The Eighth International Conference on Intelligent Technologies (InTech'07)
Sydney, Australia, 12-14 December 2007

SIMULTANEOUS MATERIAL TYPE CLASSIFICATION AND MAPPING DATA ACQUISITION USING A LASER RANGE FINDER

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Abstract—**This paper presents a method for single sensor simultaneous derivation of three-dimensional mapping data and material type data for use in an autonomous sandblasting system. A Hokuyo laser range finder's firmware has been modified so that it returns intensity data. A *range error* and *return intensity* analyzing algorithm allows the material type of the sensed object to be determined from a set of known materials. Empirical results have demonstrated the system's ability to classify material type (under alignment and orientation constraints) from a set of known materials common to sandblasting environments (wood, concrete, metals with different finishes and cloth/fabric) and to successfully classify objects both when static and when fitted to an in-motion 6-DOF anthropomorphic robotic arm.**

Keywords-component; Laser Range Finder, Three-dimensional Mapping, Material Type, Classification

I. INTRODUCTION

Consider transport infrastructure maintenance - with the exceedingly high construction costs of vital infrastructure such as steel bridges, a significant motivation exists to extend their life spans. The primary cause of premature failure is known - identified as rust, [1]-[2]; the solution is also known - removing the paint and rust via sandblasting and then applying a paint coating. Even so, due to several factors this seemingly simple solution is difficult to implement. These prohibiting factors include the physical nature of the work and the associated health risks. Expanding upon this, sandblasting is an extremely labor intensive and hazardous operation [3], workers must handle forces in excess of 100N [4]-[5] for extended periods of time. Considerable health risks also exist, a large number of bridges in Australia are painted with lead and/or asbestos based paints. With the long-term health damage of lead and asbestos now common knowledge [6] and with the risk of physical injury, workplace laws are changing. They are slowly evolving to simply prohibit humans from working in such environments Due to this, few alternatives for completing this necessary task exist other than implementing a robotic solution.

With the technological advances in robotic systems over the past years, the prospect of solving real-world problems such as these with robotic solutions seems closer than ever. However, for the use of robotics in such applications to be feasible, the robots must be capable of self-deriving an understanding of the environment that they are to interact with [7]. For true environmental awareness; the knowledge of occupied space alone is not adequate [8], the robot requires knowledge of the material type of the objects so that it may adjust its method of interaction accordingly. Both sets of data are required, otherwise operation in or interaction with the environment is potentially dangerous to both robot and environment. Without this knowledge there is an unacceptably high chance for collision or causing severe damage whilst sandblasting; perhaps plaster board would be destroyed rather than metal cleaned. Environmental awareness is typically gained in the laboratory or in industrial implementations by first limiting the complexity and content of the workspace and then by deriving the awareness manually. However, in real-world applications it is unrealistic to expect the content of the environment to be limited and the environments are too complex for the knowledge to be derived manually or through modified CAD drawings [9]. Clearly the need exists for the robot to be capable of autonomously deriving environmental awareness

The pursuit of environmental awareness for robotic solutions is a *hot* area of research. However, the problem has typically been approached in one of two general ways: via a trade-off or with multiple sensors. The trade-off methods are typically single sensor methods and generally begin with a decision being made as to what data is considered to be the most important; mapping data or material type data. A biased approach is then taken in the sensor selection and a system is produced that, whilst is capable of deriving both, performs significantly better with regards to one relative to the other. Examples of such systems include Yamauchi's, [10] and Huttenlocher's [11]. Yamauchi's is a mapping data biased system, a laser range finder is used and considerable effort is expended maintaining the quality of the map. As for the material type data, this is approached with shapes/features in the map being classified against a knowledge base. The limitation here is the knowledge base; for real world applications the derivation of material type information based on shape alone requires an enormous knowledge base. Conversely, Huttenlocher's system is heavily biased towards material type. Huttenlocher uses an analysis of imagery to determine surface features/properties and bases classification of the material upon this. Although the ability to localize exists, it is limited to small movements, with large overlaps, making complete coverage for an environment such as a bridge tedious. Such methods are clearly not desirable for our application.

The other common approach to the problem is through the use of multiple sensors such as Vandapel's system, [12]. Vandapel uses both a stereo color camera and a laser range finder to develop a less biased environmental awareness. However, in multiple sensor systems significant complexities exist. Complex three-dimensional path/coverage planning is required in order to ensure complete coverage of the mapping data with material type data. Furthermore, the use of multiple sensors introduces the need for data registration of the material type data with the map data [13]; this adds additional complexity and computational expense to the system.

Methods using a single sensor, however, do not suffer these issues. As a single sensor is used to gather the three-dimensional mapping data and to gather material type data, complete coverage of the map with the material data is inherent. It would also mean that material type information could be collected online during the mapping phase making for a more efficient system. As the Hokuyo laser range finder is the primary sensor being used for the three-dimensional mapping in our application [9] the focus of this work is to attempt to extract material type information from this sensor. A considerable amount of research has seen the successful extraction of material type data using light based sensors, [15], [18]-[19], so the task is known to be feasible. Even though, the Hokuyo's fundamental principles of operation (it emits a laser and receives the reflections off any surfaces within range: the return intensity, to an extent, is known [17]) suggest that it will respond differently to sensed objects of different material types, Hokuyo based classification has not been realized thus far in either an academic or commercial setting.

