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Towards Robotic Visual and Acoustic Stealth for Outdoor Dynamic Target Tracking

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Abstract

Covertly tracking mobile targets, either animal or human, in previously unmapped outdoor natural environments using off-road robotic platforms requires both visual and acoustic stealth. Whilst the use of robots for stealthy surveillance is not new, the majority only consider navigation for visual covertness. However, most fielded robotic systems have a non-negligible acoustic footprint arising from the onboard sensors, motors, computers and cooling systems, and also from the wheels interacting with the terrain during motion. This time-varying acoustic signature can jeopardise any visual covertness and needs to be addressed in any stealthy navigation strategy. In previous work, we addressed the initial concepts for acoustically masking a tracking robot's movements as it travels between observation locations selected to minimise its detectability by a dynamic natural target and ensuring continuous visual tracking of the target. This work extends the overall concept by examining the utility of real-time acoustic signature self-assessment and exploiting shadows as hiding locations for use in a combined visual and acoustic stealth framework.

1 Introduction

Tracking dynamic targets without being detected requires not only visual but also acoustic stealth. Whilst visual covertness has been explored to varying degrees for many years, robotic acoustic stealth is still sparsely studied. Our goal is to significantly extend these concepts by combining visual and acoustic stealth to maintain *continuous* line-of-sight observation to a moving natural object of interest in outdoor environments without being detected.

To achieve this we propose a solution around selecting pseudo-optimal monitoring locations that reduce the visual conspicuousness of the robot and offer a substantial opportunity for camouflage and observation. To reduce the robot's acoustic conspicuousness, we propose that the robot monitors the periodicy of noise sources with significant amplitude from the environment that offer a high probability of covering (masking) any ego-noise, and are cyclic enough to be predictable. Examples of significant distracting sounds include machinery and vehicles for built environments, vehicles and mobile phones in urban environments, and wildlife and wind for natural environments.

This paper presents extensions and preliminary results to our previous work in both the acoustic and visual domain [Tews and Dunbabin, 2012], allowing the tracking robot to improve its covertness in challenging outdoor environments. Section 2 overviews related research to our approach. Section 3 discusses our motivation and extensions for modelling the tracking robot's acoustic signature under various conditions and investigating how shadows can benefit visual covertness. In Section 4, the tracking robot is described and the outline of the experiments that were undertaken. Section 5 describes the results of the experiments and Section 6 summarises our conclusions.

2 Related Work

Stealthy navigation for robots has been typically focused towards minimizing the risk of exposure of the robot to known or unknown observers using either potential fields or cost functions. In unknown outdoor environments, [Birgersson *et al.*, 2003] and [Tews *et al.*, 2004] have used both approaches for navigating a robot around detected objects in the presence of a known observer location. [Marzouqi and Jarvis, 2004] has demonstrated a similar approach using a cost function to plan a path through an unknown environment that may contain sentries. The function chooses a path that offers the least exposure to open areas where the possibility of sentries was higher. In known environments, [Masoud, 2003] has demonstrated a potential field approach for evasion in the presence of multiple pursuers.

The goal of these approaches was to reduce visibility to one or more target objects (typically referred to as "observers"). In contrast, our approach requires uninterrupted (continuous) observation and tracking of a mobile target object. [Cook *et al.*, 1996] have developed a method to evaluate the information gain of strategic observation locations versus the cost of being detected. Their domain was more directed towards the scenario of military scouting from long ranges but has similarities to ours. Our approach is more dynamic, shorter range and considers the acoustic profile of the tracker and its surroundings.

There is a paucity of literature relating to the acoustic masking of a robot for stealthy navigation. The most significant work to date has been by [Martinson, 2007], who describes an approach to use known noise sources within the environment to determine the locations where a robot's own acoustic signature is minimized to a potential "listener" (known in this paper as the observer or target). Whilst the approach takes into account the listener's audio direction sensitivity, the small scale of the experiment and constant noise source limits its practicality in the natural and built environments, particularly when the noise sources are non-constant and the listener is moving along an unknown trajectory.

