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# Fusing Sonars and LRF data to Perform SLAM in Reduced Visibility Scenarios

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*Abstract*—**Simultaneous Localization and Mapping (SLAM) approaches have evolved considerably in recent years. However, there are many situations which are not easily handled, such as the case of smoky, dusty, or foggy environments where commonly used range sensors for SLAM are highly disturbed by noise induced in the measurement process by particles of smoke, dust or steam. This work presents a sensor fusion method for range sensing in Simultaneous Localization and Mapping (SLAM) under reduced visibility conditions. The proposed method uses the complementary characteristics between a Laser Range Finder (LRF) and an array of sonars in order to ultimately map smoky environments. The method was validated through experiments in a smoky indoor scenario, and results showed that it is able to adequately cope with induced disturbances, thus decreasing the impact of smoke particles in the mapping task.**

## I. Introduction

Lately, Simultaneous Localization and Mapping (SLAM) has been one of the most studied subjects in Robotics. It is a fundamental process which is responsible for building maps and, at the same time, estimating the robot's pose in the environment. SLAM is essential for autonomous mobile robots to accomplish useful tasks with no *a priori* information about the environment. There are many approaches to the SLAM problem [5] and each of them focuses on a particular issue. In spite of the evolution of SLAM in the last years, for example to scale proposed techniques to large environments [6] or performing SLAM with multiple mobile robots [9], there are still many open challenges, such as dealing with smoky, dusty, or foggy environments, where commonly used range sensors for SLAM, such as Laser Range Finders (LRFs), stereo vision rigs, or RGB-D sensors, are highly disturbed by noise induced by particles of smoke, dust, or steam.

This work is part of the CHOPIN project [15] which addresses Search and Rescue (SaR) missions in urban catastrophic scenarios, *e.g.* a fire in a large basement garage, by exploiting the human-robot symbiosis. These scenarios are usually associated with environments with reduced visibility, which drastically decrease the progress of human rescuing forces and the accuracy and robustness of robots sensorial system, thus compromising mobile robots' SLAM and navigation system. Moreover, mobile robotics is a field which is highly in focus and its techniques are constantly evolving, therefore it is foreseeable in the short- and mid-term future that mobile robots will assist and even replace human operators in dangerous, dull or dirty tasks, which are still performed by humans nowadays. This is the case of SaR missions which take place in extreme conditions and pose very difficult challenges, including navigating in reduced visibility conditions. The applicability of SLAM methods in these situations is scarce. Hereupon, it is necessary to develop new techniques.

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This work addresses the problem of successfully performing SLAM in environments with reduced visibility conditions. Existing SLAM approaches require a "clean" environment so that commonly used range sensors based on light propagation, *e.g.*, LRF, stereo vision, Time-of-Flight (TOF) cameras, *etc.*, are not disturbed by particles of smoke, dust or steam. Robots' perception can significantly benefit from fusing sensing information from different sources. This paper proposes a fuzzified multimodal sensor fusion between sonars, laser and an alcohol sensor, so as to overcome the lack of visibility and noise induced by smoke particles. The output of the fuzzy system corresponds to a normalized confidence measure for each sonar reading and corresponding section of the laser. In the next section, related work on SLAM in such environments is reviewed. Afterwards, preliminary tests are conducted and the main technical issues involved in this work are discussed. Next, an algorithm that explores the complementary characteristics of LRFs and sonars is described and validated through experiments in a room partially obscured by smoke. The mapping task using our approach is compared to a common SLAM method that does not consider the smoke phenomenon. This evaluation is discussed in section V. Finally, the work ends with conclusions.

## II. Related Work

SLAM techniques have evolved substantially for the past decade. Nevertheless, most approaches do not consider environments disturbed by smoke, dust or steam. When the scenario has reduced visibility, the majority of SLAM algorithms fail or present unsatisfactory results. The lack of visibility in the environment represents a challenge for SLAM algorithms, since it can partially or totally obscure the field of view (FOV) that is used to map the scenario.

