Landmark Navigation with Fuzzy Logic

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Abstract

Our previous research emulated aeroplane navigation for dead reckoning flight in reasonable weather conditions. In this research, we propose to tackle navigation in a more realistic environment for a mobile robot by modelling it on the case of a tourist in an unfamiliar village. When lost tourists use a variety of strategies to reacquire the path. Here we will emulate these to navigate a mobile robot. We will attempt to develop an intelligent controller, which copes with imprecise inputs, to achieve its commanded tasks safely. The controller will make use of fuzzy logic to make decisions based on data stored in a fuzzy map that is represented as sets of rules. Rules that it can use to localise and navigate towards a target.

1 Introduction

Autonomous navigation of a mobile robot is the challenge of driving along a path while constantly determining its position and course. To that end, the robot uses on board sensors to explore its environment to determine the instructions to give its guidance system.

Mobile Robots currently employ a number of navigation strategies and use various sensors as navigational aids. The selection of sensors is directly dependent on the strategy the robot employs; line-following robots use vision systems to detect and follow the line, and track robots mount and remain on the tracks using specially designed wheels. Relative positioning robots rely on dead reckoning (odometry) and error correction (Borenstein & Feng 1996). Absolute positioning robots rely on landmark detection (Ratner & McKerrow 2003, McKerrow & Ratner 2001). However localisation is a challenge for a robot that works in an unknown, uncertain, unpredictable and dynamic environment. The robot's sensor system has to perceive its environment and cope with imperfect and inaccurate sensor data. Typically, uncertainty is caused by errors in sensors, slippage and poor calibration of encoders, cross talk, and multiple sonar echoes. These errors lead to inaccurate estimation of the robot's position in its work environment.

The problem is the paradigm mismatch of attempting to represent analogue position data (perception) in a digital (mathematical) computation. Pin *et. al.* (1992) asserts that it is difficult to generate complete and exact (crisp) mathematical models and/or numerical descriptions of all phenomena contributing to the robot's and environment's behaviour. These assertions are echoed by Thrun *et. al.*(1998).

In the research proposed, we aim to demonstrate that fuzzy logic has features that allow an autonomously navigating robot to cope with the inherent uncertainties that occur when using sensor acquired location data as the navigational aid.

We seek to mimic the approaches a tourist employs in navigating a new or unfamiliar village. To travel from one point to another the tourist consults a map to plan a path from his current position to his destination. Then he would periodically check it to verify and correct his direction. In doing so, the tourist is able to cope with uncertainty (a crowd blocking a path) and take advantage of unforeseen opportunities (cut across a park, walk through a car park or a shopping mall) to reach his destination.

The tourist may also use prior experience to reach a new destination using a previously followed successful route i.e. the museum is near the library and a route to the library is already known. The tourist is able to avoid obstacles, and circumnavigate paths that become blocked from time to time. We envisage this human-like navigation ability is essential to safely expand mobile robot workspaces from confined controlled environment to the typically dynamic uncontrolled real world environment.

1.1 Sensing Landmarks for Fuzzy Maps

A robot capable of accurately sensing landmarks should be able to navigate from landmark to landmark on or along a path it plans. We seek to demonstrate that: if we can accurately sense a landmark (i.e. identify which landmark, its range and bearing) then it can navigate including the following tasks:

A. Map the world as a graph of landmarks (fuzzy map of rough distances and bearings).

B. Hypothesise the location of the robot based on the sensed landmarks.

C. Confirm the hypothesis (from B) by:

   i. Comparing sensed landmarks to its expected position from the fuzzy map and its memory of where it has been.

   ii. Moving to sense more landmarks (in turn this data would be used to build up a journey history).

D. Correctly conclude when it is lost and why (poor sensor values, sparse features populating fuzzy map, poor odometry data)

E. Reacquire its navigational path after becoming lost (localise by matching landmarks to map while taking into account the path covered so far).

F. Methods to cope with the inherent uncertainties of dynamic environments and for re-planning if a task path becomes inaccessible.

G. Understand its task command and plan a path to reach its goal when given a command in a linguistic form.

H. Record both successful and unsuccessful runs for future reference.

The remainder of this paper describes common navigation strategies, fuzzy maps and fuzzy logic control of mobile robots, landmark sensing and its importance. It will also discuss sensing strategies suited to the application of fuzzy logic to navigation, fuzzy logic approaches suited to the research proposed, experimental equipment and a brief outline of the proposed experiments.

2 Common Navigation Strategies

Piloting is a strategy that uses known landmarks in a sequential order to find the way to the goal. Piloting includes following continuous landmarks, feature matching and compass piloting. A pilot uses a compass to triangulate and determine current location. The pilot takes an initial bearing on a recognizable landmark using a compass to draw a line from the landmark to the estimated current position and beyond it. The process is repeated for a second landmark at least 45 degrees away from the first a second line is drawn. The current position is the point where both lines intersect. Repeating the process for a third or fourth landmark simply increases the accuracy of the triangulated position. The pilot can then plot a route of travel on a map, sight on landmarks for straight-line travelling and plot detours in the right direction to avoid obstacles.

