Mobile Robot Localisation and Terrain-Aware Path Guidance for Teleoperation in Virtual and Real Space

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***Abstract*–This paper concerns the development of a force feedback enhanced teleoperation system for outdoor robotic vehicles navigating in rough terrain where true-colour 3D virtual world models of the working environment, created from laser and colour image scans collected offline, can be explored by walk-throughs both before and during the robot navigation mission itself. In other words, the physical mission intended can be partially rehearsed in cyberspace[1]. Further, during a mission, the location and orientation (localisation) of the vehicle are continually determined and global collision-free paths to selected goal locations made available as advice to the operator, who can follow or ignore such advice at will. Live (real-time) 3D laser range data also provides an up-to-date scan of the volume immediately surrounding the vehicle as it moves so that dynamic obstacles can be avoided. Local terrain-roughness is taken into account in the provision of local collision-free paths, the sub-goals of which are operator determined. This live range data is matched with the pre-scanned range data to calculate the accurate robot vehicle localisation (position and orientation) which is provided continuously during the navigation mission. A force feedback 3D joystick reflects terrain roughness as a vibration in one axis and the other two axes are used to provide a 2D force to attract the operator towards following the local optimal collision-free path, but this attraction can be easily overridden by the operator. The instrumentation and methodologies used for localisation, path planning, force feedback teleoperation and 3D exploration are presented, together with some preliminary experimental results for large outdoor, natural environments.**

Keywords-Human/Machine Interaction, Teleoperation, Localisation, Cyberspace, Robot Navigation, Rough Terrain, Force Feedback.

I. INTRODUCTION

In the realm of mobile robot navigation, the research community has long held fully autonomous operation as the ultimate goal. Yet, in many practical situations, this is not currently possible and, in some, not really justifiable or even sought after. Two examples where fully autonomous robot navigation is ether not sought for or infeasible are provided as follows:

A severely disabled patient may be reliant on wheelchair navigation for his/her mobility needs [2]. Whilst providing sensor-based obstacle avoidance and safe-path guidance may contribute to the user's capacity to better engage the world of mobility, fully automating the process would impinge upon that person's freedom and also cause some reduction of capacities supporting independence still held to be of value in a quality of life sense. The second example could be in a bush fire fighting situation [3], where an operator is available to provide human judgement and mission sub-goals but should not be in risk of physical injury or death. Sensor informed feedback based teleoperation would suit that situation well. Again, some navigation support would be welcomed but full automation not really required (nor currently feasible).

This paper concerns remote teleportation of robotic vehicles, possibly in fire- fighting or search and rescue operations in outdoor rough terrain situations, with sensory feedback and path guidance support. The manner in which the human agency interacts with the system and interprets newly developing situations is considered critical to the quality of the navigation in the context of higher level mission goals.

Robot navigation systems have three essential components and several more peripheral ones. Firstly, the location and orientation (pose) of the robot vehicle needs to be known in the context of its current working environment. This is known as 'localisation'. This can be geometrical or topological in nature and may depend on the recognition of man-made or natural landmarks. Various instruments such as global positioning systems (GPS), flux-gate compasses, wheel odometry, video cameras, laser range finders and inertial systems can be employed for this. The second requirement is the availability of a map of the working terrain or the means of acquiring one whilst navigating. In recent times, considerable research effort has been expended on simultaneously localising the robot and developing an environmental map (SLAM-Simultaneous Localisation and Mapping). There are a number of difficulties using SLAM in the context of the application considered in this paper. These will be touched upon later. The third requirement is collision-free, low risk and somewhat optimal path planning. Ideally the terrain properties, including roughness as well as obstacle structures, should be taken into account by the path planning strategy.

In the SLAM approach [4,5], the environmental map takes quite some operational time to construct and optimal path planning cannot take place before the completion of the map, although piece-wise optimal strategies can be implemented within the context of partially known environmental spaces. There are also some problems with reliably recognising closures (places revisited) to distribute accumulated errors optimally.

In this paper, an alternative approach has been adopted -that of acquiring, off- line, a detailed and accurate environmental map before, perhaps one of many, robot navigation missions are executed. It is admitted that this may not be always practicable but, for many situations, the collecting of the map data can be treated like any other preparation step in anticipation of a crisis scenario which may eventuate later. Clearly, for urban environments which could be subject to natural disasters like fires, floods and earthquakes, this precaution is very reasonable. In bushland settings near homesteads this could also be seen as feasible. Even entire farms with forest stands subject to fire risk could be pre-scanned in this way. Scanning instruments with quite large operational volumes are currently available. These are somewhat expensive, but one could imagine a bureau service providing the scan data for an affordable fee and even insurance companies reducing premiums for clients who have obtained this data. Besides, this technology will become less expensive with time.

