Context, Uncertainty and Three-Dimensional Measurement

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Abstract-- **Three-dimensional shape measurement in non-ideal situations can be a hard task. Reflective and transparent surfaces can reduce the ability to make accurate measurements. At Charles Sturt University, we are examining how context can be included in three-dimensional surface measurement processes to improve measurement accuracy. By using multiple devices, we aim to generate dependence in measurement as a basis for extracting context. We propose the creation of a contextual reasoning agent as a means of automated context extraction. In this paper, we present some of the background of this work and discuss its inclusion within a three-dimensional environmental acquisition system.**

Index Terms—**Context, Data Fusion, Image analysis, Shape measurement.**

I. Introduction

THE aim of three-dimensional shape measurement is to build a representation of an object or environment. Many methods have been proposed and developed, some having reached commercial production. Automated shape measurement technology is an interface between computer technology and the real world. While humans are able to differentiate specular and transparent surfaces, the task remains very difficult for automated methods.

At Charles Sturt University, we are examining how 3D measurement techniques can be improved, to determine and measure shiny and other difficult surfaces. We are attempting record and analyse the context of traditional laser-based measurement techniques and develop a reasoning agent that can apply scenarios to measurements. The resultant output of this process will be the ability to more accurately measure the intended object or environment. Our work combines notions of context with data fusion techniques to perform difficult surface recognition and location.

This research is an extension of a project of the School of Information Technology at Charles Sturt University and the Jenolan Caves Reserve Trust to develop a multi-faceted information system to assist with the study of the karst systems under the Caves Reserve Trust's management [1].

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Full names of authors are preferred in the author field, but are not required. Put a space between authors' initials. Do not use all uppercase for authors' surnames.

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II. Previous Work

We will deal with the major strands of previous work as separate items.

A. Context

McCarthy [2] (cited by [3]) first proposed context as a formal object, asserting that a proposition is true within a context. McCarthy, Buvac and Guha [4] and others have continued to develop theoretical notions of context.

There are some attempts at applying context to spatial data. Turner [5] has been developing adaptive reasoning for autonomous underwater vehicles, where the device determines context from sensory input and "Contextual Schemas" as the basis for choosing a course of action. Panayiotou [6] is investigating how context can be modelled and used in common sense reasoning for machine vision.

B. Sensor Fusion

Currently, data fusion is a very active area of research, encompassing many applications and ambitions. Valet, Mauries and Bolon [7] have compiled a survey of recent information fusion literature. The most relevant work listed relates to environment identification and navigation for robots and intelligent vehicles.

C. Difficult Surface Detection

Three-dimensional surface acquisition devices are a commercial reality. Laser based scanners can capture thousands of points within a few minutes [8]. Despite such advanced scanning technology, difficult surfaces remain a problem. There has been little research on capturing "difficult" surfaces. Optical scanning techniques are subjected to similar limitations to all photographic techniques; they can't measure specular, transparent and dark surfaces [9]. Chen, Brown and Song [10] in a survey of surface measurement technology discuss the very limited research relating to specular surfaces.

D. Application to Present Research

Our research bridges the above areas as we are trying to develop a robust surface measurement system that can accommodate specular and transparent surfaces. We intend to use multiple sensors not only to measure accurately a surface, but also to understand the context of each measurement so errors can potentially be corrected rather than rejected. In [11], we proposed a system that could measure shiny and transparent surfaces. We presented an example of a reflective surface measurement technique used in a limestone cave measurement project and discussed its application to transparent surfaces. We demonstrated that contextual information was available, measurable and necessary to determine correctly the reflective surface location. In this paper, we discuss designing and using an artificial intelligence based system to better understand the context of automated three-dimensional measurement.

III. Uncertain Reasoning

A. *Uncertainty and Context*

Analysing contextual information from a complex environment such as a limestone cave system is a difficult task. The "reflected surface" example returns patterns of laser light which are dependant on the interaction between the laser and the measured environment, i.e. the location of any reflective or transparent surfaces within the field of view of the device. This information includes a great deal of uncertainty with potentially very little known about the surfaces other than from the context images. The first point of impact can be estimated using structured light methods [12], although uncertainty may remain. Major classification can be based on the expected number of points in the reflection pattern and their relative position to the estimated first point of impact. Further uncertainty exists through the possibility of missing points that could be caused through occlusion by surfaces or obstacles or by various random factors.

Imprecise and uncertain information needs to be analysed as such. Many methods exist for analysing uncertain information and reducing the possibilities to those reasonable for each potential situation. Belief networks [13] may offer a useful way forward as a means of classifying the contextual information although determining paths of influence would be difficult. Another option is "contextual schemas" [5]. Major point attributes such as spot intensity, shape and dispersion are available for analysis as well as regional information from previous point analysis. For example, if a series of points within a particular area of the set of context images all have a high probability of being specular, the probability of other points with the region of being specular is increased.