This paper presents a technique for determining the material type of a sensed object by analyzing the reading errors and return intensity data from a Hokuyo laser range finder, hereby known as Laser Range finder based Classification (LRC). The LRCs ability to successfully classify the material type of several sensed objects of different material types will be experimentally verified in typical indoors conditions. The sensor is also fitted to a 6-DOF anthropomorphic robotic arm and its ability to successfully classify whilst the robotic arm is in motion verified. The Hokuyo laser range finder combined with the LRC can range and classify arbitrarily colored and shaped conductive and non-conductive objects whilst simultaneously mapping, making it particularly useful for construction/maintenance applications where a self derived environmental 'awareness' is required. The experimental results will show the LRC to be robust, accurate, error/noise tolerant and capable of both object ranging and material type classification of several materials common in construction and maintenance operations such as wood, concrete, metals with different finishes and cloth/fabric.

The breakdown of this paper is as follows; firstly the fundamentals of the Hokuyo laser range finder technology that allow for material type classification will be discussed. The author's contribution to their field of research will then be displayed via a discussion of how the LRC utilizes the fundamental properties of the Hokuyo base technology to enable classification of material type. A 'Results' section will detail the results from LRC testing, these results will then be discussed with conclusions drawn and future work proposed.

II. SURFACES' PROPERTIES EFFECT ON REFELCTED LIGHT

The reflective index of a material refers to the total amount of light that is reflected from the surface (regardless of the amount of diffusion) as opposed to, absorbed by the material. Fig. 1(a) shows the effect that the reflective index has on light intersecting with the surface.

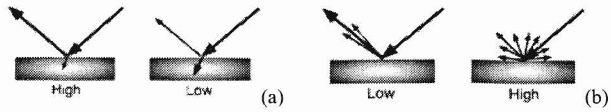


Figure 1. (a) Reflective Index Effect (b) Diffusion of Light

As can be seen in the case shown to the left of Fig. 1(a), if the reflective index of the surface is high then the majority of the light is reflected from the surface and only a small portion is absorbed by the surface. Conversely, as shown in the case to the right of Fig. 1(a), if the reflective index of the surface is lower then a smaller portion of the light is reflected and a larger portion is absorbed. The amount of diffusion light suffers on reflection from a surface is dependant on the surface roughness. Fig. 1(b) shows the effect that diffusion has on light intersecting with a surface. In the case shown to the left of the Fig. 1(b) the surface is smooth, the majority of the light is reflected with the angle of incidence equaling the angle of reflection and with only a small amount of diffusion. Conversely, in the case shown to the right of Fig. 1(b), where the surface is rough, only a small amount of light is reflected with the angle of incidence equaling the angle of reflection and the majority of the light is diffused over all angles; a significant portion returns towards the light source.

As previously mentioned, the reflective index and the light diffusing properties of a surface effect define the interaction of light with the surface. As these are both relatable to physical properties of a material's surface, such as gloss and surface roughness, than a potential for material classification, based upon these, exists if a means to measure them also exists. Research into methods of light based surface identification [18]-[19] revealed that the return light intensity was a particularly useful measurable entity that can be manipulated to yield information on both the reflective index and the diffusion properties of a surface. However in [18]-[19] the methods used to obtain intensity information saw a single light source used in conjunction with multiple light intensity measuring sensors precisely placed in known positions: the methods were cumbersome and complex. For this reason and in order to gain the aforementioned advantages the Hokuyo Laser Range Finder was evaluated as a potential light source and returned light intensity measuring device for determining these surface properties; on which classification is to be based.

The method of operation of the Hokuyo Laser Range Finder was researched [17] and it was found that return laser intensity data can be extracted from the sensor as well as range information making the use of the Hokuyo for this task feasible. However, as the Hokuyo has only a single light intensity measuring sensor, the method for using the Hokuyo for surface identification must be significantly different to the methods proposed by [18]-[19]. Furthermore, as the device contains a 'black box' circuit that automatically gains the intensity (the level of gain is unknown) to a level usable by the sensor the outputted intensity values are not absolute. This significantly adds to the complexity of using the Hokuyo to determine the reflective index and diffusive index of the surface and causes a further necessity for a significant methodology variation to those proposed in [18]-[19].

A typical method of measuring the reflective index and the diffusion properties of a surface uses a concentrated light source (such as a laser) directed with an angle of incidence to the surface of 90° and numerous light intensity measuring sensors precisely placed at known locations. The intensity at each location is then analyzed to determine the diffusion of the light. The known transmission intensity is then used with the absolute return intensity (the sum of all measured intensities) to yield a reflective index for the surface. In the case of the Hokuyo the return intensity is auto-gained to a maximum and potentially will be approximately the same regardless of the reflective index of the material. With no means of obtaining the auto-gain level there is no means of relating the return intensity to the reflective index. Furthermore, as there is only a single light intensity measuring sensor it is not possible to determine the surface roughness: there is no means of determining the diffusion of the light from a single reading.