The remainder of this paper is structured as follows. The next section describes, briefly, a number of outdoor vehicles instrumented for teleoperation as part of a research effort supporting bushfire fighting. Any one of them could be operated using the navigation system which is the subject of this paper. Next, the instrumentation, both for off-line mapping of the environment and the on-board real-time laser range scanning, which are crucial for this work, is described. Then, a section on localisation and path planning using the results of scanning follows. The whole navigation system with force feedback for assisted teleoperation is then introduced. Discussion and future work follows prior to the conclusions section.

II ROBOTIC VEHICLES

Figure 1 shows a number of standard (commercially available) vehicles which have been instrumented for teleoperation as part of a research project to support bush fire fighting, where the local Country Fire Authority (Victoria, Australia) was the industry partner. The variety of vehicles represents a number of different, yet related, activities supporting bush fire fighting. A four wheel drive farm 'bike' fitted with tracks [Figure 1(a)] is capable of climbing over fallen tree trunks up to 40cm thick and has been targeted mainly for forward scout forays to assess the severity and access possibilities along fire-break tracks prior to fire fighting itself [6]. It can also be used for very rough terrain search and rescue for firemen and property owners who may have became asphyxiated or have suffered smoke blindness. The heavy tracks are extremely difficult to steer and a powerful chain linked hydraulic ram system has been employed for changing the steering direction of the front tracks. Steering, braking and acceleration can all be operated by remote control via standard 'hobby' style servo actuators and a radio control transmitter/receiver pair or, alternatively, by computer Ethernet links to serial line servers which can operate the servo actuators. An excavator [Figure 1(b)] and a front loader [Figure 1(c)] are also teleoperable and are targeted for fire-break track clearing and smoothing for fire tanker access [7]. In both cases, in addition to mobility controls (steering, brake, accelerator), the buckets can also be teleoperated. Figure 1(d) shows a 40 foot boom truck which can used both for search and rescue, with high vantage point views, and the capability of lifting a human up from behind a wall of fire and for directing a steam of water from the boom bucket [8]. Finally [Figure 1(e)] there is a fire tanker [2] which can have 3000 litres of water and spray it at selected directions using a pan/tilt device aiming the water flow [Figure 1(f)].

Whilst all the above vehicles can be fitted with video and infra-red video cameras and laser range finders to assist teleoperation, the particular laser range finder instruments described next are the specific devices which support the main emphasis of this paper.

Fig. 1(a). Four-Wheel Drive Farm

Fig. 1(b) Excavator

Fig. 1(c) Front Loader

Fig. 1(d) 40 foot Boom Truck

Figure 1(e) Fire Tanker

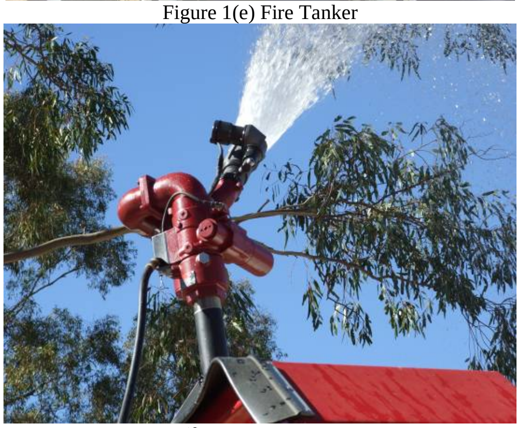


Fig. 1(f) Water Spray Monitor

FIG. 1. ROBOTIC VEHICLES

III. CRITICAL LASER RANGE FINDER SCANNERS

Two distinct laser range finder instruments are crucial in their support of this research. The first collects pre-mission environmental data (range and colour) to build an accurate 3D cyberspace of the working environment and the second collects real-time range data during the navigation mission itself.

A Riegl LMS-Z420i [see Figure 2(a)] is an accurate time-of-flight laser range finder which can be fitted with a high resolution digital camera whose image data can be registered with the range data. This instrument can range up to 800 metres with an accuracy of 1cm, collecting range values at up to a 11,000 samples per second rate. A typical medium density scan from a fixed position takes between 15 and 60 minutes, depending upon the settings used. Since not all aspects of a 3D scene are viewable from only one location, several fairly open locations are chosen for individual scans and these are later fused together under human supervision with computational support. These separate scans should overlap to allow accurate registration during integration. A two metre diameter 'dead zone' exists around the instrument since, up to this distance, the return timing is too short for the instrument to record correctly. A typical view of a scanned space is shown in Figure 2(b).