In natural and built environments, sources of potential masking sound are not necessarily available nor deterministic. However, studies have shown how people are significantly distracted by certain sounds, such as ringing cell phones, and their attention can be shifted from the task at hand [Shelton *et al.*, 2009]. Animal behavioural studies [Aaden *et al.*, 2011] have also shown that certain man-made and natural sounds are more effective at distracting certain animals from their natural behaviour. This lends us to the proposition of monitoring and classifying the soundscape to search for potential short duration "distractions" which the robot can opportunistically use as triggers to move between vantage points.

Preliminary investigations exploring the ability to acoustically mask a robots noise whilst covertly and continuously tracking a target in an unmapped environment was performed by [Tews and Dunbabin, 2012]. The acoustic covertness was achieved by opportunistically utilizing sounds from within the environment as distractions for masking its own acoustic signature to manoeuvre between goal locations. Although sound characterization was not considered in that paper, it can be performed in a number of ways such as matching point features [Chu *et al.*, 2008] or Markov model based clustering [Lee *et al.*, 2010] for example. This soundscape characterization is also beyond the scope of this paper.

3 Technical Approach

Our system consists of two major parts; stealthy navigation whilst maintaining continuous line-of-site target observation, and acoustic masking in an unknown outdoor environment. The key assumptions in this analysis are; (1) the robot knows its own location relative to a reference frame, (2) the robot knows the location of the target/s relative to its own coordinate system, (3) the robot is self aware of, or can learn its acoustic output (not necessarily constant), and (4) the robot has sensing capabilities to measure the local sound field and directional components.

3.1 Hiding in Shadows

In our previous work [Tews and Dunbabin, 2012], we demonstrated a cost function approach to select successive observation vantage points in the unknown environment that fulfilled the following requirements:

a) allow for constant visibility of the dynamic target,

b) offer some ability to camouflage the robot tracker, and

c) close enough so the robot would not require long exposed traverses.

The key question in this approach is how can the robot select locations where it can continue to observe the target whilst remaining hidden? Hiding or blending in with the environment is a key requirement to reduce the prospect of being visually detected. To this end, our method chooses locations beside or in front of detected objects with respect to the target, and would move to newer locations in response to the target's dynamic position when predicted to be acoustically inconspicuous to the target. This method is based on reducing motion and uses only laser information to detect and map objects.

However, the colour and contrast of the robot against its background is also important to reduce its visual signature in the environment. Considering our tracker is predominantly matte black (Figure 3), it seems reasonable to take advantage of dark locations in the environment. Aligned with the previous goals of hiding around objects of opportunity, we investigate the utility of hiding in the shadows cast by these objects. Figure 1 demonstrates the difference in observability of the tracker (robot) when it hides in shadows. The figure shows the view from the robot to the human target and the view from the target to the robot's location. Clearly, the robot is more difficult to detect in the shadows. The challenge now is how to detect shadows and utilise them in the evaluation of vantage locations in the environment which is discussed below.

Shadow Detection by Contrast Maximisation

Typically, robust shadow detection can be difficult or complex to implement [Benedek and Sziranyi, 2007], and be a burden on the limited resources of an economical onboard computer such as a BeagleBoard, Arduino or Gumstix. As a result, there is a trade-off between robustness and computational economy. Our approach is simple and effective for highlighting the shadows in the robot's field of view.

Since shadows typically have relatively similar low-intensity colour values, by increasing the contrast, shadows and dark grey areas tend towards blackness. The black areas then form a binary mask representing areas where the robot is more likely to blend in with the surrounding environment. However, since we are interested in shadows cast by the objects on the ground, the horizon is used as a guide to reduce the search space in subsequent analyses. The horizon is found by estimating the homography H for the mounted camera against known landmarks in the environment. H is used to find the horizontal line where it estimates an arbitrary point approaches infinity along the vertical axis. This represents the horizon, under the assumption that the environment is flat.