Dead reckoning is a process of estimating position by advancing a known position using course, speed and time to calculate the distance that has been travelled. In other words figuring out where the robot is at a certain time based on the assumption that its measurement of speed, time and bearing are correct.

Celestial navigation ascertains an unknown position from a known position using spherical trigonometry to solve a navigational triangle. This is a triangle on the earth's surface with the North (or South) Pole as one corner, the "Geographical Position" (GP) of the celestial body as another and, the Assumed Position (AP) as the third. One side is from the Pole to the assumed position (or 90 degrees minus the assumed latitude). The second side is from the Pole to the GP or 90 degrees minus the body's declination from the assumed position to the GP or 90 degrees minus the calculated height of the body above the horizon "Zenith Distance".

It is simple to find the first two sides and the angle included between them, as the assumed latitude is known, the body's declination at that moment can be gleaned from nautical tables, and the Local Hour Angle is calculated from the location data. With this information the third side, distance from the GP and the angle or direction to the GP is a simple calculation.

Sextants measure the angle between the horizon and a celestial body. These angles are measured in degrees and minutes of arc (1/60th of a degree). Measuring this angle to an accuracy of 1 minute of arc (1') will result in a positional accuracy of 1.852 km. Accurate sextants can measure this angle to an accuracy of 0.2'. This means that theoretically, a user can determine their position to within 321 meters. Additionally, precise time of day is essential to accurately compute the GP of the celestial body. A 1 second error will cause a positional error of up to 402 meters (Cozman and Krotkov, 1995).

3 Fuzzy Maps

Fuzzy logic is in a way a mimic of human knowledge and experience when dealing with uncertainties in a control process. Control is fuzzy logic’s most useful application. Fuzzy logic is particularly suited to condition where only approximate and uncertain data prevails. As our proposed research will deal with imprecise information about an operating environment, which cannot be expected to behave predictably a fuzzy control system is particularly applicable to our research. Our proposed fuzzy logic control system will combine the knowledge of its operating environment represented as rules that make up fuzzy sets. A collection of these rules about a given locale can be viewed as a fuzzy map of that locale (Cox and Kosko, 2002).

The fuzzy map is a graph of paths and landmarks. The paths are represented by arcs that contain approximate distances and bearings between landmark points. Nodes represent landmark points. Landmark points that are intersection of paths are on the paths. Landmark points that represent landmarks near the paths contain geometric information about the location of the landmark relative to the landmark points on the path.

This map is expressed in terms of descriptors of a physical location (fig 1, 2).

The fuzzy controller runs/interprets these rules in parallel such that it considers run history, sensed environment features, and expected features as per the relevant fuzzy set to where it hypothesizes it is. Accumulating evidence for and against, it tests every hypothesis. As each rule is processed it contributes to the final conclusion the controller reaches fig (3).

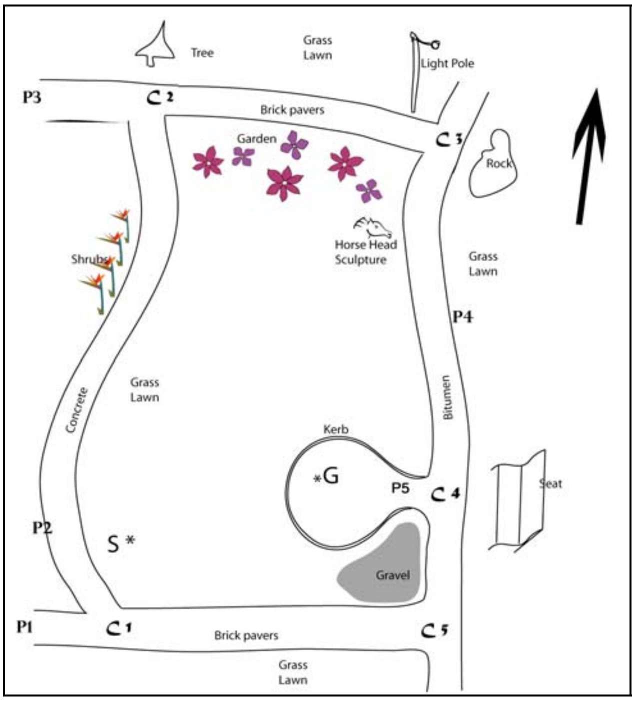

Fig 1 Map of a test location, C denotes corner, P denotes path, S* denotes starting point and *G denotes goal.