The second laser range finder is a Velodyne HDL-64E S2 [see Figure 3(a)] which spins at a rate of 5-15 Hz to collect range data up to 120 metres away (dependant upon the target surface albedo) at a date rate of up to 1.8 million samples/second at an accuracy of 2cm.

The Velodyne contains 64 independent laser sources and sweeps 64 live scans around the axis of rotation, collecting data from +2° to -24.8° in elevation. When mounted high on a vehicle it allows the volume that vehicle can move through to be analysed for obstacles and also permits the terrain undulations and holes to be analysed. A typical scan is shown in Figure 3(b).

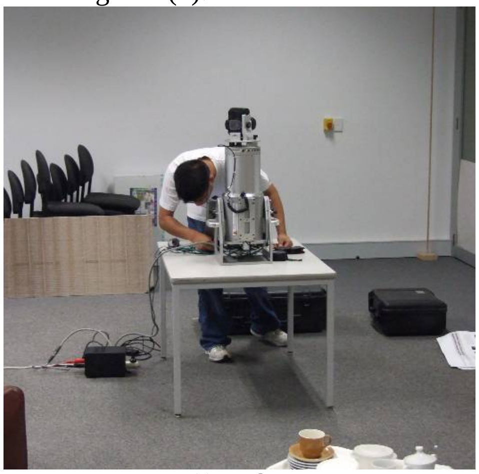


Fig. 2(a) Riegl Scanner

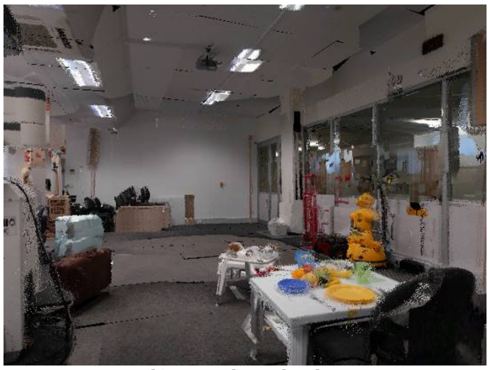


Fig. 2(b) Typical Riegl Indoor Scan

Fig. 3(a) Velodyne Range Scanner

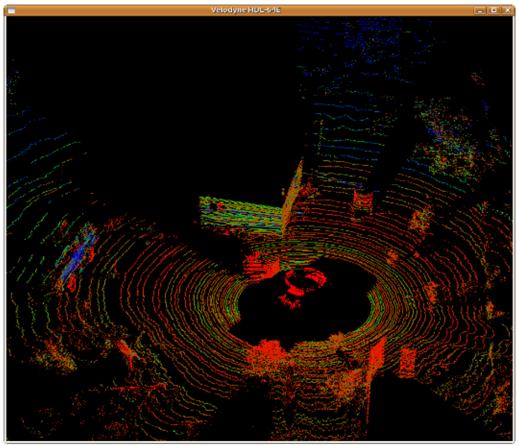


Fig. 3(b) Velodyne Outdoor Scan Example

Both instruments can be powered by standard 12Volt batteries and are connected to the controlling computer via Ethernet, but with the digital camera requiring a USB port.

The range and colour imagery collected by the Riegl scanner and attached digital camera at various locations and subsequently combined, can be explored as a virtual world, moving, through it at ground level or from a 'fly over' elevated view. This exploration can be used for pre-mission familiarisation and for noting specific aspects such as the location of dwellings or water sources, fences, gates etc. which may assist in the mission itself. It can also be used to make judgements on tolerances for obstacle avoidance which should be used during the mission and where grass and bush may be navigable despite perhaps being regarded as obstacle space because of its height.

IV. LOCALISATION AND PATH PLANNING

The knowledge of the pose (position and orientation) of the robotic vehicle is an important requirement for efficient path planning and following, even if it were not strictly necessary for teleoperating a vehicle using on-board sensors alone (eg. cameras and range finders).

A data-base of range 'signatures' is first extracted from height thresholded (between 0.5 and 1.0 metres) range data from the Riegl scanner at intervals over a 0.1 metre grid over the working environment, associating the range to obstacles of 180 radial rays at 2° intervals around the 360° sweep, with each ray length larger than 50 metres marked as 0 (keeping only values clearly within the range scope of the Velodyne). This data-base is constructed off-line so its computational time cost is not crucial. Some local averaging is done to smooth the data to enable better spatial matching tolerances. In real-time, whilst the robotic vehicle is navigating, a similarly constructed 'signature' from height thresholded Velodyne range data and matched through searching the 'signatures' in the data base is used to determine the pose of the vehicle. A rough match is followed by a more refined one to improve the efficiency of the method. The robot vehicle can be localised, typically, within ~15cm of its actual location and ~1 degree of its actual orientation at the rate of 0.35 seconds per fix using a fast Intel i7 2.67 GHz processor with 6 Gb of RAM. Continuity constraints are used to limit the search requirements once the vehicle is initially localised, a complete initial search taking a number of seconds.

