety envelope reflects a low safety margin whereas a small safety envelope reflects high safety.

Figure 6 illustrates the MFs for the FIS output variable. The size of the safety envelope is classified into three MFs, namely small, medium and large. The MF for the small safety envelope ranges from 0 to 4 m. The MF for the medium safety envelope ranges from 3 to 7 m and the MF for the large safety envelope ranges from 6 to 10 m.

3.2 *Fuzzy rule set*

Once the fuzzy sets of input and output variables are determined, the next step is to define fuzzy rules by combining the input and output variables using logic

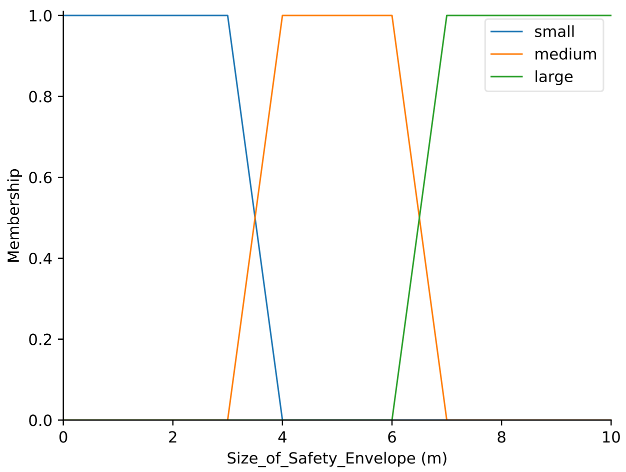

Figure 6: Membership functions for size of safety envelope (m)

statements. Table 2 lists the twenty seven fuzzy rules resulting from the three input variables. The fuzzy logic operator AND is used to derive the inference from input variables.

It has to be noted that the input variables and their influence on the output variable is different. For example, a low TTC is not favorable as this would mean that the obstacle is in close proximity to the AROV. On the other hand, low vehicle velocity and PASF are favorable. Relative importance of inputs are not considered in this paper. Weights are not allotted to the input variables and therefore the fuzzy rule set do not favour certain rules over others. All rules are given equal importance.

3.3 *Deffuzification*

The process of obtaining crisp values from fuzzy inputs is known as defuzzification. The Scikit Fuzzy library supports numerous defuzzification methods, such as centroid, bisector, mean of maximum (mom), min of maximum (som) and max of maximum (lom) (Warner et al. 2017). Centroid defuzzification method is used in this paper because it provides conistent crisp output values when compared to other deffuzification methods within the uncertainty constraints. The centroid defuzzification method aggregates the total area under the membership functions of the input variables and calculates the centroid of the combined area (Sivanandam et al. 2007).

4 LABORATORY SETUP AND TESTING

Figure 7 illustrates the laboratory setup to test the dynamic safety envelopes. The Mission Orientated Operating Suite (MOOS) middle-ware (Newman 2006) stores and retrieves information from the AROV. Four acoustic sensors are installed on the bed of the pool and two on the AROV. The acoustic sensors provide the localization measurements, such as position of obstacle and AROV, velocity and orientation of

Table 1: Rule sets in the fuzzy inference system. vehicle velocity (VV), probability of acoustic sensor failure (PASF), time to collision (TTC)

Rule number	Antecedent: VV & PASF & TTC	Consequent: Size of safety envelope
1	Low & Low & Low	Large
2	Low & Low & Medium	Medium
3	Low & Low & High	Small
4	Low & Medium & Low	Large
5	Low & Medium & Medium	Medium
6	Low & Medium & High	Medium
7	Low & High & Low	Large
8	Low & High & Medium	Large
9	Low & High & High	Large
10	Medium & Low & Low	Large
11	Medium & Low & Medium	Medium
12	Medium & Low & High	Medium
13	Medium & Medium & Low	Large
14	Medium & Medium & Medium	Medium
15	Medium & Medium & High	Medium
16	Medium & High & Low	Large
17	Medium & High & Medium	Large
18	Medium & High & High	Large
19	High & Low & Low	Large
20	High & Low & Medium	Large
21	High & Low & High	Medium
22	High & Medium & Low	Large
23	High & Medium & Medium	Large
24	High & Medium & High	Large
25	High & High & Low	Large
26	High & High & Medium	Large
27	High & High & High	Large

the AROV. The localization module shares the data with MOOS. The shared control module retrieves data from the localization module via MOOS and utilizes it to control the AROV either autonomously or via shared control between the AROV and the AROV supervisor. The communication to the AROV is established through an umbilical.