Merging Shadows into the Occupancy Grid

The approach performs maximum contrast and mid-tone enhancement of the source image to highlight the darker/black regions. From the blackest regions, a binary image is constructed to mark locations of potential shadows. Whilst other image processing techniques are available, this approach proved reliable for revealing the primary shadows around obstacles in the built environment.

The method for extracting potential shadows and inclusion into an occupancy grid [Elfes, 1989] combines both a source image and a corresponding horizontal planar laser scan of the environment. Once the binary shadow candidate image is extracted from the source image as described above, the corresponding laser scan of the environment is processed in Cartesian coordinates to extract obstacles. Knowing the laser and camera alignment transformation (relative to the robot) as well as the camera intrinsic properties, the coordinates of a region of interest around each obstacle scan point (e.g. box of 2 m square) is transferred to the image space. This image region of interest is a mask for the binary shadow image to limit searches to potential shadows close to obstacles where the robot could hide. If a pixel in the shadow image falls within the region of interest, it is transferred back to Cartesian coordinates. The regular occupancy grid is then created on a presence/absence basis for both the laser scan and transferred shadow coordinates. The outputs of each stage of the shadow occupancy grid generation is shown in Section 5.

Choosing New Vantage Locations

Our approach for choosing vantage locations is based on evaluating objects in the environment near to the

Figure 1: Four scenarios illustrating the increase covertness of the tracking robot when placing itself within a shadow compared to a non-shadow for the same vantage point/obstacle. In the top four images, the robot hides around a stationary vehicle. In the lower four images, it hides around a tree. The left images show the target's view when looking at the robot, with the right images showing the corresponding robot's view of the target.

target that the tracker can take advantage of for hiding. Given that we desire the robot to continually observe the target, it needs to maintain a direct line-of-sight. As a result, it can potentially be seen unless it chooses locations that can offer some form of camouflage. In our preliminary work, [Tews and Dunbabin, 2012], locations were chosen in front of objects under the assumption that the robot would be concealed which was reasonable considering the approach was based only on a range-based 2D occupancy grid for simplicity and feasibility determination. The addition of a camera allows the robot to identify shadow areas as described above, and add them to the occupancy grid. As the shadow areas are attached to objects detected in the laser scans, they offer alternative, potentially more attractive vantage points as the robot will be more concealed. The evaluation of the occupancy grid for new vantage points is undertaken by extending our original cost-function analysis [Tews and Dunbabin, 2012] to incorporate shadows. Each occupied or cast shadow cell xy visible to the target (i.e. not blocked by an object) is evaluated by the equation:

$$cost_{xy} = \frac{1}{\beta}|cell_{xy} - tracker_{xy}| + |\alpha - |cell_{xy} - target_{xy}|\,| \tag{1}$$

where α is set to 6m to exclude all cells close to the target and β is set to 2. Additionally for shadow cells, their values are decremented by an empirically derived value of 5 to make them slightly more attractive than their neighbouring object cells. This also allows freedom for locations to be chosen in front of objects as before, in case there are no shadows. From the resulting cost analysis, the lowest valued location is chosen as the best vantage point to move to. An example of this approach is demonstrated in Section 5.

3.2 Acoustic Masking

Acoustic masking is the idea of using either sounds from within the environment to saturate (mask) the robot's own noise as heard at the target, or to use intermittent environmental noise sources to both mask the robot noise and/or "distract" the target so their attention is directed away from the robot.

Tracking an observer without being detected acoustically requires that the noise level perceived at the observer when the robot starts to move does not exceed a "just-noticeable difference" threshold. An example of the minimum distance that a robot with a fixed acoustic emission must be away from the target is shown in Figure 2 for a range of background sound pressure levels. As seen, for a robot with a SPL of 64 dBA at 1 m, it would have to be as far as 40 m from the target with low background levels such as light breeze or still night-time conditions (< 35 dBA). However, this can decrease to only meters when operating in more industrialised environments with higher background levels.