The simple matching formula used is as follows: Given two ‘signatures’, one extracted from the current Velodyne range scan and one selected from the Riegl pre-scanned data base, S1 and S2, respectively, each with 180 range components.

S=Sum[exp(-Abs(S[i]-S2[i])**2/(2*Sig)] over i=1 to 180 where Sig is a experimentally selected standard deviation and Abs the absolute value operator. This produces a Gaussian weighted measure which downplays badly matching range rays.

Then X= w+b*S where w and b are experimentally determined parameters. The final score is calculated by Score= 1/(1+exp (-X)) which is between 0.0 and 1.0. The larger the score, the better the match. Further details can be found in [9].

Clearly, more sophisticated matching techniques can be developed but this first approach was found adequate for our purpose, since the terrain we used in our initial experiments was reasonably planar. The pose data (position plus orientation) is exported continuously to a text file for the path planner to access when necessary, the most recent information overwriting the previous pose data. Figure 4 shows a coherent sequence of localisation traces (in real space with a physical vehicle) with the current location for each ‘screen shot’ showing the Velodyne range rays which were matched against the pre-scanned Riegl data to determine the location/orientation of the vehicle. The view of the cyberspace model obtainable from that point is also shown from ground level. One can identify correspondences between objects in that view and some structures in the plan map showing the localisation point. The vehicle is approaching a shack with a fire tanker (red) looming larger. The smoothness and continuity of the traces is clearly impressive and indicates a very high confidence in the reliability and accuracy of the methodology used.

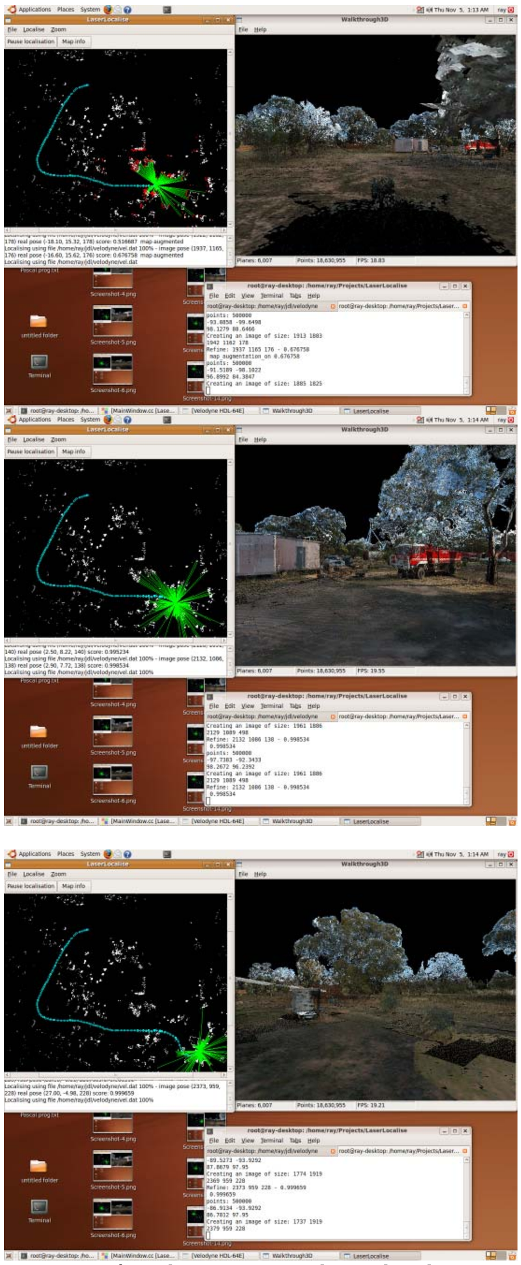


Fig. 4 Sequence of Localisation Traces and Virtual Reality Viewpoints for an Actual Physical Experiment.