The collision avoidance module posts and retrieves collision data to and from MOOS. The two parts of the collision avoidance module are the dynamic safety envelope and the subsea traffic rules. The subsea traffic rules are set of assigned safe navigation maneuvers that can be performed by the AROV to increase the vertical and/or horizontal separation (distance) from the obstacle (see Section V of Candeloro et al. (2016)). The subsea traffic rules are developed based on the rules from collision regulations (COLREGs) in the maritime and from the TCAS in the aviation industry. Each Octant in the Level 2 Octree in Figure 1 is assigned a subsea traffic rule to maximize vertical and/or horizontal separation from the obtascle.

The pseudocode implemented to derive the dy-

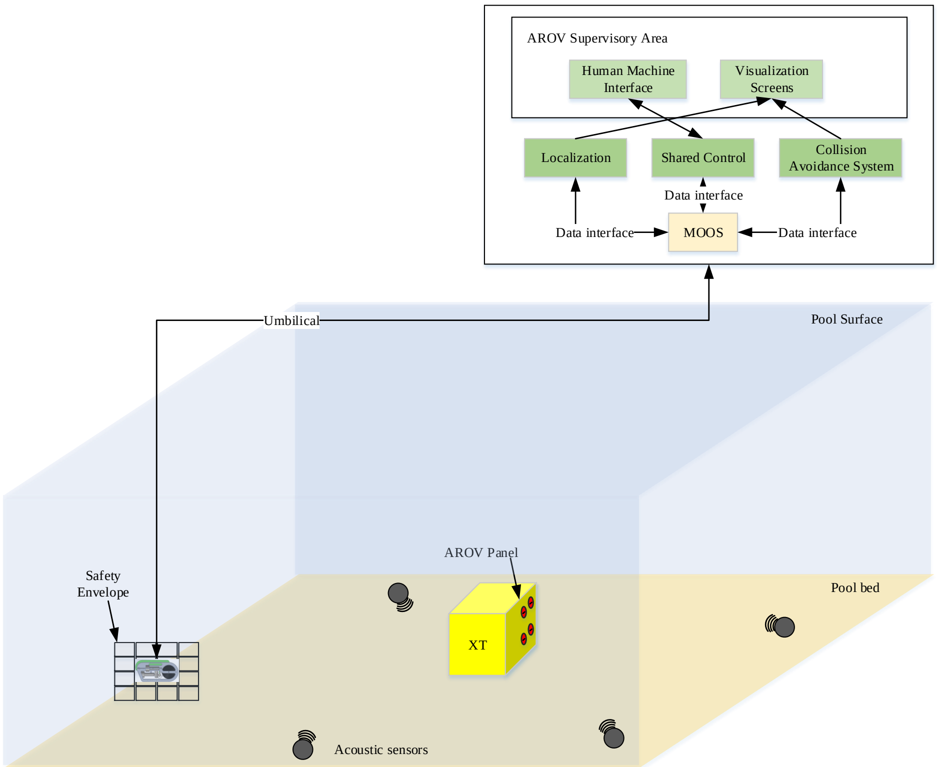

Figure 7: Laboratory setup to test feasibility of dynamic safety envelopes

namic envelopes from the proposed FIS is as listed in Listing 1. The first step is to retrieve the velocity and position variables from MOOS followed by the distance to the potential obstacle. Then the available acoustic ranges are counted and a sensor voting scheme of $4oo8$ is used to derive the PASF. The velocity of the AROV, distance to the obstacle are used to calculate the TTC. When the input data are collected, they are routed to the FIS as described in Figure 2.