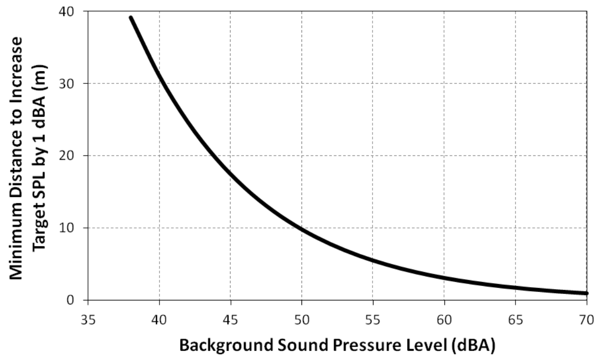


Figure 2: Example showing the minimum distance at which a robot with a 64 dBA acoustic signature must be from an observer to not increase the sound pressure level by 1 dBA with varying background noise levels ranging from still night to light industrial site conditions.

In order to mask the acoustic signature of a robot, it must first be aware of its own acoustic emissions, and secondly, be able to predict its contribution to the noise level at the observer. In this study, the approach for determining when the robot should move is to predict the expected sound pressure level (SPL) increase at the target. We assume the background SPL is reverberant and locally the same at both the robot and target, and adopt a spherical spreading model to estimate the direct sound of the tracker to the target. Using these sound field approximations, two estimation steps are conducted onboard the robot either offline or when the robot is not in tracking mode; (1) adaptive estimation of the background SPL, and (2) estimation of the robot's own egomotion noise.

Although we assume the background SPL is reverberant and the same at the target and tracker, it can vary temporally to account for time of day and general background noise sources. The background SPL estimate ($\hat{L}_{BG}$) is determined whilst the tracker is stationary by the recursive moving average approximation:

$$\hat{L}_{BG_k} = \min\left\{ \frac{L_k + (n-1)\,\hat{L}_{BG_{k-1}}}{n}\ ,\ L_k \right\} \tag{2}$$

where L_k is the instantaneous measured SPL at timestep k and n is the number of time-steps for the averaging window. As any intermittent high-level distractions can bias the background estimate, we force $\hat{L}_{BG}$ to the lower of the estimate and actual level.

The second estimation is conducted whilst the tracker is moving within the environment. Here we assume that the local sound field only consists of the background and that produced by the tracker. Therefore, we map the tracker's own SPL as a function of its velocity (v) and turn rate ($\dot{\psi}$) such that:

$$\hat{L}_R(v,\dot{\psi}) = 10\log\left(10^{L_P/10} - 10^{\hat{L}_{BG}/10}\right) \tag{3}$$

where L_P is the peak sound pressure recorded during $(t_1 \leq k \leq t_2)$ given by:

$$L_P = \max\left[L(k)\right]_{k=t_1}^{k=t_2} \tag{4}$$

The estimated total SPL at the target is then the logarithmic sum of the direct and reverberant SPL's. Therefore, the estimate of the robot's SPL at the target is given by:

$$\hat{L}_{R/T} = 10\log\left(10^{\left(\hat{L}_R(v,\dot{\psi})-20\log(r/r_o)\right)} + 10^{\hat{L}_{BG}/10}\right) \tag{5}$$

where r is the range from the robot to the target, and r_o is the reference distance from the robot's sound source to its onboard sound pressure level meter.

In this study, we consider the masking provided by the observed increase in SPL above background at the target resulting from changing environmental noise levels, known here on in as "distractions". In order to predict a tracker's contribution to the target's observed SPL, we assume we know the approximate relative direction of the distraction sound from the robot to the target (θ) as observed by the robot.