A number of path planning methodologies have been published [10,11,12]. Many treat the search space as a Euclidean geometry domain made up of points and lines with polygonally enclosed obstacle spaces. Details can be found elsewhere [10]. An alternative approach is grid based, where the search space is made up of tessellated (generally rectangularly) cells which are either occupied by obstacle or not (free). A path in such a space is a sequence connected free cells form a start cell to a goal cell. The computational burden of such methodologies is highly related to the resolution chosen for the environment space representation. A big advantage of the grid cell based approach is that, in addition to occupancy or not of obstacles, other cost structures can be represented in the cellular structure so that properties such as visibility or terrain roughness etc. can be accommodated in the path optimality calculations. One can even include tolerance costs in relation to the proximity of obstacles so as to allow the robot to stray off its path to some extent without collision.

A Distance Transform (DT) path planning strategy was used in this study as it has a number of advantages which suited the needs of the project [13] despite there being more recent and complex alternatives. It is simple to compute, can accommodate costs over the cell structure, including collision risk tolerance and probabilistic structures and can easily be extended into time/space for both deterministic and probabilistically estimated cost structures projected into the future. It can include multiple goals and provides an optimal path from any cell in free space to the least cost acquirable goal simply by following a steepest descent trajectory in the DT space. This last properly is particularly useful, since, if the robotic vehicle is driven off the currently mapped out path, a new optimal path from its new position is instantly available using a new steepest decent trajectory in the already calculated DT space. The details of the DT method can be found elsewhere [13] but an outline is provided here for completeness and for better being able to explain the path-guided teleoperation approach which is described later.

First consider the simple case of an initially rectangularly tessellated N x N cell space with free cells marked '0' and obstacle cells marked '1' with only one goal.

1. Leave the goal as '0', putting a large number in all other free-cells (say > N^2) and mark the obstacle cells with computer infinity (say $2^{32}-1$).
2. In raster order (left to right, top to bottom, one step at a time), skipping over obstacle cells, replace the free cell value with the least value (cost) of recently visited neighbours (3 x 3 region) plus 1 (assuming that costs from entering the cell from any of its neighbours to be identical). In fact only 4 comparisons are needed (three cells in the previous line and the one to the left) but all can be used without error. The goal cell should not be altered as it is zero cost from itself.
3. In reverse raster order (right to left, bottom to top, one step at a time) repeat the operation described in 2. Now only the cells in the line below and to the right need to be looked at.
4. Repeat 2 & 3, above, alternatively until no further changes occur.
5. The resulting map is the Distance Transform and a steepest descent trajectory from any free-cell will lead to the goal with the least number of steps

Some border conditions need to be set so the rasters, are usually carried out over a (N-1) x (N-1) grid.

A simple example of a DT result is shown in Figure 5(a). If the cost of a diagonal move is preferred to be $\sqrt{2}$ compared to a up/down or left/right cost of 1, the approximation of a weight of 3 for diagonal moves and 2 for the others can be used [see Figure 5(b)]. In fact, 4:3 is even better and 17:12 almost perfect. In this case the candidate cell value is replaced by the least value of the sum of its neighbour's cost plus the cost of entering the cell from that neighbour. If costs are to reflect distances as well as roughness, tolerance or probabilities, the same process can be used, as long as all costs are non-negative. No local entrapment occurs using this strategy and the paths formed by steepest descent trajectories are truly global at all times. Only unreachable cells (enclosed by obstacle cells) are indeterminate.

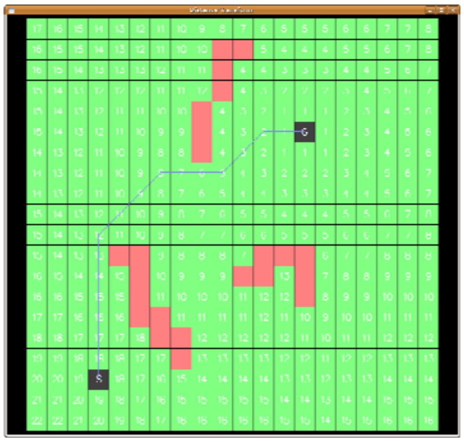


Fig. 5(a) Simple DT Result

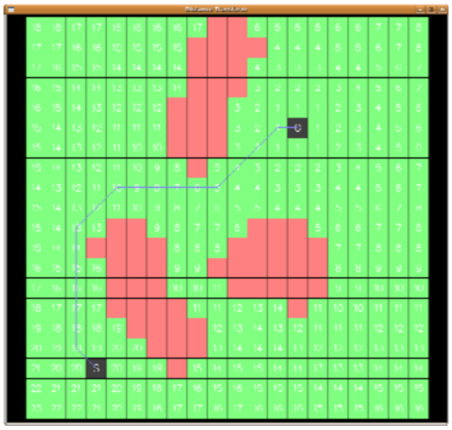


Fig. 5(c) Grown Obstacle Field

A particularly elegant way of 'growing' obstacles to increase collision-free tolerance and/or to allow for the physical dimensions of the robotic vehicle, is to initially treat all obstacle cells as pseudo goals (set to 0) and carry out the DT computation which leaves all free-cells with values equal to their distance from their nearest obstacle cell. Returning all values larger than a set threshold (say equivalent approximately to the radius enclosing