The FIS computes the new size of the safety envelope and publishes the new size of the safety envelope to MOOS. The 3D renderer updates safety envelopes to the new size and the detection algorithm updates the potential detection volume.

Listing 1: Pseudocode of FIS implementation in the underwater collision avoidance system

```
#Initialization
Get position, velocity of AROV and obstacle
Get count of acoustic sensor ranges
Get envelope size

#Dynamic safety envelope
Set MFs for VV, PASF, TTC
Set fuzzy rule set
Compute PASF and TTC
Compute new size of safety envelope (FIS)
Update envelope size to new size
Update detection volume to new size

#Collision detection
Make empty list collisions
If new envelope collides with world:
   for each octant in new envelope:
      If octant collides with world:
         append octant to collisions
```

5 RESULTS

In Figure 8, the Vehicle velocity is 0.02 m/s (MF = low) and PSAF is 0 (MF = low) and TTC is 391.01 s (MF = high). These inputs result in application of Rule 6. The resulting size of safety envelope is 1.76 m (MF = small). In Figure 9, the Vehicle velocity is 0.03 m/s (MF = low) and PSAF is 0.38 (MF = medium) and TTC is 391.01 s (MF = high). These inputs result in application of Rule 6. The resulting size of safety envelope is 5.00 m (MF = medium). Observations from the laboratory tests are as listed in Table 2.

Table 2: Observations from laboratory tests

Data point	VV (m/s)	PASF	TTC (s)	Size of safety envelope (m)
1	0.02	0	449.12	1.76
2	0.24	0	22.12	2.49
3	0.63	0	16.52	5.00
4	0.03	0.38	391.01	5.00
5	0.25	0	18.52	2.58
6	0.20	0.12	12.69	1.83
7	0.33	0.25	5.68	3.68
8	0.36	0.25	10.56	4.11

6 DISCUSSION

This section discusses the learnings from the process and the impact to industrial applications through the development of the proposed dynamic envelopes.

The key drivers in development of safety envelopes in the aviation and maritime industries (TCAS, Ship