Brunner *et al.* [1] proposed a SLAM approach robust to smoke based on different sensing capabilities of visual cameras and Thermal Imaging Cameras (TIC). The fundamental idea was to counterbalance the limitations of the visual camera in the presence of smoke with the robustness of a TIC in these situations. Experiments were performed in a smoky scenario using a robot equipped with a Raytheon Thermal-Eye 2000B Infrared (IR) camera and a Point Grey Bumblebee XB3 camera set. Smoke was generated using a smoke machine. The authors concluded that a reasonable algorithm can be obtained, but the localization accuracy decreased in the presence of smoke when only data from the TIC was used.

Deissler *et al.* [4] presented a SLAM algorithm based on a Ultra-Wideband (UWB) radar with a bat-type antenna array. This algorithm was developed for catastrophic scenarios where the environment is corrupted with smoke or dust. Since it is a radar-based approach, the smoke/dust particles in the environment do not affect this algorithm. The biggest challenge is data association, *i.e.* assigning the time of flight of a given measurement from the radar to the corresponding landmark [4]. This situation is solved using a Rao-Blackwellized Particle Filter (RBPF). A two-dimensional geometrical algorithm is used to determine the features in the environment. The RBPF is used only for the data association process and an Extended Kalman

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Filter is used to estimate the state vector. The algorithm was tested through simulations and data acquired previously. The authors concluded that the different propagation characteristics of walls, corners and other features in indoor environments can be used to distinguish those features, locate them, and use them as landmarks for navigation [4].

Castro *et al.* [2] proposed a reliable perception system based on sensor fusion between a millimeter-wave radar and a Laser Range Finder (LRF). Although the LRF cannot penetrate heavy dust and smoke, the mm-wave radar can. The matching between LRF scans and radar scans is done by computing the 3D Euclidian distance between each laser point and the closest radar target. The experiments were done using an all-terrain UGV equipped with 4 LRFs and a FMCW Radar. The results obtained in two different areas showed that most dust points in the LRF scans were removed. However, some dust points (false negatives) remained. Marti *et al.* [11] addressed mobile robot navigation in smoky areas by using visual artificial landmarks.

Pascoal *et al.* [12] carried out a set of tests in order to analyze the behavior of distinct LRFs within low visibility scenarios. Smoke was progressively injected in the scenario using a smoke machine, and spread by means of a ventilator. The main conclusions obtained in these benchmarking experiments were that all the LRFs tested provide different levels of noisy and erronous results with saturated outputs, which makes them almost unusable in these conditions. Similar conclusions were obtained in [16]. In a recent comparison [13], the Hokuyo URG-04LX, which was used in the experiments reported in section V, presents the highest values of disparity and error in depth measurements of all compared LRFs.

As distinct to previously described works, we propose in this work a multi-sensor approach based on a LRF and a sonar array which, in spite of being based on an affordable setup using only off-the-shelf sensors, might provide a robust solution when LRF measures are partially disturbed by the presence of particles that compromises visibility.

## III. SLAM UNDER LOW VISIBILITY CONDITIONS

The implementation of a SLAM technique hugely depends on the correct choice of sensors, which is related with the environment where the robot will operate. The accuracy of most range sensors decreases drastically under low visibility conditions. The most evident solution to this situation is fusing data from different types of range sensors, by using one optical-based range sensor (LRF, stereo camera, *etc.*) that is ideal in normal visibility conditions with another sensor that is less disturbed or immune to visibility disturbances, though providing sparser or less accurate range measurements. Examples include LRF with sonars, LRF with TOF cameras and sonars, *etc*.

As mentioned before, LRFs are one the most adopted range sensors in 2D SLAM algorithms. They are extremely accurate in clean environments and easy to use. However, the main goal in this work is to develop and verify a SLAM approach in environments with smoke, dust or steam particles, which easily corrupt LRF readings. In order to decrease the impact of such disturbances in 2D laser-based SLAM algorithms, multimodal sensor fusion is required.

The mobile robot used in our work was a Nomad Scout, a differential mobile robot equipped with an array of 16 uniformly distributed sonars. These sensors are Polaroid transducers with a beam angle of $20^o$ and a maximum range of about 5 m. Sonars use the propagation model of acoustic waves at higher frequency than normal hearing to extract information of the surroundings. Since they use acoustic waves, they are virtually immune to low visibility conditions. As mentioned before, the LRF used in all the experiments reported herein

(a) The Nomad Scout. (b) Experimental conditions.