To assess the validity of the distracting noise so that it can be used to mask the robot's ego-motion noise at the target, we need to also estimate its contribution to the target's observed SPL. The robot observes the instantaneous increase in SPL and determines the strength of the distraction without the background contribution to be:

$$L_{D/R} = 10\log\left(10^{L_k/10} - 10^{\hat{L}_{BG}/10}\right) \tag{6}$$

We assume a disturbance is a temporally distinct point source and is modelled via spherical spreading. We then consider if the distracting sound source is on the same side of the robot as the target (i.e. $\cos(\theta) > 0$), or on the other side ($\cos(\theta) \leq 0$). In the case where $\cos(\theta) > 0$, we also assume that it originates beyond the target (i.e. not between the tracker and target). Therefore, the estimate of the distraction SPL at the target is:

$$\hat{L}_{D/T} = \begin{cases} 10\log\left(10^{\left(L_{D/R}+20\log(r/r_o)\right)} + 10^{\hat{L}_{BG}/10}\right) \\ ,\ if\ \ \cos(\theta) > 0 \\ 10\log\left(10^{\left(L_{D/R}-20\log(r/r_o)\right)} + 10^{\hat{L}_{BG}/10}\right) \\ ,\ otherwise \end{cases} \tag{7}$$

In practice, the robot does not move unless $\cos(\theta) > 0$, as the directionality of the distraction and robot sound could direct attention towards the tracker/robot.

The final step is to predict when the robot considers itself to have sufficient masking to avoid acoustic detection. If the expected SPL of the robot at the tracker including the background level is less than 1 dB less than the expected total SPL of the robot, background and distraction at the target, then we assume the robot will be acoustically masked and flag the robot's controller that waypoint navigation is possible. The expected duration of acoustic masking is dependent on the type of distraction, its persistence and can be prespecified or predicted. In this preliminary experimental evaluation, we consider a weighted temporal difference of $\left(\hat{L}_{D/T} - \hat{L}_{R/T}\right)$. This simplification assigns the maximum expected level and duration of distraction. This is a gross assumption and it is a current topic of research to predict the distraction parameters more accurately based on the frequency content and likelihood from learnt soundscape parameters.

4 Experiments

A number of experiments were conducted in order to evaluate the feasibility of predicting and modelling the acoustic signature of a moving outdoor robotic platform as well as improving the stealthy navigation strategies by detecting and utilising shadows.

The robotic platform used in these experiments was a Jaguar 4x4 developed by Dr Robot (www.drrobot.com) fitted with a top-mounted Hokuyo 30LX laser, Microsoft LifeCam, Microstrain 3DMG GX3 IMU and externally mounted laptop running the software for sensing and control (Figure 3). Two sound recording devices were installed on the robot at different phases of the experimental campaign. The first was a calibrated Sound Pressure Level Meter with an analog output proportional to the measured SPL in dBA. The second was a MP3 recorder used to measure and record the sound level, and was carried at a constant orientation by the target. The MP3 player allowed frequency content analysis of the soundscape for characterisation and prediction of distraction sounds (not considered in this paper).

Experiments consisted of operating the vehicle at different speeds and distances from an observer whilst recording SPL at both the robot and observer with varying background noise levels. We conducted experiments during the day and night to allow the robot's acoustic signature to be estimated at different velocities, orientations and wheel slip conditions.

Further experiments consisted of operating the robot in a semi-industrial environment at the CSIRO Queensland Centre for Advanced Technologies whilst collecting

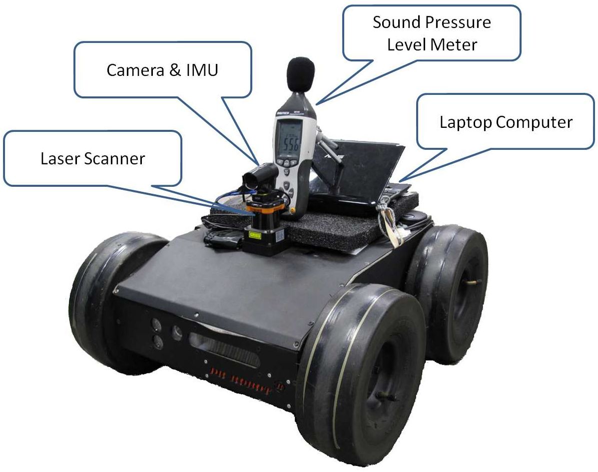


Figure 3: The robot used in the experimental campaign showing the sound pressure level meter, Hokuyo laser scanner, IMU, camera and computing hardware.

images and laser data to refine the shadow detection and stealthy vantage point selection algorithms.