Without imposing strong constraints upon the environment being measured, the potential number of classifications may remain high.

B. *Error Tolerance*

By using multiple sensors to capture real world data, the potential exists of using Byzantine agreement methods for dealing with measurement error. Although this may be a reasonable approach for multiple sensor data, it falls short of what we are attempting to achieve. In a classical Byzantine type problem, the aim is to determine any faulty (in this case) measurements and not include them in the point analysis. While this needs to be a part of the total analysis, we are imposing another step before assuming erroneous data.

By including context, we are reducing the possibility of misrepresenting correct data by first attempting to fit the data to a set of measurement scenarios based upon the contextual information.

IV. Current Work

A. *Measurement of Difficult Surfaces*

While using laser distance measuring equipment to collect spatial measurements of the Abercrombie Caves system, we recognised that many surface types presented problems for automated surface measurement techniques. The major difficulty was measuring the surface and floor of Grove River, which passes through the cave system. This highlighted the difficulties associated with measuring reflective and transparent surfaces, where returned measurements may not be of the intended location. Instead, the laser beam may be reflected or refracted, returning a composite measurement (see fig 1). Applying standard surface reconstruction techniques to convert a point cloud into a virtual surface, measurements such as these would either be treated as surface outliers and discarded or result in an incorrect surface being generated.

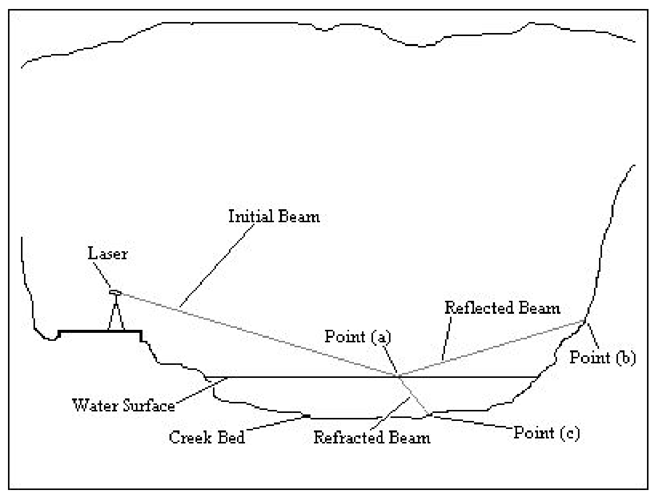

Fig. 1. The geometry of the laser-based measurements

We proposed that observing laser based measurements with a further device such as a CCD, the measurement context could be recorded and analysed, potentially as an automated process [11]. By using multiple sensors, the devices have the opportunity to interact and hence create dependence. A Time-of-flight laser and a CCD are an ideal combination, with an active measurement device being observed by a passive device that incorporates a much larger field of view (A similar configuration might be possible using ultrasonic transducers).

Device dependence is a necessary quality for context extraction. Assuming one device is performing active measurement and hence, interacting with the environment, a second device (or more) is required to observe the interaction. Three sorts of dependence are possible:

- Spatial dependence, where two or more devices measure the same location.

- Time domain dependence. Devices record measurements at the same instant. This is a crucial type of dependence in an environment that is changing at a measurable rate with the time frame of the measurement period.

- Device dependence, where a single device or set of devices makes a series of measurements.

The greatest degree of dependence will exist where all three types of dependence occur across the same series of measurements, reducing potential uncertainty.

Dependence is a very powerful tool for the process of context extraction. Adjacent measurements with device and spatial dependence form a strong basis for this process. "Similar" adjacent measurements over multiple devices may imply a constant context. Conversely, large changes may indicate either a change in context or in the nature of sensor interaction. In experiments so far, all these scenarios occur.

Contextual Schemas, or as we are defining them, Contestual Frames are connected areas of similar sensor response. Normally contextual frames are considered bounded and this occurs at a place of discernable change in the nature of sensor information received. In our experiments so far [11], contextual frame boundaries are reasonably easy to determine. Points of significant change in sensor data returned were indicative of a change in context, requiring a change in the method of surface calculation..

B. *Actual Measurements*

Several series of measurements of the surface of Grove River were recorded, each measurement with a corresponding image to provide context. Context was determined by the location of reflection patterns secondary to each laser measurement. Fig. 2 shows contextual information for a measurement similar to that described in fig. 1.