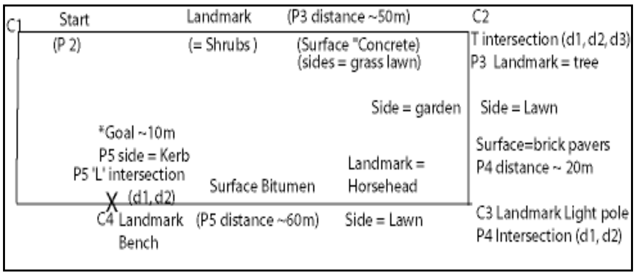

Fig 2 Robot journey can be expressed in rules from the map

At starting point *S**, the experimental robot Titan (described in 5) is instructed to travel to **G* (fig 1). The controller consults the fuzzy map to plan a suitable path to travel towards **G*. The controller concludes that given the current position and heading it would:

i maintain current direction on path *P2* to corner *C2*
ii turn right onto path *P3* and travel to corner *C3*
iii turn right onto path *P4* travel to corner *C4, and*
iv turn right onto path *P5* travel to goal **G*

As Titan enters a path segment it locates the first landmark and plans a path along the sub-segment to that landmark (or follows a continuous landmark). When it nears the end of the sub-segment it looks for the landmark. When it finds the landmark it repeats the process for the subsequent sub-segment and segments. Figure 2 shows that when travelling along *P2* Titan expects to sense Surface = concrete, Landmark = shrubs, Wheel-Encoder reading = travel 50meters where Titan expects *C2* Landmark = Tree.

Titan will calculate its Localisation hypothesis at regular intervals (fig 3) and the fuzzy controller will test their veracity against sensed landmarks as it travels. Where a test returns a false outcome the controller will then need to determine from supplemental sensing if Titan is lost or the false test was due to outliers in its fuzzy data.

In the case where the controller determines that the false test means Titan is lost, it will stop Titan in order to test all the relevant locale rules. When locale data are processed and defuzzified the controller can reach a conclusion (with a high measure of confidence) as to where it is (I am where I expected to be) or determine that it is lost.

Planning – 2 paths → to goal
Location (Titan) → I think I am on P3
History → Left on P3 with Landmark Tree
Scan → Expect to find
Surface → Brick Pavers
Surface → Grass Lawn
Light Pole

Fig 3 Robot controller defuzzifying its location data

The goal of using rules to hypothesize the robot's current position is to reduce localisation uncertainty (fig 4). A set of observation data from a mobile agent can be matched to a similar set of stored data to draw an inference as to the current location of the robot. In reality the robot can use an incomplete set of observation data to localise itself within a measure of acceptable certainty by matching its observation to the fuzzy map data.

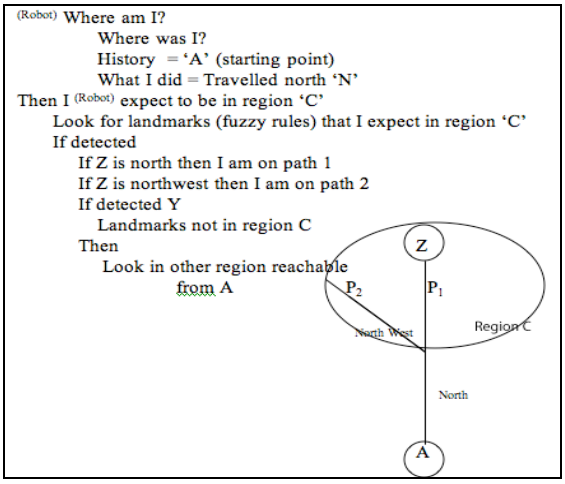

Fig 4 Fuzzy Inference Using Rules from Fuzzy Map

Navigation using the stored fuzzy maps (as proposed in 1.1.B) becomes a simple landmark-to-landmark course selection exercise (fig 5). The task can then be broken into short legs and the appropriate fuzzy map is selected for each leg (Gasós and Martin, 1996).

From A	NW	NNW	N	NNE	NE
Z	P_2		P_1		
M		P_4			
Q					

Fig 5 Fuzzy Data Sets

4 Fuzzy Logic Control of Mobile Robots

Autonomous robot control in a priori unknown, real-world, unpredictable, dynamic workspaces, where engineering all the uncertainty away is not possible is at best computationally hard. We propose to use approximate reasoning as a computationally inexpensive alternative to uncertainty analysis and propagation techniques. This approach was demonstrated to be viable in a scheme of six behaviours and fourteen rules by Pin *et. al.*(1991). This approach allowed the progressive merging of behaviours into schemes that resolved situations encountered in a dynamic environment. In Pin *et. al.*(1991) the mobile agent successfully achieved obstacle avoidance, and wall following behaviours, and did not get trapped in local minima.

Fuzzy Logic does provide a robust method to derive reasonable controls from limited sensor data. The fuzzy sets with which we propose to populate the fuzzy map, define relative positions and classes of objects characterized by angle and distance. The fuzzy map we propose will include the stable features of the environment such as buildings, lampposts, surface textures, trees, fences, bicycle racks, sculptures and other outdoor features in the University of Wollongong's campus grounds as well as their approximate locations expressed as fuzzy sets.

