Abstract: Gas source localization is the concept of locating the source of a chemical substance spreading in the environment. Within the oil, gas and petrochemical industry, there is an extreme focus on health, safety and environment (HSE) issues. Hence, being able to locate the source of a gas leakage in an accurate, reliable and quick manner, is of greatest interest to the industry. Although robotic gas source localization has been an active field of research for over fifteen years, large scale real world applications are still lacking. Towards closing this gap, this work presents the results of a comparative study between five different algorithms for robotic gas source localization. The first three are taken from the literature, while the last two are novel modifications and combinations of them. In addition to describing these algorithms, this paper presents the details of the conducted comparative study and the results thereof.

Keywords: Industrial robots, Gas source localization, Autonomous mobile robots, Control algorithms.

1. INTRODUCTION

During the last fifteen years, robotic gas source localization has been a prominent research area with numerous practical studies. Even though different environments and platforms have been used, the typical practical study has been made on a ground vehicle (Lilienthal et al., 2006). Intended scenarios include locating bombs, earthquake victims or other gas-emitting objects in unknown surroundings. However, to the best of our knowledge, there have been no experimental and comparative studies conducted in industrial environments. These environments differ from those of earlier studies in that networks of pipes and other infrastructure can be expected to distort the airflow. Furthermore, the position of potential gas sources, such as tanks and pipes, are likely to be known. In addition, industrial robots have never been used as platforms for gas source localization and it remains to be investigated how the algorithms developed for ground vehicles perform on industrial ones. Exact robot localization, strong processing power and capability of high-precision three dimensional movements is much more easily accessed on an industrial robot than on a traditional mobile platform. One of the main purposes of this paper is to investigate the performance of gas source localization algorithms in such a setting. Further, very few comparative studies between gas source localization algorithms have been made at all and there seem to be no consensus on the algorithms relative performance, even on a mobile ground platform. Conducting such a study is another main contribution of this paper.

Within the field of robotic gas source localization, many different categories of control algorithms can be discerned. To provide a point of reference, Kowaldo and Russell (2008) outlines a taxonomy within the field. However, for the purpose of the current work, a simplified view will be sufficient and hence adopted. In essence, most of the proposed gas source localization techniques can be divided into two categories, namely purely reactive ones and those who collect data over time to estimate the source location with the help of an inner dissipation model. This paper follows that classification and Section 2.1 describes a reactive algorithm. In Section 2.2 and 2.3, two algorithms belonging to the category of estimation/model-based strategies are presented. For a more comprehensive literature study, see Lilienthal et al. (2006).

2.1 Algorithm 1: Transient based reactive strategy

Ishida et al. (2005) describes a transient-based reactive system for gas plume-tracking. Thanks to the use of transient analysis and fall-back search mechanisms that slows down and turns the robot if it is about to leave the plume, good performance is achieved (Kowaldo and Russell, 2008; Lilienthal et al., 2006). The platform used for the experimental studies of that paper, is a differential wheeled robot equipped with three gas concentration sensors (left, center, right) and a device for telling the wind direction. The algorithm acts directly on the resistances of the sensor elements, which decreases with an increased gas concentration.

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The behavior of the robot is divided into four states. In the first state, the plume is found (defined by a certain threshold), in the second one, an upwind tracking algorithm takes over. If the plume is lost during the second state, the third state, in which the robot turns back 90 degrees to try to recover the plume, is activated. If this fails, a transition is made to a fourth state and the robot performs a spiral search until it is inside the plume again. After a successful recovery of the gas plume, the second state is once again activated. To find a finite state representation, pseudo code, or other details of this algorithm, the reader may wish to consult Ishida et al. (2005).

2.2 Algorithm 2: Time averaged model strategy

Based on a model of the gas dissipation and multiple sensor measurements at different locations, it is possible to estimate the location of the gas source. This idea underlies both the time averaged model described here-below, as well as the infotaxis strategy explained in Section 2.3. A frequently used model for gas dissipation have been variations of Hinze’s turbulent diffusion model as described in Kowaldo and Russell (2008). This is a time averaged model of the gas concentration in the area around the source,

\[ C(x, y) = \frac{q}{2\pi K} e^{-\frac{\sqrt{r}}{\lambda}} (r - \Delta x) \]

where

\[ r = \sqrt{(x_0 - x)^2 + (y_0 - y)^2}, \]
\[ \Delta x = (x_0 - x) \cos \theta + (y_0 - y) \sin \theta. \]

Here, \( C(x, y) \) is the concentration at point \((x, y)\), \( q \) is the release rate of the gas, \( K \) is the turbulent diffusion coefficient, \( U \) is the wind speed and \( \theta \) is the angle of the upwind direction counter-clockwise from the x-axis. In addition to the gas source location \( x_0, y_0 \), which we are searching for, also \( q \) and to some extent \( K \) are usually unknown and have to be estimated.