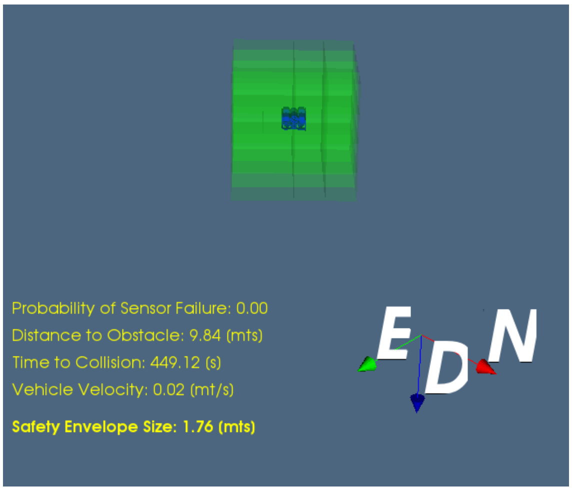

Figure 8: Rendering of data point 1

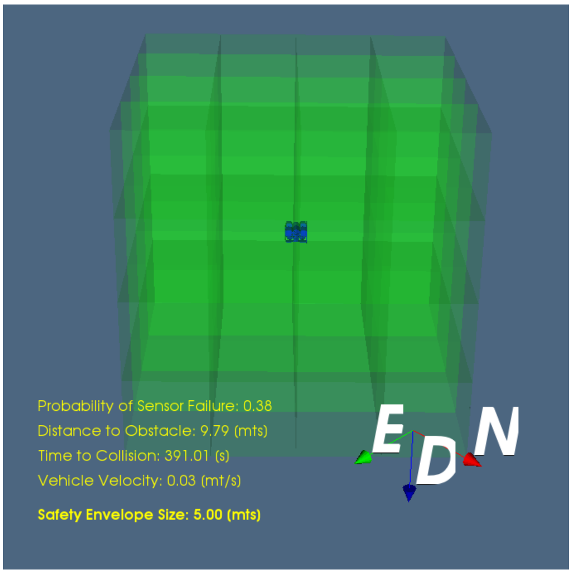

Figure 9: Rendering of data point 4

Domain) are asset/personnel safety and ability to design an intelligent collision avoidance systems. By fusion of both active and passive sensor technologies, the safety envelopes in the aviation, maritime (surface vehicles) and automotive industries currently utilize dynamic safety envelopes. In comparision, current remotely operated vehicles are controlled by human operators. In the future, AROVs will also need to be able to make decisions both in presence or in absence of the human operators. Development of dynamic safety envelopes can be seen as the first step towards ensuring asset safety of AROVs by identifying, assessing, and mitigating the risk of underwater collisions.

As applications of AROVs to inspect and repair subsea production systems, offshore aquaculture systems, offshore wind turbines and facilitate subsea mining, asset safety of AROVs is vital. The proposed process to build dynamic safety envelopes using fuzzy logic allows the system developers to tweak the membership functions and fuzzy rule sets according to their respective industrial requirements. This allows for application specific dynamic safety envelopes. For example, requirements for dynamic safety envelope for subsea IMR operations and subsea mining operation may vary as the later is more vulnerable to seabed collisions than collisions with the man-made subsea structures.

Use of fuzzy logic (expert-based systems) ensures that the system developers can understand the inherent behaviour of the system under different input conditions. However, two limitations of fuzzy logic in engineering applications can be highlighted. First, fuzzy logic is a form of deductive reasoning i.e., to conclude on a specific truth by using generic inputs (Ross 2009). An example for deductive reasoning is the ground is wet (input) therefore, it must be raining (truth). Second, the subjective nature of defining the membership functions of the fuzzy variables and deriving fuzzy rule set can be challenging. This is true for any technical system where experts are needed to provide input and they can disagree with each other's judgment. For example, in the proposed fuzzy rule set, weightage to different inputs are not implemented. All rules and input values are given the same importance. In the future, a modification may be necessary to include the relative importance of input variable. Is the TTC more important than PASF and VV or vice-versa?

The proposed dynamic safety envelopes are highly dependent on availability of reliable sensor measurements. The laboratory setup used in this paper consists of a grid of six acoustic sensors providing eight range measurements. Measurements from the acoustic sensors were used as the primary input to calculate the orientation, velocity and position of the AROV and the obstacle (passive sensor grid). However, the advantage of the proposed dynamic envelopes is that it can be easily modified to include input from either passive or active sensors. For example, active sensors, such as sonar and LiDAR can detect both known and unknown obstacles. This is possible because of the underlying architecture of the implemented 3D rendering program, which allows for scalability. In addition, if the sensor module comprises of redundant sensors, failure of one sensor type can be tolerated by the overall collision avoidance system. For example, if the acoustic position sensor fails to measure the depth of the AROV, measurements from a dedicated depth sensor can still provide a reliable source to the proposed FIS.

7 CONCLUSIONS

This paper proposes a novel approach to developing dynamic safety envelopes for autonomous remotely operated vehicles (AROVs). A proof-of-concept of the dynamic safety envelope is presented in this paper.

The proposed dynamic safety envelope was developed by using a fuzzy inference system (FIS) to adapt the size of the safety envelope. Three fuzzy input variables were used in the FIS, namely vehicle velocity, probability of acoustic sensor failure and time to collision. A FIS was implemented in an existing underwater collision avoidance system. Observations from the laboratory tests performed to verify the feasibility of dynamic safety envelopes are presented. Results show that the AROV safety envelope can increase or decrease in size depending on the three input variables. This allows the AROV to decrease or increase the obstacle detection area in a highly uncertain and sensitive subsea environment.

In presence of uncertainty, visualizations of obstacles that pose the risk of collision to the AROV may aid situation awareness of human operators. The size of the safety envelope can be used to make decisions related to maneuvering of the AROV either autonomously by the AROV or remotely by the human operator. To safely maneuver the AROVs during collision scenarios, further development and testing is required to implement dynamic safety envelopes together with the subsea traffic rules.

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