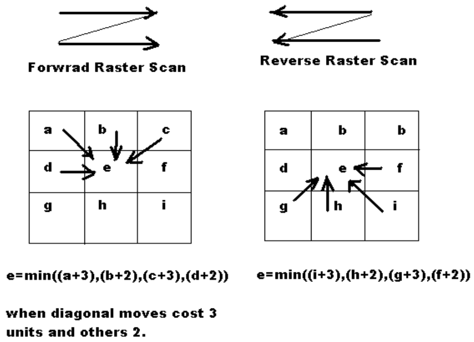


Fig. 5(b). Raster Ordering and Calculation

circle of the vehicle, or more) to free-cell status are marking the remainder as obstacles will achieve the desired obstacle growth automatically [see Figure 5(c). Furthermore, the absolute difference of the value of cells (other than those set as obstacle cells after the DT process) from the maximum value over all non-obstacle cells can replace the cell value as a risk of collision cost which can be incorporated into the path planning process. The local maxima of the DT field provides a digital version of a Voroni construction and can represent safe 'roadways' through obstacle space. A more complex DT example is shown in Figure 5(d), showing the global qualities of the methodology.

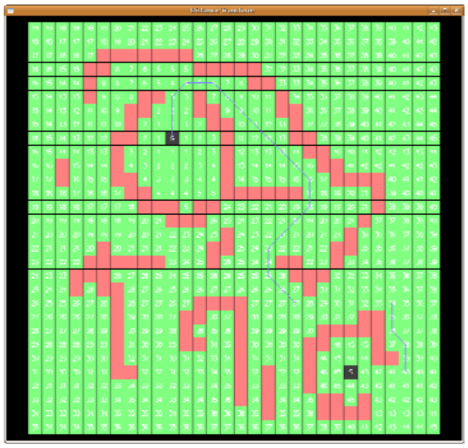


Fig. 5(d) More Complex DT Example

Two levels of path planning using the DT methodology are used in this project, one applied to the obstacle field data from the integrated Riegl scans one for the local Velodyne live obstacle field data. For the Riegl data a path from the current location to a nominated goal is calculated. As the position of the robot vehicle is changed a new path is calculated. Note that the DT need only be calculated only once for each new goal specification in this case. The goal point can be changed at any time, the DT being recalculated when required or simply continuously to avoid checking the goal change status. For the Velodyne obstacle field data case, the DT is always continuously recalculated (whether or not the goal status has changed),since dynamic obstacles may appear and , in any case, the robotic vehicle is moving.

For this project, given that the raw Velodyne 3D range data provides terrain height data, a roughness factor was be calculated at each free cell location based on the sum of absolute height differences from the candidate cell to each of its eight neighbours and this sum was weighted into the cost of entering a free cell, with 3:2 distance component included as well. All obstacles were grown by a nominated number of cells beforehand as described earlier.

V. TELEOPERATIONAL NAVIGATION SYSTEM WITH FORCE FEEDBACK CONTROL

Figure 6 gives the block schematic for the whole teleoperational navigation system. The off-line Riegl data collection and localisation 'signature' data-base is entirely fixed and calculated prior to mission time. The environment Virtual Reality (3D plus colour) model [see Figure 7(a)] can be explored in detail at any time either before or during physical navigation. One may 'walk through' this virtual space at ground level or from any elevated viewpoint. During navigation one can either explore at will or use the localisation fixes provided by the system to position the viewpoint (elevation can also be changed independently). Live data from the Velodyne range scanner scan data, provided at 10 Hz rotation speed, is matched against the Riegl data-base (signature matching) to provide the current robotic vehicle pose. The local environment obstacle map derived from Velodyne range data is centred on this localisation fix with the vehicle direction of orientation always up on this map. The live 3D Velodyne data can be viewed simultaneously from a variable orientation view point and zoom.