5 Results

Experiments were conducted to acoustically characterise the robot and validate the modelling assumptions of Section 3.2. Firstly, the robot's intrinsic noise levels, such as fans, motors and gearbox, were measured by lifting the wheels off the ground and running the motors at full speed to remove the more variable ground/tyre contribution. Figure 4 shows the measured SPL at 1m around the robot with background noise levels removed. As seen, the robot's SPL is relatively consistent with direction.

To estimate the robot's total SPL (intrinsic levels plus tyre/ground interaction), the robot was driven at various speeds and the SPL measured on board the vehicle. Figure 5 shows the SPL translated to 1m from the robot with varying velocities. For estimating the expected SPL at the target, an assumed acoustic signature of the robot was adopted as shown by the black line. As seen, this is conservative for speeds less than 1 ms^{-1} which is typical of the tracking speeds used in our stealthy navigation experiments. At higher speeds, the robot bounces around more as illustrated by the slightly increased SPLs. Note this figure shows all data for accelerating and decelerating as well as constant speed hence the increased variability.

Experiments were conducted to validate the acoustic modelling assumptions when determining the contribution of the robot to the target's SPL. The robot was commanded to undertake linear velocity runs at set distances from the target in a built environment with the SPL recorded at both the robot and target. Figure 6 shows the results of the SPL recorded at the target and

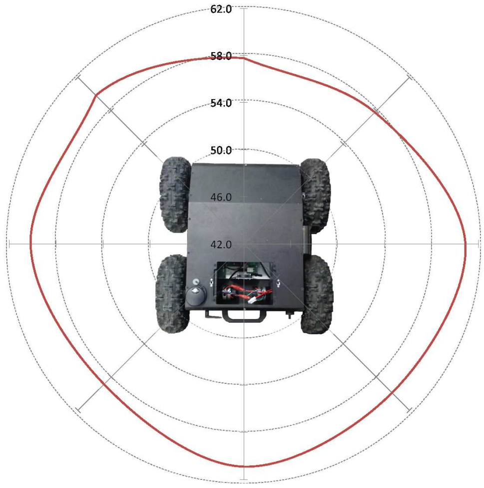


Figure 4: Measured SPL at 1m around the robot platform with motors running (no ground contact).

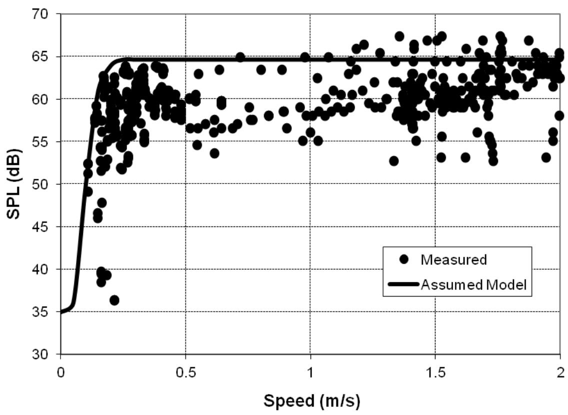


Figure 5: Variability of estimated robot SPL at 1m with robot speed, taken from day and night time experiments. The black line shows the assumed acoustic SPL model adopted for low-speed (< 1 ms^{-1}) experiments campaign.