Using fuzzy inference rules such as:

If surface = paving bricks
If heading = north west
If Last Landmark = Horse Sculpture
If distance from Last Landmark $\approx$ *50*
Then Location = Engineering bike rack
If landmark = bike rack
Turn East 120 degrees…

Each fuzzy set is examined, compared and correlated to a locale in the fuzzy map. Related controls for the robot's speed and steering angle are fired to modify its heading or speed to reach its target or to re-localize if it determines it is lost. When unknown obstacles are detected on the planned path, obstacle avoidance behaviour will be employed to pass the obstacle. (Roth and Schilling, 1995).

Fuzzy techniques implement basic behaviours that are robust to uncertainty, co-ordinate the execution of multiple behaviours to achieve an overall goal, and maintain the robot self-localised with respect to a fuzzy map. The robot controller selects the controls that best satisfy all the behaviours required to reach a target. At times, this may not be possible, especially if some behaviours prefer opposite actions the later should be recognised as a potential deadlock situation due to uncertainty, that indicates that the fuzzy controller needs modification.

Behaviours are not equally applicable to all situations. Path following is applicable in/on a clear path, but obstacle avoidance behaviour is more applicable when there is an obstacle in the way on the path, for example a pedestrian or cyclist. So a controller has to make a decision as to which behaviour is chosen. The fuzzy controller computes all the needed behaviours to reach a target, blends them according to a desirability function/matrix, and finally chooses one-control value and fires appropriate actuators.

At any given point in time, the robot will hypothesize its own location in the fuzzy map represented by a fuzzy set. During navigation, the robot's sensors will recognize features and the map will be searched for matching objects. Each match is used to build a fuzzy hypothesis of the robot's location (a localizer). In other words, a fuzzy set representing the approximate location on the map where the robot should be in order to see the object features it has observed. Each localizer is then used as a source of information about the actual position of the robot. All the localizers at a given point in time plus the robot's memory of where it has come from (history) are combined by fuzzy intersection to produce the new location hypothesis and the cycle repeats (Saffiotti, 1999).

The selection process for a suitable behaviour in a novel situation is a complex task. Research is needed to develop a suitable selection algorithm. Kristian Hammond et. Al. (1993) considered complexity vs. simplicity and noted that planning is problematic as it makes some overly optimistic assumptions. These assumptions are: a stable world that behaves predictably, planning time is independent of execution, correct input data was used for planning and initially correct plans will remain correct and can be carried out. However, it is unrealistic to expect the dynamic environment of a mobile agent to remain static and to behave predictably. These two issues alone add a measure of complexity to a planner's task, rendering it NP hard, even NP incomplete.

In its dynamic world, our mobile robot planner will confront a stream of conjunctive goals such that if treated singly, the planning computational overhead will skyrocket and in the absence of parallelism the planning time alone will deplete the time available for execution. We concur with Hammond et. Al. (1993) and Thrun *et. al.*(1998) that it is unrealistic to expect our robot's planner to have complete information about its dynamic domain at any given point in time. Furthermore, execution time failures are inherent as a plan perfect at time t becomes less perfect at time t+1, the planner would need to be able to Re-plan, Recover and Repair the plan.

Most importantly, since the dynamic environment will seldom match the planner's projection and its plans may miss goals at planning time that may be opportune at execution time. The executor must be able to notice and exploit opportunities at execution time, Hammond et. Al. (1993). Plans should be modified by the planner at execution time to take advantage of opportunities to achieve goals. Planners should also study failures as a means of learning so that future plans and executions can avoid failure should similar circumstances arise. When the mobile robot has concluded that it is lost, and has re-localized by sensing landmarks, it can re-plan a completely different path to the goal from its current position instead of attempting to resume its previously planned path.

5 Experimental Robot

The experimental robot "Titan" is a 4-wheel drive robot built from a redesigned electric wheel-chair used in previous research (Fig 6) (Ratner and McKerrow, 1999). Differential velocity control, castoring front wheels, and a floating 4 bar linkage on the front-end wheel assembly allow Titan to achieve skid free Ackerman steering with differential-velocity control of the wheels (Fig 7).

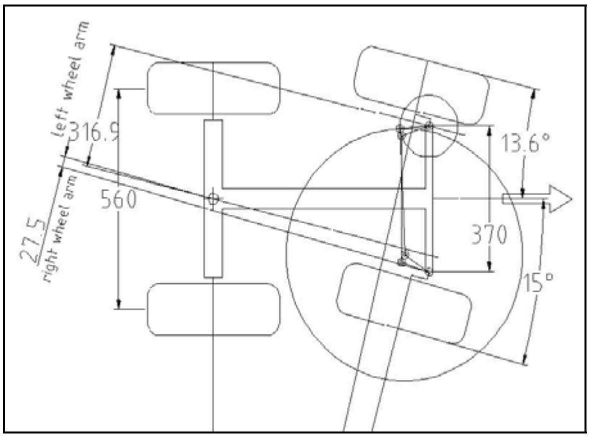

Fig 6 Titan's chassis diagram

Titan travels on 4 low-pressure pneumatic tyres, which provide traction on most terrain, and double as a simple suspension system on uneven surfaces. Titan can be manually driven using a joystick. The joystick provides forward and reverse movement with directional control (turn left and turn right steering) that are achieved by varying the voltage to the motors. Reverse can be achieved by reversing the voltage polarity to the motors, but directional control is difficult due to the mechanical castoring of the front wheels.