Fig. 1: The experimental setup used in this work.

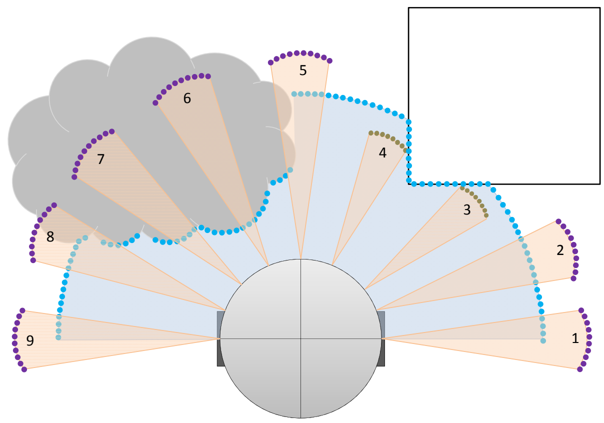



Fig. 2: Nomad Scout sensors arrangement: LRF readings (blue dots) vs. sonar array readings (purple dots).

was an Hokuyo URG-04LX. It has a maximum range of 5.6 m, an angular resolution of about $0.36^o$ and a FOV of $180^o$. Since the FOV of the sonar array is $360^o$, only 9 sonars (*cf.* Fig. 2) are considered in this study in order to guarantee a common area with range data information from both sensors.

### A. Sensor Limitations

Before proceeding to the development of the proposed multi-sensor fusion method to perform SLAM under reduced visibility conditions, it is necessary to study the behavior of the selected sensors in several situations. A special case is the behavior of the LRF in smoky environments.

In order to further understand this behavior and have some useful data for the development of the method proposed in section IV, some preliminary tests were carried out. However, it was not possible to reproduce a test with smoke from a typical firefighting scenario. The Nomad Scout equipped with the Hokuyo LRF was placed in front of a flat wall and smoke was injected between the robot and the wall. The smoke machine used was a Magnum 800[1]. Fig. 2 illustrates an example of the behavior of the LRF sensor in the presence of smoke. In order to successfully perform a mapping task in these conditions, it becomes clear that the sonar ring available can be useful to compensate the misreadings of the LRF, because sonars can measure through the smoke.

Other challenging situation occurs when the robot turns. If the environment is filled with smoke, the LRF will return wrong measures, and it may happen that the sonar ring may return similar values due to its low resolution that is extremely

[1] http://www.martin.com/product/product.asp?product=technofog&newseg=ent&mainseg=ent

problematic in robot rotations. Therefore, to overcome this situation, not only we disregard sonar readings beyond 2.5 m, but also included an additional sensor to inform about the concentration of smoke in the environment. In this work, we used an alcohol sensor due to the nature of the smoke used in our experiments, as it will be detailed later on.

### B. *SmokeNav approach*

In a previous work [10], several SLAM methods available in the Robot Operating System (ROS) [14] were analyzed. The evaluation conducted served as a guide for choosing the most suitable technique to adopt in this work. According to the obtained results, *GMapping*, an implementation of the RBPF algorithm proposed by Grisetti *et al.* [8], appeared to be one of the most accurate and robust approaches. It makes use of scan matching and odometry to improve the efficiency of its particle filter and, since the Nomad Scout provides fairly accurate pose information, it was considered the most suitable choice.

On one hand, the ROS driver of the Nomad Scout retrieves the sonar information in a sonar range message. On the other hand, *GMapping* was developed to work with LRFs and receives laser scan data as input. The code of the *GMapping* algorithm could eventually be changed to accept both type of messages. However, the proposed approach for reduced visibility scenarios would be restricted to the use with this particular algorithm which is not advantageous. The idea behind this work was to provide a multimodal sensor fusion layer, denoted hereafter as *SmokeNav*, which fuses the output of each sensor and adjusts, rectifies or ignores that information according to the measurement context. This layer adapts to any set of range sensing data and provides the filtered data to potentially any generic 2D SLAM algorithm under low visibility conditions, in the form of a combined *LaserScan* message.