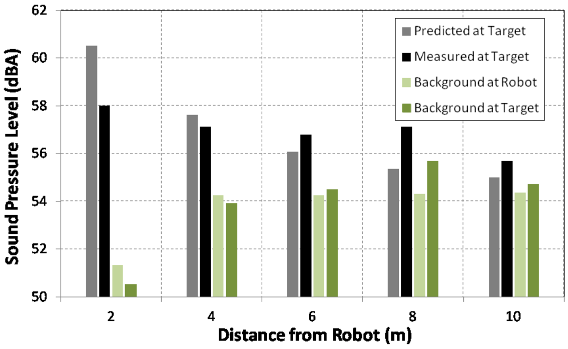


Figure 6: Measured and predicted sound pressure levels at the target from the robot moving linearly at set distances from the target. Also shown is the background SPL estimate measured at the robot and target.

that predicted by the robot, including the variability of background SPL at the two locations.

As seen in Figure 6, the robot predicts the SPL at the target reasonably well. The main error results from the differences in background SPLs at the robot and target showing that in more cluttered environments, the less predictable the local sound fields.

Figure 7 shows the results of the robot's prediction of the observed SPL compared to that measured at the target from a set of experiments whereby the robot was driven past the observer at varying speeds and distances. As can be seen, the robot in general over-estimates its contribution (i.e. is conservative) to the actual SPL observed at the target. Reasons for this include the significant amount of local noise at the robot due to motion of the SPL as it moves across the terrain, as well as background noise variation between the target and robot.

To evaluate the ability to incorporate shadows into the occupancy grid for improving visual stealth, the robot's onboard camera and laser scanner were used to collect images and corresponding horizontal planar laser range scans in a semi-industrial environment. The processing steps in the shadow extraction technique are shown for an example potential hiding location in Figure 8. It can be seen that the simplified shadow image extraction method has identified the main shadow regions within the image and the corresponding laser scan points match well with the structure in the image space. The largest source of error arises from laser and camera alignment as these were not overly rigid on the robot making calibration difficult.

By using the approach outlined in Section 3, the shadow pixels are added to the occupancy grid. Using the known tracker and target locations, Equation 1 is applied to the occupancy grid to extract the next vantage location. The resulting vantage locations allow a

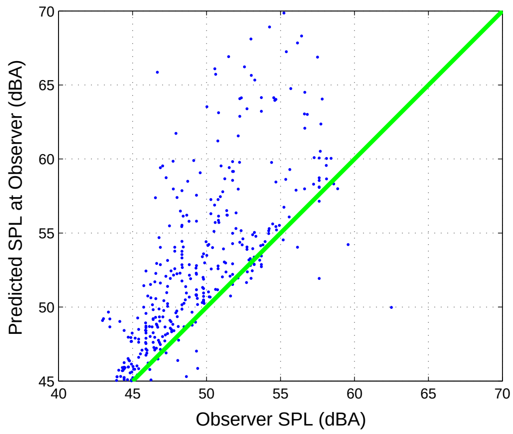


Figure 7: The robot predicted sound pressure level contribution at the target compared to the measured sound pressure level at the target for varying speed and distances. Above the green line is a conservative prediction.

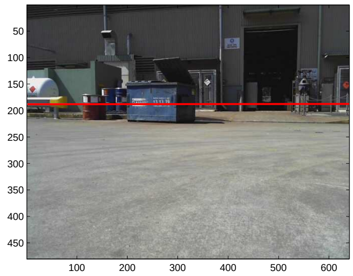
direct path to be navigated between them.

The scene from Figure 8 is used to demonstrate the method of incorporating shadows for new vantage location selection. Figure 9(a) illustrates the occupancy grid showing the locations of the tracker and target along with the key objects (the blue industrial bin and the red barrels) that can be used to conceal the tracker. Vantage locations using the shadow and non-shadow versions of our algorithm show the utility of the approach with the shadow of the industrial bin being selected as the key observation location. To put this in perspective, Figure 9(b) shows the actual appearance of the tracker in the non-shadow location and Figure 9(c) where it is in the shadow. Clearly, it is more difficult to detect the robot in the shadow and the robot can continue to observe the target undetected. An avenue of future work is to measure the effectiveness of concealment (i.e. tracker conspicuousness) as observed by the target.