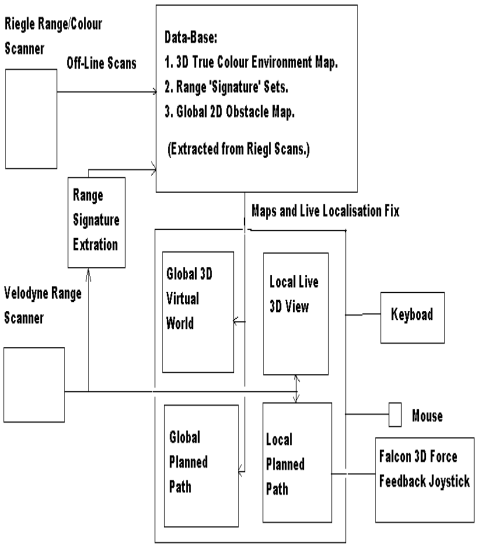


Fig. 6. System Schematic

A global environment obstacle map is also provided [see Figure 7(b)]. The global goal can be selected via a text file or using the computer mouse. The current localisation position defines the start point of optimal path trajectories to the goal (or least cost goal if there is more than one goal). The optimal (shortest) path shown on the global map is for grown static obstacle avoidance alone.

Fig. 7(a) 3D Virtual Reality Model

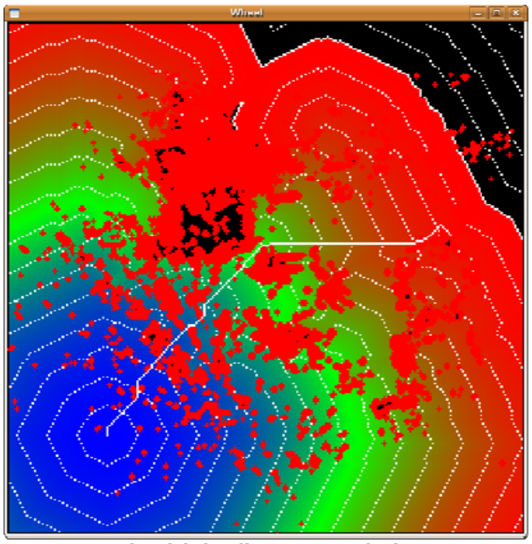
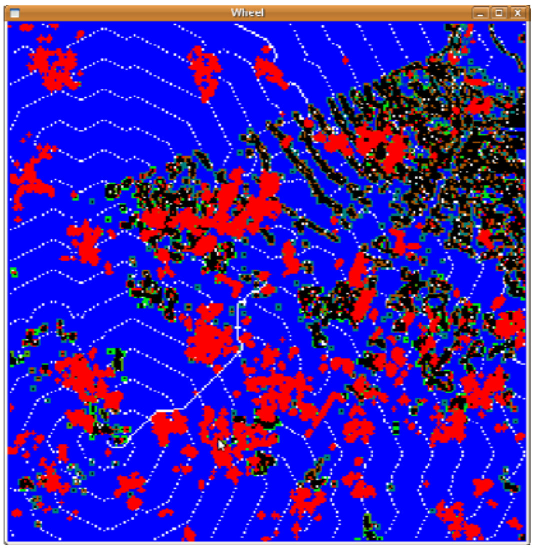


Fig. 7(b) Global Collision-Free Path Planning

The local obstacle/terrain roughness map shows live data updated from Velodyne data quite rapidly (e.g. at 0.5 second intervals). The local path trajectory (using a DT which accommodates distance as well as terrain roughness after growing obstacles a specified amount) is for advice to the operator with the centre of the map representing the current robotic vehicle location [see Figure 8] and the local goal selected using a computer mouse. In Figure 8, two different goal positions are selected; for the second image, it can be clearly seen how rough terrain is avoided at the cost of a longer path. The operator is free to choose a local goal consistent with the global path trajectory shown in the global display but can select any local position if variations to check environment details are preferred. It would even be possible (but has not yet been done) to make the local goal some number of steps forward along the globally determined optimal path as a default. Even when the local optimal path trajectory map reflects the operator's local goal selection the operator is free to ignore it. Given that the Velodyne 3D range data is live, any dynamic obstacle will be taken into account in the local path trajectory (but can not be so accommodated in the global fixed data unless the

Velodyne data is made to temporarily overwrite the Riegl data which has not been done, so far).

Now this is where the 3D Falcon force feedback joystick [see Figure 9] comes in. The horizontal/vertical movements of the joy stick control the driving of the robot vehicle (off the planned path if so desired) but force is applied to the joy stick to pull it back towards following the local planned path. However, each excursion away for the path defines the starting point for a new path so the force field is continually changing. Lightly holding the joystick allows the vehicle control to be consistent with the local planned path. Also, the third degree of freedom of the joystick (in our case in and out) is vibrated by a magnitude proportional to the terrain roughness factor calculated as described earlier so that driving over rougher terrain can certainly be felt by the operator. Only full field trials (not yet carried out) will determine how best to provide the force controls described above. It may prove necessary to provide some smoothing filters in the force feedback loop to reduce overshooting jerkiness. It would be hoped that the path preference and terrain roughness force feedbacks will give an intuitive feel to the operator and also effective navigation naturally without stress.