In this paper, the set of sensors is restricted to a LRF and a sonar array. So, it is necessary to convert to a *LaserScan* message type the sonar data that is received as sonar range messages from the ROS driver of the Nomad Scout mobile robot. The worst-case situation for the SLAM algorithm is when the smoke concentration is so high that the entire LRF readings are corrupted. In such extreme case, the mapping task must be done using only the sonar ring. Therefore, it is important to verify if this conversion allows *GMapping* to successfully map the environment using only sonar data. Yet, the quality of the resulting map is expected to be low, due to the low resolution and lower accuracy of sonars.

In order to assess the concentration of smoke particles, we would typically use a dust sensor. However, the smoke machine that was used in our experiments spreads a glycol-based vapor. So, an alcohol sensor was used instead to detect different concentrations of glycol-based vapor, thus emulating a dust sensor in a real scenario (*e.g.* indoor fire). The sensor model used was the MQ303A[2], which is manufactured by Seeed Studio, being the output voltage inversely proportional to the alcohol concentration in the air. By identifying the presence of smoke, the alcohol sensor provides a way of interpreting correctly data coming from both sensors in low visibility conditions.

Incorporating the alcohol sensor to assess the concentration of smoke in the environment contributed to the development of the proposed technique, as shown in Fig. 3. The algorithm receives messages from both range sensors and processes data by taking into account the time stamps of both scans. The information arriving from the alcohol sensor is constantly monitored to infer the visibility conditions of the environment.

[2]http://www.seeedstudio.com/depot/images/product/MQ303A.pdf

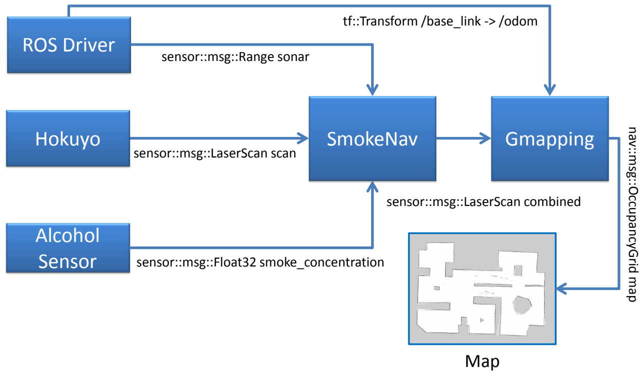



Fig. 3: Overview of the *SmokeNav* layer integration.

It should be noted that the data of each sensor is published at a rate of about 10 Hz.

The synchronization of messages from the sonar ring and from the LRF is possible due to the message filter API[3] available in ROS. Every time a *LaserScan* message and a *Range* message arrive, their time stamps are compared using an approximate time policy. After that, the ranges received are transformed from the sonar frame to the LRF frame, in order to analyze and compare both readings in the same reference frame. Each point given by a range message corresponds to a section of the sonar "scan". The section is determined by transforming the point to the polar form and using the FOV of the sonar. This is illustrated in Fig. 3.

## IV. Multimodal Sensor Fusion Method for Low Visibility Scenarios

The method proposed herein benefits from fuzzy logic [3] to handle the sensing information arising from the sonars, laser and alcohol sensor. Other proposals with different formalism to multimodal sensor fusion, such as Bayesian decision analysis [7], could be adopted as well. Nevertheless, fuzzy logic allows to address the problem in a natural way as it resembles human decision making with an ability to generate precise solutions from certain or approximate information. The successful development of a fuzzy model is a complex multi-step process, in which the designer is faced with a large number of alternative implementation strategies and attributes.

In sum, based on the information extracted from the inputs, namely the alcohol sensor, sonar and laser readings, the fuzzy logic system can infer normalized trust measures, which can be used to decide on whether to choose the sonars or the laser (Fig. 4). These two outputs can be perceived as the probability on trusting on a given sonar reading ($\rho_S$) or the probability on trusting on the laser readings within the same section of that sonar ($\rho_L$). It is noteworthy that these probability measures are not mutually exclusive. In other words, it is possible to reject the readings provided by both sources, *e.g.* if a high intensity of smoke detected by the alcohol sensor, a sonar reading above 2.5 m is likely to result in probabilities on trusting on either sources near zero. In these cases, *GMapping* will be fed with a value greater than the max range of the sensor, thus considering it as a saturated reading.