The experimental studies of Alg. 2 (time averaged model), build upon the strategy provided in Ushiku et al. (2007).

2.3 Algorithm 3: Infotaxis strategy

The infotaxis strategy is a so called probabilistic method which view the gas leaking from the source as small patches of gas that follow the airflow downwind and and decay with a certain rate (Morand and Martinez (2010); Pang and Farrell (2006); Vergassola et al. (2007); Masson et al. (2009); Farrell et al. (2002)).

In infotaxis, the estimated probability distribution from a trace, \( T_i \), of uncorrelated gas encounters is calculated as

\[ P_t(r_0) = \frac{\mathcal{L}_{r_0}(T_i)}{\int \mathcal{L}(T_i) \, dx} = \frac{\exp \left[ - \int_0^t R(r(t')) \, dt' \right] \prod_{i=1}^n R(r(t_i) | r_0) \exp \left[ - \int_0^t R(r(t')) \, dt' \right] \prod_{i=1}^n R(r(t_i) | x) \, dx}{\int \mathcal{L}(T_i) \, dx} \]

where \( \mathcal{L}_{r_0}(T_i) \) is the likelihood of observing the trace, \( T_i \), of gas encounters/non-encounters for a source located at \( r_0 \). Further, \( H \) is the number of encounters and \( t_i \) denotes the time of the \( i \)th encounter. The function, \( R(r_1 | r_0) \), denotes the mean rate of encounters at position \( r \) for a source located at \( r_0 \). The resolution of \( R(r_1 | r_0) \) in two dimensions reads

\[ R(r | r_0) = \frac{R}{ln(\frac{2}{t})} e^{\frac{-\sqrt{r^2 - r^2_0}}{\lambda}} K_0 \left( \frac{|r - r_0|}{\lambda} \right), \]

\[ \lambda = \sqrt{\frac{D\tau}{2\pi}} \]

where \( R \) is the release rate of detectable gas patches from the source and \( K_0 \) is the modified Bessel function of the second kind. The patches have a lifetime of \( \tau \), propagate with a diffusivity \( D \) and are advected by a mean wind \( V \) blowing in the negative y-direction. The parameter \( a \) denotes the size of the circular object detecting the point-sized gas patches (alternatively, the size of the patches detected by a point-sensor) at rate \( R(r_0) \).

The infotaxis strategy, combines the probabilistic model with a method for moving the robot in a way that maximizes the rate with which new information is acquired (Vergassola et al., 2007). The basic idea is to move in the direction that minimizes the entropy of the search area. As the entropy decreases faster close to the source where gas patches, i.e., information, arrives at a higher rate, the robot will be guided to the source. The expected change of entropy from moving from one point to another is calculated as

\[ \Delta S(r \rightarrow r_j) = P_t(r_j) [-S] + [1 - P_t(r_j)] [p_0(r_j) \Delta S_0 + p_1(r_j) \Delta S_1 + \ldots] \]

The first right-hand term corresponds to the case where the source is found whereas the second one represents the cases of 0,1,2... gas patch encounters not being at the location of the source. The symbols \( \Delta S_0 \), denote the change of entropy between the fields \( P_{t+1}(r_0) \) and \( P_t(r_0) \) in case k encounters are made. The probability of encountering \( k \) patches during one time-step \( \Delta t \) is denoted by \( \rho_k \) which is the Poisson distribution

\[ \rho_k = \frac{h^k e^{-h}}{k!} \]

with the expected number of occurrences \( h(r_j) \) estimated as

\[ h(r_j) = \Delta t \int P_t(r_0) R(r_j | r_0) \, dr_0. \]

3. REAL-WORLD EXPERIMENTS

To implement and compare the gas source localization strategies described in Section 2 in a real environment, a system consisting of several hardware and software parts was constructed. In this section, we initially present and discuss the experimental setup and the implications it has on the aforementioned strategies. This is done in Sections 3.1 and 3.2. Then, results from the comparative study are reported in Section 3.3.
3.1 Experimental setup

Gas release  In order to ease the comparison of our results with those of earlier studies, ethanol was chosen to serve as the leak gas. A device was built that let compressed air flow through the mixture of ethanol and water and eject through a small hose (see Figure 1).