Titan is equipped with a number of sensors for use in outdoor navigation research. Two 2500 pulses per revolution optical encoders are coupled to the rear wheel hubs (Fig 8) and the third to the front left wheel hub to measure distance travelled and steering angle (Ratner and McKerrow 2003).

Bearing is measured with a gyro-stabilised compass. A 2-axis inclinometer measures Titan's angle of inclination from the horizontal.

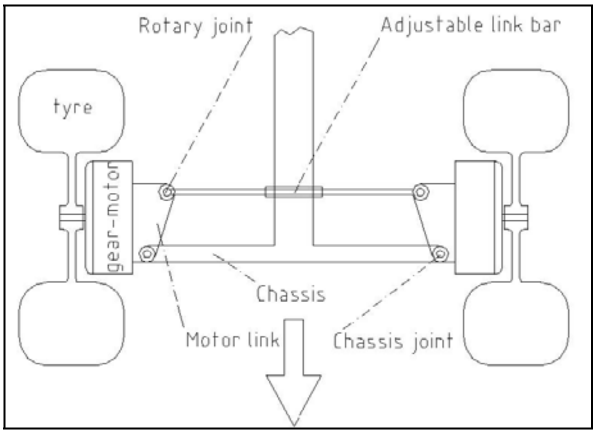

Fig 7 Titan's steering assembly

Titan is equipped with a CTFM sonar sensor: a 20-element phased array transmitter at the top of the device and 4 receiving transducers arranged below it (Fig 9). When installed on the robot, the sonar head is mounted on a directionally controllable Pan & Tilt unit (Fig 10). The sonar is connected to an onboard sound system to allow the researcher to listen to the landmark signatures in the frequency domain. The tone of the sound output from the speakers is directly proportional to the target distance (Ratner & McKerrow, 1999).

This CTFM sensor produces an acoustic density profile (depth area measurement) (McKerrow and Harper, 2001). Features can be extracted from this profile to use in recognising objects in the environment such as plants, poles, paths, etc. The CTFM phased array when mounted on the front left corner of the robot (Fig 10), is capable of producing a vertical sheet of ultrasonic energy with a horizontal beam angle of 3˚ from axis to first minima and a vertical beam angle of 30˚(Ratner & McKerrow 2001).

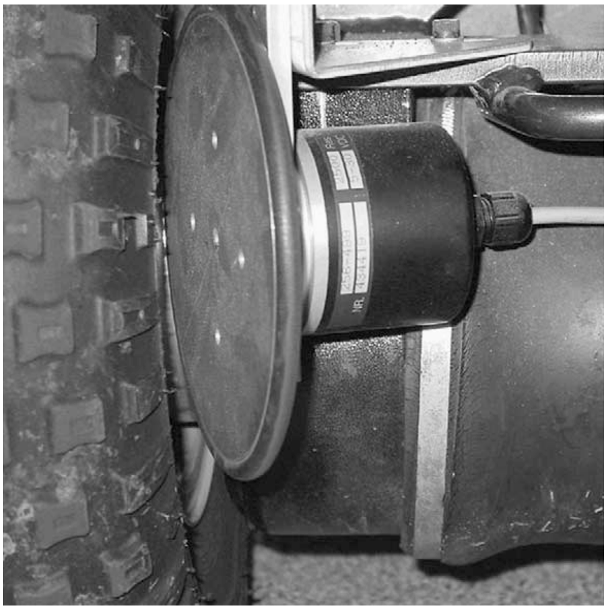

Fig 8 Encoder driven by rear wheel through friction coupling.

Titan's current sensors will be augmented with a K-sonar CTFM (http://www.batforblind.co.nz/) (Fig 11) ultrasonic sensor developed by Leslie Kay as a mobility aid for blind people. It has a horizontal beam angle of ± 19˚ and a vertical beam angle of ±8˚ measured relative to the beam axis (Fig 12) (McKerrow and Yong 2006).