The control architecture presented in Fig. 4 is executed at each iteration $t$ and for each section $\sigma$ (Fig. 2), thus returning the probability of accepting the sonar $\sigma$ at time $t$, $\rho_S(\sigma,t)$, and the probability of accepting the laser readings from section $\sigma$ at time $t$, $\rho_L(\sigma,t)$. The inputs of the fuzzy

[3]http://wiki.ros.org/message_filters

system comprise the sonar reading from section $\sigma$, $s_R[\sigma, t]$, the alcohol sensor reading, $a_R[t]$, and the standard deviation of laser readings, $STD(l_R[t])$. The later was chosen to improve the decision mainly due to the alcohol sensor limitations, *e.g.* it is slow to recover when the smoke concentration is decreasing. By monitoring the standard deviation of the laser readings, it is possible to observe that the standard deviation of the laser readings significantly drops when affected by the smoke (Fig. 5). This is an expected behavior since the smoke tends to uniformly constrain the readings. Although experiments were carried out by considering the standard deviation, other measures of dispersion or correlation could be used.

As Fig. 4 depicts, the overall organization of this architecture resembles the commonly used feedback controllers wherein contextual knowledge is extracted from data, followed by a reasoning phase to provide the adequate information to the robot (*i.e.*, map and localization). Hence, based on the LRF, sonars, and the alcohol sensor, one can assess the relation between the inputs and outputs of the fuzzy system. The choice around this relation depends on the characteristics of the readings arising from each source.

Considering the characteristics of the sensors previously highlighted, and by observing Fig. 5, one can outline a considerably vague or fuzzy rationale: *"The laser readings may only be trusted when alcohol readings are below 20 or the standard deviation of the laser readings is above 0.8. If not, only trust the sonar readings if they are less than 2.5 m.*

Although the input information to the system may be imprecise, the results of fuzzy analysis are not. Fuzzy sets need membership functions, *i.e.*, mathematical equations that can take certain shapes. Examples of reasonable functions are $\Pi$-shaped and bell-shaped functions, because of their simplicity and efficiency when considering computational issues. In spite of this, and considering the above rationale, the membership rules represented in Fig. 6 and described below were defined.

The membership function $\mu_{s_R}(s_R[\sigma, t])$ represents how *Confident* the sonar is. The membership function $\mu_{a_R}(a_R[t])$ represents how *Alcoholized* the environment is. The membership function $\mu_{l_R}(STD(l_R[t]))$ represents how *Dense* the smoke is. As for the consequent functions, one can simply define the same bell-shaped membership relation for softening both outputs, as represented in Fig. 6.

The *Mamdani-Minimum* was used to quantify the premise and implication. The defuzzification was performed using the center-of-gravity (*CoG*) method [3]. The *CoG* is a continuous method and one of the most frequently used in control engineering and process modeling being represented by the centroid of the composite area of the output fuzzy term.

Considering the above rationale and figures, the following diffuse ***IF-THEN-ELSE*** rules are considered:

**if** $a_R[t]$ **is** Alchoholized **or** $STD(l_R[t])$ **is** Dense **then**
  $\rho_L(\sigma, t)$ **is** Laser-driven
**else if** $S_R[\sigma, t]$ **is** Confident **then**
  $\rho(\sigma, t)$ **is** Sonar-driven
**end if**

The decision on whether to choose the sonar or the laser at a given section $\sigma$ and time $t$ is then evaluated by simply comparing which one has a higher trust probability and if that trust probability is equal or superior to a given threshold. For instance, one will choose the sonar $\sigma$ at time $t$ over the laser readings within the same section if $\rho_S(\sigma, t) > \rho_L(\sigma, t)$ and $\rho_S(\sigma, t) > \rho_T$. In this work, we consider the threshold to be the expected value of a an uniform probability distribution with sample space between 0 and 1, *i.e.*, $\rho_T = \frac{1}{2}$.