Wind generator  Wind has a huge influence on the spread of a released gas. Except in completely windless environments, turbulence will dominate over diffusion as the main mean of dissipation. This means that the gas concentration in a particular spot fluctuates over time with a rather high frequency. In this work, only the situation where a wind blows in the environment was considered. That is a likely assumption in an oil and gas environment of Norwegian standards where the plants are located offshore or next to the sea. To create an artificially uniform wind field, a fan was placed inside the process module, about a meter behind the gas source (see Figure 1).

Robot  The choice of robot platform, a track-mounted industrial ABB robot (IRB4400) has some notable advantages including exact positioning and trajectory following, a high maximum payload and thus a negligible need for miniaturization, easy connection to workstation/network and a three dimensional workspace. Due to the fact that the robot was mounted on a track, the work area was sufficiently large for the tests conducted in this paper.

Path planner  The in-house developed path planner enables on-line calculation of collision free paths between any two reachable positions and orientations in the laboratory. Because of its general nature, some of its properties did however not fit the gas source localization algorithms very well. For example, as the pathplanner solves the entire pathplanning task, no control is left to the calling program over what way the robot, and more specific, the tool should take. Sometimes, the robot is not able to move linearly between the two points but may pass waypoints some 50cm away. Further, it takes approximately 2.5-5 seconds to perform the online path planning calculations. To speed this process up, old paths and waypoints are saved in memory. To enable the reuse of old paths, a robot is made to move to a stored point if there exist one within 5 cm of an intended target and as long as no robot joint calculated for the new target deviates more than 0.17 radians from the angles of the robot joints connected to the stored point. If not taken into account, this feature will hamper exact positioning of the tool.

One adaptation of the pathplanner was made to make it fit the gas source localization algorithms better. To make the robot disturb the gas flow as little as possible, its base was always placed in a position downwind of the tool’s orthogonal projection onto the track.

Sensor circuit and calibration  For gas sensing, two Figaro TGS 2620 semiconductor gas sensors were chosen. This sensor model has been used in many of the previous studies and is inexpensive, fairly sensitive but, compared to its biological counterparts, slow. Practical investigation as well as literature indicate a response time of about 5 seconds after a increase in gas concentration and a recovery time of about one minute (Ishida et al., 2005).

3.2 Implications on the algorithms

In order to be able to run the comparative tests, all algorithms had to be complemented and modified slightly as to be compliant with the constraints imposed by the real-world experiments. In this section, these modifications will be mentioned and discussed.

To start with, some of the algorithms are not a complete gas source localization system covering everything from detection of a leak to moving strategy and final definition of the source location. Consequently, the non-complete algorithms had to be modified so that they all cover the entire process of gas source localization.

Other constraints were imposed by the hardware, most notably the limited performance of synthetic gas sensors. The lack of a wind sensor forced the assumption of a steady uniform wind flow.

Implications on Alg. 1 (reactive) As far as Alg. 1 (reactive) is considered, the main limitation stems from the relatively long cycle time where every move takes more than 2.5 seconds. Although not explicitly mentioned, deeming from steering plots in Ishida et al. (2005) the system considered in the original paper was considerably faster than 1Hz. To address this issue, the influence of the gas sensors on the steering was calculated according to

\[
\text{Sensor Bias} = \log \left( \frac{C}{C_L} \right) / \log (I)
\]

where \( C \) is the measured concentration, \( C_L \) is the lowest concentration measured since the last drop and \( I \) is the increase rate. In the original study and in the simulations, the stepwise increase was 10%, corresponding to an \( I = 1.1 \), if effects of discretizations are omitted.

Another concern affecting Alg. 1 (reactive), was the fact that the pathplanner is not always able to move the robot linearly between two points but may need to pass waypoints some 50cm away in order to generate a collision-free path. As the sensors are continuously active and measuring, they are influenced by the concentration along the
whole trajectory. Consequently, these movements typically give rise to odd responses.