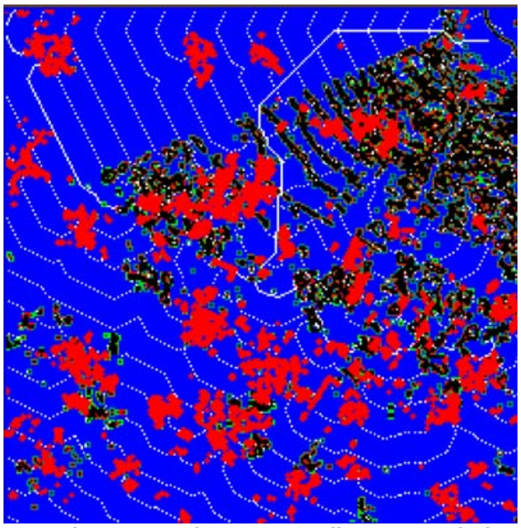


Fig. 8 Local Terrain Roughness Aware Collision-Free Path Planning

Fig. 9 Novint Falcon 3D Force-Feedback Joystick

VI DISCUSSION AND FUTURE WORK

The three central elements of the work described here are as follows:

1. The Riegl range and image data is used to build a virtual world [14] of the robotic vehicle's work space and provides the 'signature' data-base for localising the vehicle by scan matching. The Virtual Reality world can be explored in detail at ground level or an elevated position either before or during navigation (in this latter case the current position and orientation

can be used for viewpoint determination if so wished).
2. The Velodyne real-time 3D range not only provides 'signature' data for run-time localisation by scan matching against the Riegl 'signature' data-base but also provides dynamic local data on obstacles, ruts, moving objects, terrain roughness and the like whilst the robot is navigating and forms the basis of local path planning, force feedback navigation control and roughness vibration magnitude data in real-time.
3. The 3D Falcon force feedback joystick provides the operator with the capability of freely driving the robotic vehicle but with path planning guidance with preferred direction force feedback for driving and vibration feedback for terrain roughness monitoring.

Whilst not mentioned explicitly earlier in the paper, once the Riegl data has been collected and integrated, the vehicle can be confidently navigated at night since the virtual environment world is lit and the Velodyne data needs no ambient lighting to collect. Whether rain and/or smoke would seriously compromise this operation has not yet been investigated.

Also, in the future, more sophisticated data matching for localisation in very rough terrain might be explored to provide accurate and reliable 3D localisation fixes. Eventually, the navigation of smaller robotic vehicles in 3D man-made constructions may be possible using this approach.

In some earlier work [15], it was shown that an 'appearance-based' localisation method, where unwarped panoramic images collected on-board and compressed using Haar transformations were matched against visual signatures (similarly compressed) constructed off-line from the pre-collected range/image Riegl data base, could yield acceptable localisation results without using an on-board laser range finder. Particle filter methods were used to achieve approximate localisation. However, the accuracy achieved by this approach was not as good as that possible using range matching. The 'appearance-based' results would have been worse in more sparse environments where less position/pose discriminating views could be extracted. Furthermore the 'appearance-based' approach would be inoperable in poor ambient lighting conditions (or at night) whereas the range based system can operate in any lighting conditions. Figure 10 shows two snapshots of a localisation trace being calculated. The central inserted panel show the unwarped current view from the on-board panoramic camera. The test environment is a partially covered outdoor, paved, flat environment with high visual business. In Figure 10(a), the initial spread of the particles over the environment indicates a wide search to find the starting position by image matching. In Figure 10(b), tracking based on continuity constraints allows the particle scatter to shrink; the weighted average point is taken as the calculated location.

(a)

(b)

Fig. 10 Appearance Based Localisation Example

VII CONCLUSIONS

This paper has introduced the idea of terrain roughness and path planning guidance for the teleoperational control of a robotic vehicle in outdoor rough terrain with force feedback to assist control and terrain roughness monitoring with the added advantage of exploring a virtual world of a 3D visual model of the working environment either before or during a navigation mission. Application areas such as bush fire fighting and search and rescue have been used to motivate this approach which allows both some degree of autonomous navigation to meld smoothly with teleoperational human guidance. Physical experiments to test the localisation methodology described in this paper have been successful in demonstrating the speed, accuracy and reliability of the approach, all of which were very satisfactory, even using the simple matching formulations described. More work on human factors need to be carried out to properly gauge the value of this approach to bridging the gap between pure teleoperation and fully autonomous navigation.

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