TABLE I: Error estimation for each trial.

| Trial | With SmokeNav layer | Only LRF data | Sonar usage |
|---|---|---|---|
| 1 | 2.69 | 18.02 | 23.33% |
| 2 | 10.14 | 19.07 | 40.25% |
| 3 | 15.83 | 23.33 | 21.53% |

## V. RESULTS & DISCUSSION

Several experiments with a mobile robot in a realistic scenario were performed to validate the algorithm developed. A large arena was built in a class room of University of Coimbra. Additionally, a ground truth map of the arena was built as a reference (Fig. 7), and a run with *GMapping* on the Nomad Scout in this arena with clean conditions was conducted. The resulting map is shown in Fig. 8.

Relevant data was extracted by running several trials using the robot in the new arena and recording them with the *rosbag* tool available in ROS, which saves all sensor data throughout the experiment, such as odometry pose, sonars readings, laser scans, alcohol sensor readings, *etc*. This allows to run the algorithm after the experiment and also to test *GMapping* in the same exact conditions without the *SmokeNav* layer, and thus verify whether there were significant improvements, *i.e.* whether the algorithm was able to cope with smoke.

In every trial, the robot started in a clean zone and performed the same path as illustrated in Fig 8. The robot was teleoperated using a Wiimote remote controller. In order to evaluate the algorithm and its limitations, the smoke concentration has increased from the first trial to the last one. Results of three trials are shown in Fig. 9.

In all trials, when *GMapping* is fed solely with laser data, *i.e.* without the *SmokeNav* layer, it is unable to map zones corrupted with smoke. Even when the robot leaves the smoky zone, the estimation of the robot's pose becomes erroneous and the SLAM algorithm is not able to correctly recover and update the robot's pose. This is not surprising since it is only using the LRF and the scan matching process fails due to false readings.

From the analysis of the results, it can be seen that the proposed method provided a means to successfully map the arena in most of the cases. The poor results obtained in the third trial are justified by the greater density of smoke during all the experiment, which was an extreme case. However, when the switch from the LRF to sonars occurs, the quality of the map drastically decreases, as expected. This happens because of the much lower resolution of the sonars and other limitations previously mentioned in Section III-A.

The same error metric used in our previous work [10] was used with the aim of quantifying error. However, due the low quality of the obtained maps, the alignment with the ground truth was not possible. So, in order to estimate the error, the robot was correctly positioned under some marks in the beginning of each experience. By doing this, the initial pose in each experience is similar and we can align the maps according with that information. The resulting error for each trial is shown in Table I. Also, the usage of the sonar data was evaluated by counting the time that sonar data was used.

Yet, the improvements are significant and it has been shown that SLAM in such harsh conditions is possible using a multimodal sensor fusion approach. Also, the developed layer does not introduce significant computation delays in the system. The solution proposed is affordable, using only off-the-shelf, fairly cheap sensors. Better results would be obtained using sonars with more stable readings. Beyond that, it is the authors' belief that a solution based on a radar sensor (instead

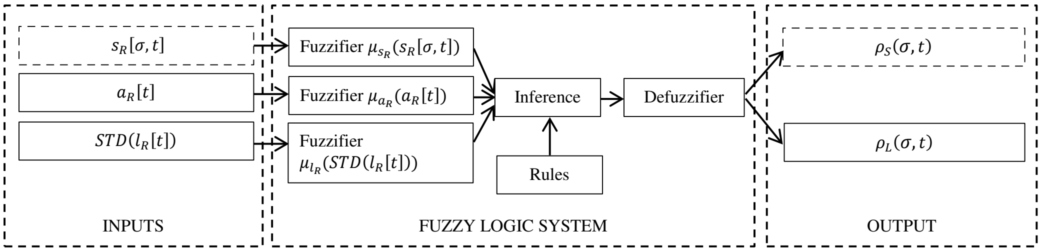



Fig. 4: Fuzzy logic system to choose the adequate reading.