In Section 3.1.4, it was also described how the robot might end up in a point up to 5 cm away from where it was originally commanded due to rounding to stored positions. Obviously, this was not accounted for in the implementation of Ishida’s original reactive system.

Implications on Alg. 2 (time averaged model) A correct value of the turbulent diffusion coefficient $K$ is essential if good gas source locations estimations should be achieved. In Fukazawa and Ishida (2009), two techniques to estimate $K$ are proposed. One of these was used to estimate the parameters of the laboratory, not only $K$ but also the wind speed $U$, which in the lack of an anemometer could not be measured. The parameter estimation is done by running gas source location estimations with different parameters. For each parameter value, the root-mean-square distance, $\sigma$, to the source, is calculated for the grids with a grade above 80% of the highest grade as,

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (d_i)^2}$$

where $d_i$ is the distance of grid $i$ from the actual source location and $N$ is the number of cells with grades over 80% of maximum. This gives a value, $\sigma$, of how close to the source the source location estimation got, and thereby, how applicable the environment parameters in question are. As an outcome of this procedure, $K$ was estimated to 0.108 and $U$ to 0.8 m/s.

One aspect of particular importance to Alg. 2 (time averaged model) is the non-uniform properties of the artificial wind in the laboratory. As it is created by a single fan, its strength and direction varies as one moves perpendicular to the fan’s direction. The wind strength also varies right in front of the fan, depending on the distance to it.

Implications on Alg. 3 (infotaxis) As the input to infotaxis is binary cues and not concentration levels, the extracted information had to have the right form, i.e., binary cues that are more frequent in the vicinity of the source but independent of the amount of gas released. Three methods to extract such information were evaluated. The input to each method was a number of consecutive samples taken at the same point, divided by their mean to be independent of the amount of gas released. The three methods either calculated

1. the variance of these values,
2. the mean of the few largest sample-to-sample increases (steepest upward slopes), or
3. the number of samples exceeding the mean of the preceding few samples by a certain value.

If these calculated values reached certain thresholds, detection was generated. The three different techniques were applied to the samples taken 21 to 102 seconds after the sensors arrived at every point and the results were compared to what the model using method (2) would predict. As an outcome, the first two methods, i.e., the highest variance- and the steepest slope methods, showed best results. As the steepest slope-method was thought to be the one best suited for smaller sample sets, it was chosen to be used for the experimental studies involving infotaxis.

Another issue that differed between our experiments and the original study presented in Moreau and Martinez (2010) is the presence of obstacles and the size and decomposition of the workspace. In our case, the workspace was decomposed into a grid having 27x27 cells, each covering 25x25 cm. Not all cells were accessible by the robot as some were occupied by obstacles while some cells were simply out of reach of the track mounted robot. If the first position suggested by the infotaxis algorithm turned out to be such an inaccessible location, the robot was instead moved in the direction that was feasible and offered the largest expected decrease in entropy.

To make the conditions of the infotaxis experiments more equal to those of the other algorithms, both gas sensors were used simultaneously, together taking two sets of samples during each iteration. The steering algorithm of infotaxis was however acting as if only one sensor with a doubled chance of making detections existed: The entropy estimations according to (3) were calculated for the tool-coordinates, roughly situated right between the two sensors, with the value of the release rate $R$ doubled.

3.3 Comparative Study

The three algorithms described in Section 2 were initially run in a simulated environment so that the necessary components around them could be implemented, debugged and have their basic functionality verified. These simulations gave an opportunity to add and test extra functionality to the algorithms so that they all cover the entire process of gas source localization. During this process, two novel algorithms were derived from the original ones by combining Alg. 1 (reactive) and Alg. 2 (time averaged model) in two different ways.

Alg. 4 (Sampling combo) This algorithm utilizes the time averaged model of Alg. 2 to estimate the gas source location. However, instead of collecting the samples in a “mow the lawn”-fashion as described in Fukazawa and Ishida (2009), it collects the samples in accordance with movement generated by Ishida’s transient based reactive algorithm (Alg. 1).