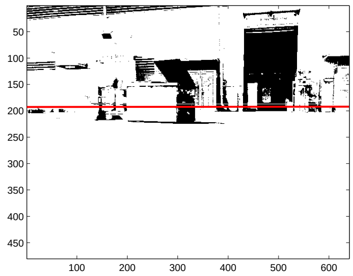
6 Conclusions

Covert robotic tracking of human or animal targets requires a greater level of stealth than has been previously reported in the literature. In addition to not being visible to the target whilst trying maintain continuous observation, the robot needs to be as silent as possible. However, as real robots have non-negligible acoustic signatures and operate in large unmapped environments a methodology to combine visual and acoustic stealth is required.

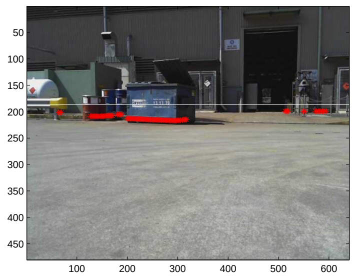
This paper has built on previous work into one such methodology whereby visual and acoustic masking of a robot is achieved by opportunistically utilising distracting sounds within the environment to mask its



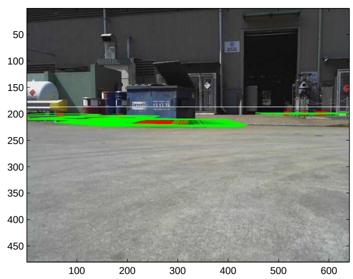
(a) Original source image taken by the tracker.



(b) Estimated shadow image.

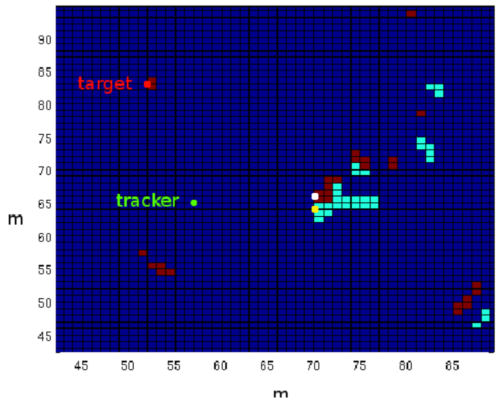


(c) Laser scan superimposed on image.



(d) Region of interest mask for shadow identification.

Figure 8: Example showing the steps in extracting shadows from a source image and laser scan for inclusion in the occupancy grid. Note the red line in (a) and (b) shows the approximated horizon.



(a) Occupancy grid showing the objects detected by the laser in brown and shadows in cyan. Free cells are shown in dark blue. The target's (red circle) and tracker's (green circle) locations are shown and the vantage locations shown as chosen with (yellow circle) and without (white circle) the shadow cell evaluation.

(b) The tracker at its selected vantage location after evaluation of the non-shadow approach.

(c) The tracker at its selected vantage location (in the shadow on the right of the blue bin) after evaluation of the shadow approach.

Figure 9: Example scenario results showing algorithm solution for utilising shadows to improve covertness.

motion between vantage points. Particularly, we have demonstrated and evaluated a method that estimates the robot's acoustic signature in real-time in addition to reliably predicting its contribution to the sound pressure level observed at the target. Furthermore, we have enhanced the visual covertness strategy by incorporating shadow detection into the evaluation of the environment to determine vantage locations which allows greater visual covertness whilst maintaining constant line-of-sight observation of the target. Future work will incorporate real-time classification of the soundscape to better predict distracting sounds as well as human and animal responses to acoustic and visual distractions to for moving between vantage points. Additionally, different environments, different targets, gaze detection and prediction are elements of future work.

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