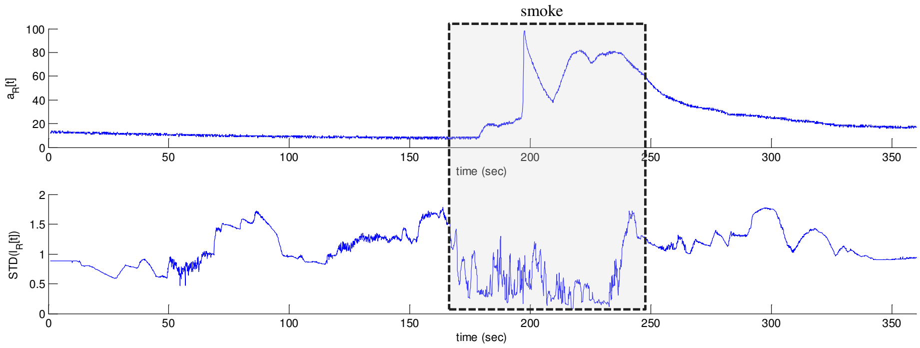



Fig. 5: Top: alcohol sensor readings over time $a_R[t]$. Bottom: standard deviation of the laser readings over time $STD(l_R[t])$. The alcohol sensor presents significant variations when facing smoke. However, it also presents a slow response. On the other hand, the standard deviation of the laser readings proves to be a relevant complement to the decision-making.

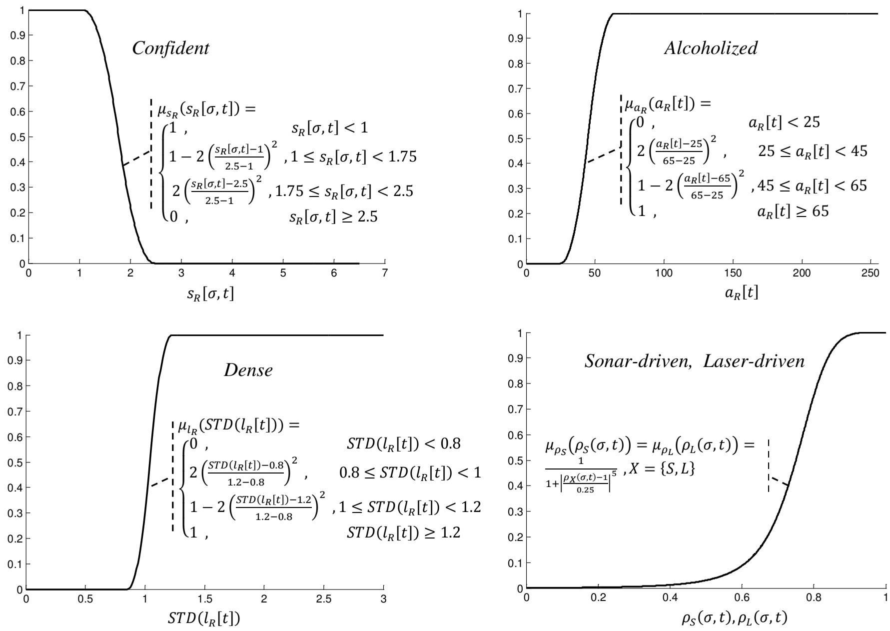



Fig. 6: Membership function for each input used to quantify the consequents. Top-left: input sonar reading from section $\sigma$, $\mu_(s_R) s_R[\sigma,t]$); Top-right: input alcohol sensor reading, $\mu_(a_R)(a_R[t])$; Bottom-left: input standard deviation of laser readings, $1mu_(l_R)(STD(l_R[t]))$; Bottom-right: output probabilities $\rho_S(\sigma,t)$ and $\rho_L(\sigma,t)$.

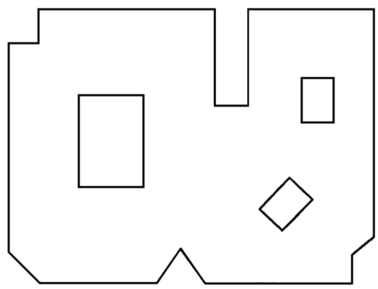


Fig. 7: The *R3.2 Arena* with dimensions: 8.62 m $\times$ 6.55 m.