Alg. 5 (Full combo) While Alg. 4 only uses the sample points produced by Alg. 1 (reactive), this full combo version also utilizes the result generated by Alg. 1 (reactive) along the way. More precisely, Alg. 5 (full combo) combines the result of the reactive algorithm in the direction perpendicular to the wind direction, while the coordinate in the wind direction is taken from the estimation based on the time averaged model. This idea is illustrated in Figure 2.

After the simulation of a particular algorithm was finished, real world experiments were run in the robot lab. Adjustments were made to the algorithms with regard to limitations of the real system. Parameters were tuned and the algorithms were finally run with their behaviors and results logged for comparisons. A typical run with Alg. 1 (reactive) can be seen in Figure 3.
Fig. 2. Plot showing how Alg. 5 (full combo) fuses the results of Alg. 1 (reactive) and the results of Alg. 2 (time averaged model). While the result of the model-based estimation is used in the wind direction, the result of the reactive algorithm is used in the perpendicular dimension. The combined result (blue circle) is thus projected onto the (blue) line parallel to the wind direction that crosses the result-coordinates of the reactive algorithm. The black star marks the real location of the source and the black horizontal line is the rim of the process model.

Due to space limitation, it is not possible to include result details of all runs. The interested reader may find these in Persson (2010). However, a compilation of the results of the five algorithms tried out in this study is displayed in Table 1. When it comes to distance to target, two kinds of results are presented: Side-way distance to the “wind line” and absolute distance to the source. As the robot is not allowed to run into the process module, Alg. 1 (reactive) does not produce any information regarding how deep into the process module the source is located. Because of this, it cannot provide any absolute distance to the source. The other lines of Table 1 represent number of runs, mean completion time and mean number of iterations it takes to complete the gas source localization task. The last line in Table 1 regards the possibility of extending the algorithms to localize gas sources in three dimensions.

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Potential of Further Improvements The completion times of Alg. 2 (reactive) has as indicated in Table 1 not been optimized, but, it is probably not possible to decrease them by more than 50% without loss of precision, meaning the times will still be relatively long. Further, as has been shown in Section 5.4 in Persson (2010), in an obstacle free environment, it is possible to double the precision and speed of Alg. 1 (reactive), most likely improving the performance of Alg. 5 as well, if only the control system is adapted to the task. Apart from this, the potential of further improvements of Alg. 1 (and hence, the reactive part if Alg. 5), is however limited. Alg. 1 (reactive), with all its details and fall-back mechanisms, is clearly an optimization of reactive gas source localization in one plane. The algorithm is thus already relatively mature and would have to be completely re-worked to function in three dimensions. When it comes to the estimators of Alg. 2,4 and 5, the model of gas dissipation (1) is a greatly simplified picture of the environment. If the estimator were to be improved, the time averaged model itself would probably have to be replaced with a more advanced model. The current approach of using fuzzy membership functions would however be possible to reuse. Depending on model, a change could also enable three dimensional estimations.

Infotaxis The first and most obvious conclusion that can be drawn from Table 1 is that Alg. 3 (infotaxis), is not yet ready for industrial usage. Discarding the failed runs, the results were still worse than those of any other algorithm in nearly every aspect. The estimations were further from the source and the runs took longer to perform, but in light of this, infotaxis showed some strengths as well. To start with, the strategy was possible to integrate with the pathplanner to a higher degree than the other algorithms. The advantages with this property accrue specially in the case of a more obstacle-filled environment. Further, a three dimensional implementation of infotaxis would be relatively straight-forward to create as it has already been described and simulated in Masson et al. (2009). Infotaxis also solves the entire problem of detecting, finding and declaring the position of a gas source in a more complete way then the other algorithms. Even so, as the results clearly reveal, significant improvements have to be made to gas sensors, especially in terms of speed, before infotaxis can be subject to real world applications.

Best Algorithm Establishing the best algorithm is not easy as this selection does depend on how different factors, such as completion time and accuracy, are prioritized. Nevertheless, Alg. 5 (full combo) is clearly superior to the reminiscent Alg. 4 (sampling combo). Thus, combining estimator results with reactive ones is a rewarding approach. In one dimension, Alg. 2 (time averaged model) does however reach even higher precision while it in two dimensions performs on par with Alg. 5. On the other hand, Alg. 1 and 5 are considerably quicker than Alg. 2. With the time factor taken into account, Alg. 5 (full combo) is thus the most attractive overall choice of this comparison. If time is not an issue however, Alg. 2 is the algorithm of choice, and if only the sideways results are of interest, the estimator-free Alg. 1 (reactive) is quicker.