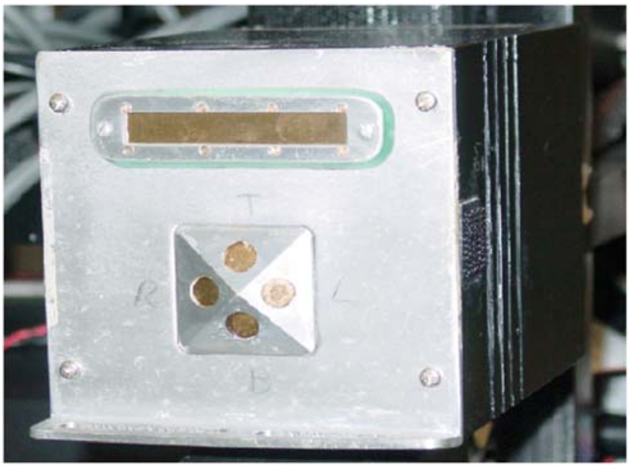

Fig 9 Titan's Sonar array

The K-sonar will primarily be used for obstacle detection while the phased array will be used for landmark detection (Fig 11).

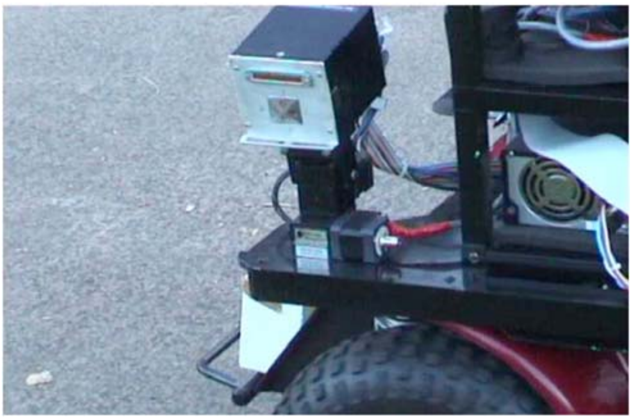

Fig 10 Titan's Sonar array pan and tilt mounting

Titan's sensors and motors are connected to an onboard computer, currently a Mac G3 power book via interface card in a PCI extension chassis [Ratner & McKerrow, 2003].

For our proposed work the G3 is to be replaced by a 1.66 GHz Intel Core Duo processor Mac Mini coupled to a Firewire and USB port-replicator (AcomData mini Pal).

Titan's sensors and actuators will be interfaced via a National Instruments USB general purpose I/O card which includes 8 general-purpose digital I/O lines that supports programming, testing, communicating and simultaneous sampling of: ADCs, Micro controllers, Sensors (accelerometers, gyros) among others.

6 Landmark Sensing

Man made landmarks (building, fences, lampposts...) are characterised by straight geometric edges unlike the chaotic nature of many naturally occurring landmarks.

Fig 11 K-sonar CTFM

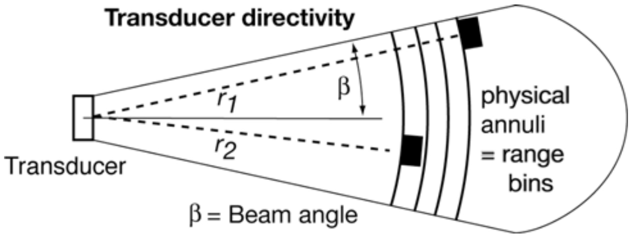

Fig 12 K-sonar CTFM transducer

For example paths have straight edges that are easily detectable as a contrasting region to their surrounds. A raised path, when perceived using a CTFM sonar, will appear contoured by a shadow region where no echoes are perceived. Where the grass rises above the path a corner reflection gives a strong echo (Ratner and McKerrow, 2003). Likewise a fence or wall will give a strong specular echo. It is with those characteristics in the outdoor environment expressed as fuzzy sets that we propose to use to populate the fuzzy map.

As discussed earlier Titan's navigation ability will be dependent on its ability to perceive its surroundings. Successful perception of landmarks is the basis of its ability to localise. Localisation is the robot's ability to determine, within an acceptable level of certainty, its location in the physical world from information gathered by its sensors. Localisation using sensor observation of landmarks provides a degree of certainty unmatched by dead reckoning as encoder data are prone to cumulative errors.

Ratner and McKerrow (2003) decomposed landmarks on the basis of geometry into four distinct classes: simple discontinuous, simple continuous, complex discontinuous and complex continuous (Fig 13). They correlated each landmark class to an acoustic feature set suited for detecting it. They concluded that a direct correlation existed between navigation strategies and the type of landmarks used (continuous/discontinuous). Similarly, a direct correlation existed between sensing strategies and landmark features (simple/complex).

Harper and McKerrow (1997) extracted an acoustic density profile from the echoes off plants using a CTFM ultrasonic sensor. From this profile they extracted a set of features to classify plants.