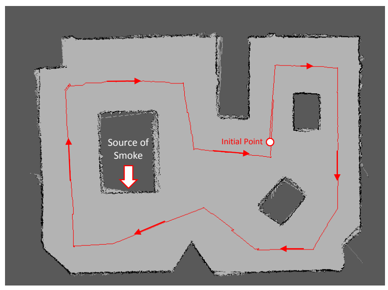
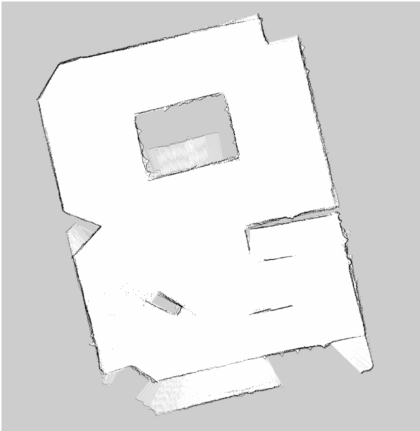



Fig. 8: Resulting map of a run with *GMapping* without smoke in the scenario.

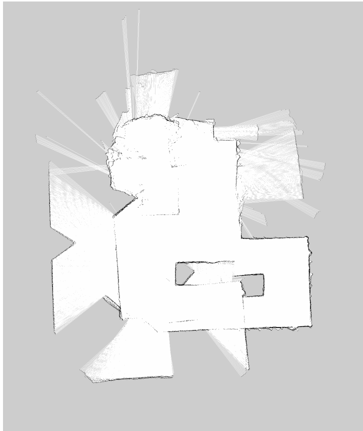
of sonars), even though being much more expensive, would be ideal to solve the problem while maintaining maps of high quality, independently of the smoke density in the environment.

## VI. Conclusion

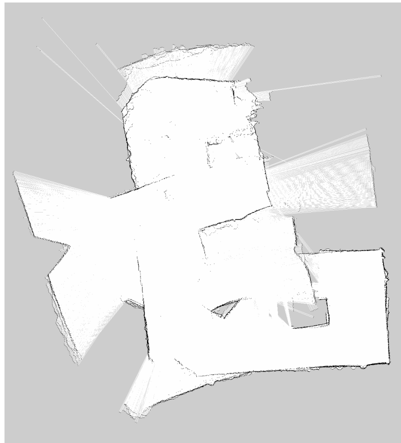
In this paper, a sensor fusion method with application in 2D SLAM under low visibility scenarios was presented. In the development of the method, it was verified that the information obtained using only two sensory modalities might be insufficient in more extreme situations, therefore an additional sensor to assess smoke density was used. The proposed fuzzified sensor fusion method makes use of multiple sensors in order to successfully map environments corrupted by smoke, dust or steam particles. It is a simple and easily adaptable approach that can potentially be applied with different 2D SLAM algorithms, simply by replacing *GMapping* with another algorithm.



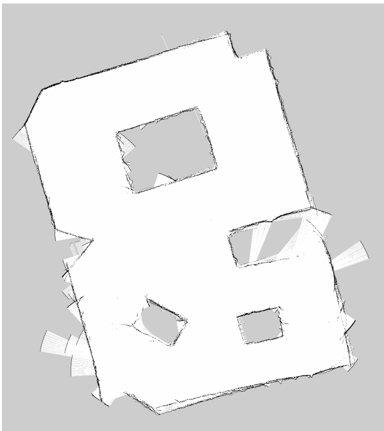
(a) Trial 1: *GMapping* only with LRF data.



(b) Trial 2: *GMapping* only with LRF data.



(c) Trial 3: *GMapping* only with LRF data.



(d) Trial 1: *GMapping* with the *SmokeNav* layer.

(e) Trial 2: *GMapping* with the *SmokeNav* layer.

(f) Trial 3: *GMapping* with the *SmokeNav* layer.

Fig. 9: Results of three trials. Top images are the resulting maps from *GMapping* only with LRF data and the bottom images are the maps obtained using the proposed multimodal sensor fusion technique.

SLAM experiments carried out in a 2D environment disturbed by smoke highlighted the method's usefulness in low visibility conditions. It was shown that it is possible to surpass reduced visibility situations by using the complementary characteristics of multiple range sensors. In future work, it would be interesting to compare our fuzzy logic method with sensor fusion approaches using a different theoretical framework.

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