Fig. 3. The path of the tool-tip and sensors while running Alg. 1. The color shows the strength of the measured concentration. The “X” shows the location of the gas source, the arrow the wind direction and the white boxes represents the obstacles, namely the process module at the top and a tool stand at the bottom.
Table 1. Compilation of the results of the real world comparative study. The columns represent the five considered algorithms (Alg. 1-5).

<table>
<thead>
<tr>
<th>Algorithm 1</th>
<th>Algorithm 2</th>
<th>Algorithm 3</th>
<th>Algorithm 4</th>
<th>Algorithm 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ishida’s transient-based reactive system</td>
<td>Estimation based on time averaged model. Sample collection: &quot;Mow the lawn&quot;</td>
<td>Infotaxis</td>
<td>Algorithm 4</td>
<td>Combination: Reactive in one dimension, time average model based estimation in the other</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of runs</th>
<th>25</th>
<th>13</th>
<th>12</th>
<th>12/12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance to target/wind line in dir. parallel to module’s side</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean distance (cm)</td>
<td>24.4</td>
<td>19.2</td>
<td>42.6&lt;sup&gt;(1)&lt;/sup&gt;</td>
<td>41.8</td>
</tr>
<tr>
<td>Success rate: Within 10 cm</td>
<td>32%</td>
<td>0%</td>
<td>8%</td>
<td>8%</td>
</tr>
<tr>
<td>Success rate: Within 25 cm</td>
<td>64%</td>
<td>92%</td>
<td>17%</td>
<td>8%</td>
</tr>
<tr>
<td>Success rate: Within 50 cm</td>
<td>92%</td>
<td>100%</td>
<td>42%</td>
<td>75%</td>
</tr>
<tr>
<td>Absolute distance to source</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean distance (cm)</td>
<td>Not available</td>
<td>36.0</td>
<td>84.8&lt;sup&gt;(2)&lt;/sup&gt;</td>
<td>45.5</td>
</tr>
<tr>
<td>Success rate: Within 25 cm</td>
<td>Not available</td>
<td>31%</td>
<td>0%</td>
<td>8%</td>
</tr>
<tr>
<td>Success rate: Within 50 cm</td>
<td>Not available</td>
<td>77%</td>
<td>25%</td>
<td>50%</td>
</tr>
<tr>
<td>Success rate: Within 75 cm</td>
<td>Not available</td>
<td>100%</td>
<td>33%</td>
<td>100%</td>
</tr>
<tr>
<td>Mean completion time (s)</td>
<td>163</td>
<td>760&lt;sup&gt;(2)&lt;/sup&gt;</td>
<td>1243&lt;sup&gt;(3)&lt;/sup&gt;</td>
<td>Time of Ishida’s transient-based reactive system + estimation time</td>
</tr>
<tr>
<td>Mean number of Iterations</td>
<td>24.2</td>
<td>8.0</td>
<td>40.7&lt;sup&gt;(4)&lt;/sup&gt;</td>
<td>Same as Ishida’s transient-based reactive system</td>
</tr>
<tr>
<td>Possibility of adaptation to three dimensions</td>
<td>Hardly possible</td>
<td>Partly possible&lt;sup&gt;(5)&lt;/sup&gt;</td>
<td>Easy</td>
<td>Hardly possible</td>
</tr>
</tbody>
</table>

<sup>(1)</sup> Among the 7 runs not deemed as failures  
<sup>(2)</sup> Not optimized  
<sup>(3)</sup> The estimation adds some 1-2 seconds per iteration  
<sup>(4)</sup> Much more complex model needed  

4. CONCLUDING REMARKS

In our comparison, Alg. 5 (full combo) came out as the best overall method for gas source localization in an industrial environment, but Alg. 2 (time averaged model) showed good results as well in the case when low completion time is not prioritized. Alg. 3 (infotaxis) turned out to be effectively unusable in association with the slow gas sensors.

Future development towards industrial application and three dimensional searching should be focused on Alg. 2 and 5. This work re-confirmed the fact that the poor performance of the artificial gas sensors is the main hurdle for allowing industrial commercialization.

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