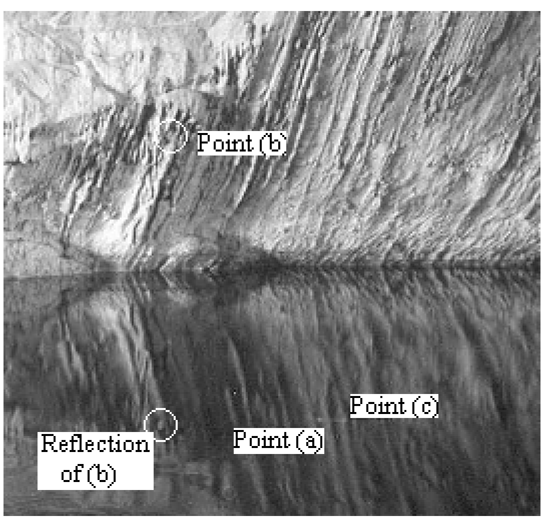

Fig. 2. Contextual information of a laser-based measurement with both reflected and refracted components visible. Points (a), (b) and (c) correspond to fig. 1

Three separate contexts can be identified in the example described in figures 1 and 2. The frame boundaries are:

i) where the water meets the far cave wall (indicated by a significant change in the reflection patterns – main change being in the intensity of the primary impact of the laser); and

ii) where the measured beam changes from being reflected by the water surface to being refracted - indicated by a large change in measured beam length with little change in reflection patterns)

We developed an algorithm to process the measurements and determine surface location. With our aim of automating the process, we have developed further the algorithm, with the major steps being:

- Registering each image against a base image to normalise raw contextual information.

- Extracting laser pattern information. This is a relatively simple task as the laser is of known frequency allowing the background image to be striped by application of a notch filter.

- Determine the most likely point candidate for "first point of contact" using a structured light location technique and using more contextually based methods to refine the position and reduce uncertainty.

- Apply reasoning process to the image-point information, measurement and the known world to determine the reasoner "case". All information needs to be retained because of the possibility of belief revision after further measurement-image pairs have been collected and analysed.

- Determine all points that lie on diffuse surfaces.

- Use the location of diffuse surfaces, "case" information and measurements to determine specular and transparent surfaces.

- Optimise surface location by re-examining data given the improved surface knowledge.

V. Discussion and Future Work

Context as relating to our research, is the interaction between an attempted measurement and the environment in which it is made. Measurements normally are treated as independent events, with surfaces manufactured from point clouds using reconstruction algorithms. Data fusion techniques are used when information is collected using more that one device or source.

I have introduced the concept of Contextual Frames as related to our research. Frames provide us with the means of grouping like measurements. While frames are determinable, this research needs to be extended to perform automatic contextual frame boundary extraction, classification and surface analysis. An immediate task is to test and validate our assumptions of Contextual Frames and their boundaries.

We aim to bring these separate strands of research together. The ultimate outcome of this work is the construction of a contextual reasoning agent that will handle uncertain data by choosing a measurement model of best fit rather than apply a single model to all data. We will develop a generalised framework that will handle multiple sensors for both active measurement and contextual observation. Fig. 3 describes a model of the contextual reasoning agent. We have split the agent into its two major functional components, the determiner of surface type and the estimator of surface location.

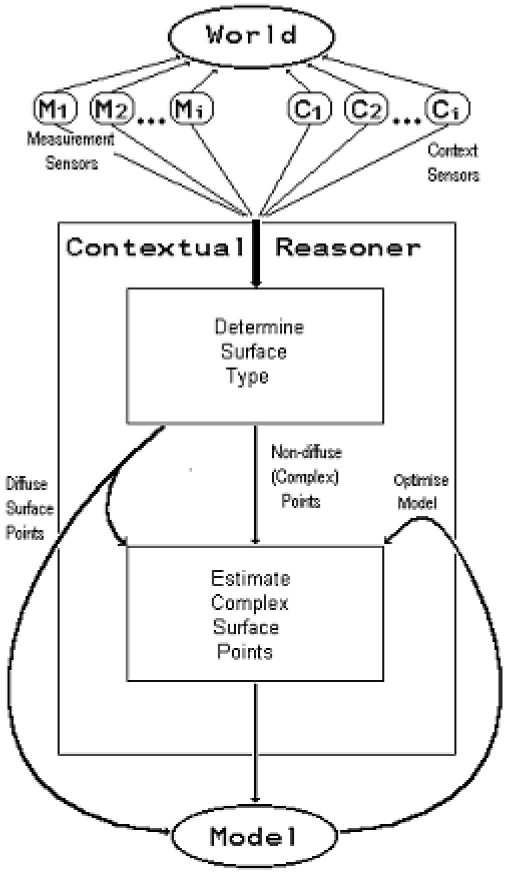

Fig. 3. The contextual reasoning agent.

The "Determiner" is responsible for making the initial judgement of surface type. This decision can be modified later with more reliable and complete knowledge of the environment. The "Estimator" locates the surface given the information provided by the determination process. It makes use of diffuse surface knowledge as a basis to fit specular and transparent surfaces and then optimises the surface as better knowledge is generated. Our current work is a subset of this aim. We have performed some preliminary work to determine contextual information is available and extractable. The next task is to develop a basic version of the analysis system (the contextual reasoning agent) to establish the surface type at a given location. This is a very significant task for the project, especially as we desire to generalise the model for more complex specular and transparent surface combinations.

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