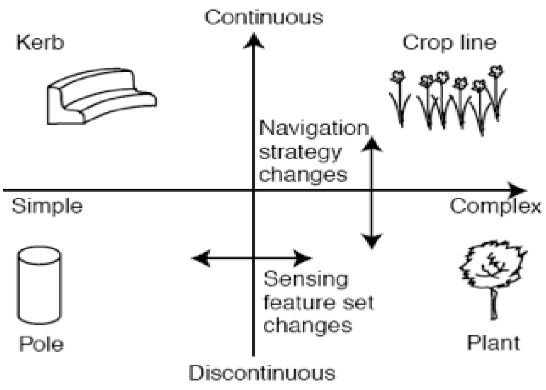

Fig 13 Taxonomy of Landmarks (Ratner and McKerrow, 2003)

They (Harper and McKerrow 1999) concluded that a highly symmetric plant is a highly suitable landmark for autonomous navigation purposes, as the likelihood that a mobile agent's sensors will ever isonify a plant from exactly the same angle twice is low, yet it would still get a good recognition confidence of it as the landmark sought.

They have also concluded that a partially asymmetric plant is also a suitable landmark, because most asymmetric plants have regions of symmetry where the features change slowly. The robot can divide the plant echoes into sectors with partial symmetry. As the robot moves around the plant, it is able to use the feature information detected to identify it as a landmark and determine its orientation relative to it. Furthermore, the mobile agent is unlikely to attempt to sense any more than an 180˚ sector of the plant it is isonifying. They also pointed out that a plant which displays high local symmetry is a very good landmark as the sensor may be a few degrees from the expected orientation and still get good correlation and hence recognition.

In our proposed work, many parameters of the environment will be outside our control. Often they will vary from the conditions that are ideal for recognition. One set of features that is constant is the geometry of the sensor relative to the ground. Titan is a wheeled robot and we can control its speed, and the distance and angle of the CTFM array relative to the ground.

Careful design of sensor geometry results in parameters that render surface roughness an ideal feature to use for navigation purposes. McKerrow and Kristiansen (2006) used a three-step process, which succeeded in measuring and classifying the surface roughness using CTFM ultrasonic sensing. First they extracted features from the echoes, thence they identified the best features for classification and finally developed a measurement for discriminating between surfaces using the Mahalanobis distance (Euclidean distance with normalised vectors). The Mahalanobis distance is a statistical measure of the probability that a target object belongs to a given class. The vector of feature values for the target object is reasonably closer to one of the training objects than to the others.

McKerrow and Kristiansen (2006) demonstrated that data gathered by ultrasonic sensing provides a reliable method for identifying surfaces using features from previously classified surfaces (learned) as references. As the preconditions for surface roughness classification match those we envisage for our work: namely learning the landmarks, as we manually drive Titan to collect data for the fuzzy map, we will also collect training data for the surface roughness classifier. It is our intention to utilise this identification method in conjunction with the fuzzy map rules as one of our primary landmark recognition navigational aids.

Many other navigational strategies exist. In considering the published literature we noted examples of some we deemed better suited for conditions other than those we propose to work with. The sense-Model-Plan-Act is an approach whereby a mobile agent observes its environment using sonar or vision, and then its own state using compass or wheel encoders, to construct a plan and then executes it. This approach was developed to attempt to render the problem of modelling the environment more tractable by Saffiotti (1997). He found that the dynamic nature of the environment decays the validity of the plan rapidly, coupled to the fact that modelling a dynamic environment is computationally hard. He also noted that using a feedback loop approach to constantly update the model slows the mobile agent's response time, thus requiring further updates and so on. Saffiotti (1997) concluded that the viability of the Sense-Model-Plan-Act as a mobile agent control mechanism is low.

The research of Wullschleger *et. al.*(1999), Dissanayake *et. al.*(2001), Ratner and McKerrow (2003), and others suggest that the key to navigation is reliable sensor data, where good sensing is achieved Kalman filtering is rarely needed. A Kalman Filter is a set of mathematical equations that provides an efficient computational mechanism to recursively estimate the state of a process, in a way that minimises the mean of the squared error. It has several advantages such as its ability to estimate past, present, and even future states, and its ability to do so even when the precise nature of the modelled system is unknown.

Wullschleger *et. al.*(1999) used an extended Kalman filter for localization when exploring and mapping a structured environment. Dissanayake *et. al.*(2001) observed "in any real application a Kalman filter needs to employ a huge state vector (of order the number of landmarks maintained in the work space map), and is in general computationally intractable" (Dissanayake *et. al.* 2001). Similarly in their research with Iterated Extended Kalman Filter (IEKF) and the Julier-Uhlmann-Durrant-Whyte Kalman Filter (JUDKF) Chong and Kleeman (1999) allude to the high memory and processing demands.

Kalman filtering is better suited to environments other than the dynamic environments where we seek to operate Titan. The overhead in data collection and processing becomes computationally too expensive in the recursive process. Also Kalman filter is limited in the range of probability distributions it represents, and only works with point features.

7 Disambiguating Location

We will explore the relationship between the feature richness of the fuzzy map and its role in propagating uncertainty. Gasós and Martin (1996) held that data extraction from noisy sensor data generates uncertainty on position, range, size and bearing, uncertainty that must be compensated for. We will attempt to demonstrate that the feature richness of the fuzzy map has the direct corollary effect of reducing the uncertainty and inherent inaccuracies that arise from encoder and other reading errors.

One of the first questions we will address is the relationship between linear velocity and observation frequency. As described earlier the velocity is one of the controllable parameters of this robot and as such we will determine optimal velocity for sensing as a first step of our experimental work.

Likewise, we will consider sensor orientation and task (the feasibility of using a single sensor for multiple tasks) in the early stage of our work. Following this we will develop both sensor motion and sensing strategies to achieve the task of collision avoidance, avoidance of confining spaces and controlled driving. Once we have confident control over the robot travel, the main experimental work of implementing our fuzzy controller will commence. The physical size of Titan described in Section 5 precludes it from pivot turning hence the need to avoid confined spaces. Other questions include how to localise following a reversing movement. Another research goal is to determine the effect of landmark persistence on long term reliability.

Hutchinson *et. al.*'s (1988) mobile agent sensed and then reasoned about its observations in order to select a suitable follow up sensing operation with the expressed desire to disambiguate its hypothesis as to what it is observing. They advocated that the next sensing operation is characterised by both the sensor and the viewpoint it uses.

To carry out its commanded task a mobile agent must decide which landmarks should or could be sensed from its correct location. For this it needs an initial scan of its environment correlating its observation data with its assumed current position. Simply put "I think I am here. Am I?"

In order to validate this initial hypothesis a subsequent sensor observation would seek to confirm or disprove the hypothesis. After consulting the fuzzy map our mobile agent will orient its sensor to attempt to observe a known landmark. The presence or absence of which could confirm or disprove its hypothesis. In a chaotic environment, multiple, subsequent sensor observations and multiple sensor observation data would be fused to give a characteristic map of the location for the agent to validate its hypothesis with an acceptable measure of certainty.

The certainty measure is proportional to the uniqueness of the landmark characteristic. A kerb when sensed may yield a very low confidence measure of a location while a sculpture or garden ornament may give a high confidence measure of a location.

A feature rich fuzzy map is necessary for a mobile agent to reliably navigate and localise in a dynamic environment. The agent constantly needs to disambiguate its hypothesised location by correlating its location with known features recorded in its fuzzy maps. Sparsely populated fuzzy maps are poorly suited as a navigational aid, except when following a continuous landmark.

8 Experiment Design

Our proposed experimental environment consists of the following components. The Titan mobile outdoor 4-WD robot as described in 5, and the Fuzzy Map described in 7. The Experimental environment is the campus surround of the School of Information Technology And Computer Science. This area has wide concrete, asphalt, and brick paved paths that are bordered by grass, buildings, fences, and gardens. The paths include geometric junctions, where they join with curves, and angles from one path to another, and are heavily trafficked by students. Our experiments will be conducted in this typically dynamic environment.

In preparation we physically surveyed the experimental space and noted geometric features suited as localization landmarks due to their uniqueness. We also noted the rate of change in the dynamic experimental space (a building was demolished since our survey, the space where the building stood is being groomed for open space lawn area, two trees were removed, a gravel path was resurfaced and a telecommunication manhole was remodelled beyond recognition).

As mentioned earlier we will manually drive Titan through the surveyed experimental space and record sensor data from potential landmarks using the CTFM phased array, record bearing from Titan's onboard gyro stabilized compass, record distance travelled as measured by the wheel encoders, and inclination data as measured by the inclinometer. Once recorded these sensor data will be used to develop a data set that will become the Fuzzy map. Any subset of the data set (Fig 5) can be used for localization and to plan the robot's journey to reach a goal.

As part of our proposed research we will develop a Linguistics Input Interpreter for the mobile agent to understand its task command, convert the goal command to fuzzy set of landmarks and use them to plan a path to reach the goal. We do not envisage this interpreter as a voice command input as the problems associated with voice recognition are beyond the scope of our work.

8 Conclusion

The research we propose will attempt to develop an intelligent mobile robot controller that is capable of navigating Titan safely in a dynamic real world environment. We will seek to build into the controller abilities akin to human navigation ability, so that it is capable of dealing with the uncertainties that are inherent in a dynamic, often-chaotic real world. Titan will need to be able to decide if it is on course or lost and re-localize when it determines it is lost, Titan will re-localise by matching local landmarks to the fuzzy map while taking into account the path travelled so far. Then it will replan its path to reach the goal.

We have surveyed the experimental space. The survey data will be used to develop the fuzzy set that makes up the fuzzy map. Once Titan's upgrade is complete we aim to implement the experiment design in software using LabVIEW and start our test runs.

Our work is possible because of reliable sensor data. Modern ultrasonic sensors give high quality information that permit more detailed observations of the environment than previously possible with point data. We are able to determine complex feature of an object, its texture and distance, constantly without resorting to complex and computationally expensive filtering techniques. This in turns will allow us to use those features for reliable sensor based navigation without incurring the overhead time penalty generally associated with filtering.

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