Due to the Hokuyo's inability to determine the reflective index or the diffusion properties of the surface in the typical manner a new method is required. The proposed method, shown in Fig. 2, sees the Hokuyo's rays from -20° to +20° (the 0° ray need not be perpendicular to the surface but at least one ray within the range must be) used to gather range and intensity information. On the assumption that the surface being tested is flat, the relative change in the return intensity data for the rays at the varying angles of incidence to the surface is indicative of the values of the reflective index and the diffusion properties of the surface. Fig. 3 illustrates the theory of the relative change in return intensity over the range of angle of incidences.

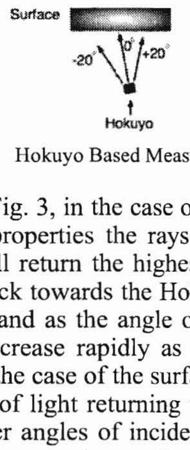


Figure 2. Hokuyo Based Measurement

As can be seen in Fig. 3, in the case of a surface with a low or medium diffusive properties the rays intersecting with the surface at near 90° will return the highest intensity values (as more light is reflect back towards the Hokuyo – marked by the solid black rectangle) and as the angle of incidence decreases the return intensity decrease rapidly as less light is reflected towards the sensor. In the case of the surface with low diffusive properties the amount of light returning to the sensor may not be detectable at smaller angles of incidences. In the case of a more diffusive surface, a rougher surface, the amount of light returning to the sensor is approximately equal over the entire range of angle of incidences.

The rays intersecting with the surface at near 90° may also give an indication of the reflective index of the surface. For instance, in the case of higher reflective indices the Hokuyo's inbuilt auto-gain circuit may not be able to gain the return intensity such that circuit saturation is avoided. This will most likely result in an obvious error in the range measurements (the test surface is known to be flat).

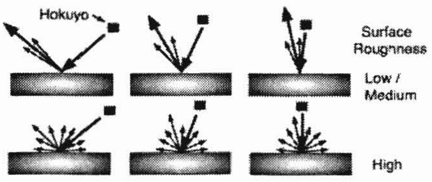


Figure 3. Return Intensities Over a Range of Angles

At this point the LRC methodology allows for an indication of the reflective index and the diffusion properties of the surface only. It is planned future work that absolute values for the reflective index of the surface and the surface roughness (diffusion properties) be determined by the LRC. A potential limitation of this light based method, is that it is non-penetrating, thus it is possible for two different materials with the same coating (e.g. paint) to be indistinguishable.

III. LASER BASED CLASSIFICATION

As detailed in the previous section, the magnitude of the return intensity of the laser light from the Hokuyo has a direct relationship with the angle of incidence of the light to the surface and the physical properties of the surface. The LRC functions by using a continuous series of return data from the Hokuyo (20 consecutive rays' values) and then estimating the reflectance ratio – the ratio of difference between the adjacent rays. The estimation of the reflectance ratio is then compared to those of the environments expected materials.

This is achieved as follows: Firstly a scan is taken and the intensity and range data plotted. A low order polynomial fit is applied to each and the mean-squared error of the fits are calculated. Using a low order polynomial's degree of failure (mean-squared error) to accurately represent a curve is a computationally inexpensive means of curve representation. Following this, the material type is classified by comparing the MSEs to empirically derived reference values. Fig 4. shows a flow chart of the LRC process.

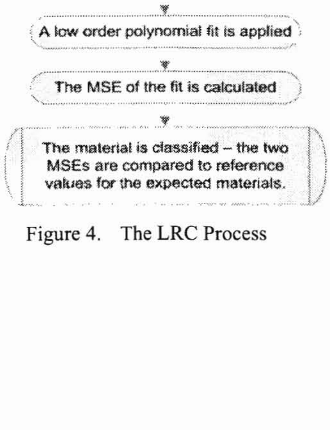


Figure 4. The LRC Process

IV. RESULTS

Fig. 5 shows an example of a three-dimensional map produced using the same scan data used during the classification process. This result was generated as part of previous work [9]; this paper is an extension to this work.

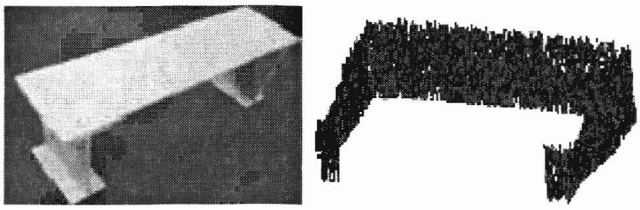
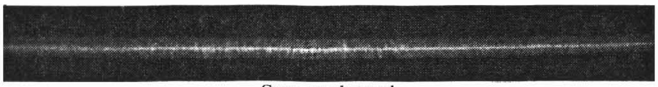


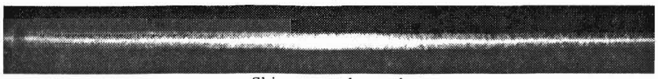
Figure 5. A three-dimensional map created using he same data used for material type classifcation

A. *Laser Reflection off a Surface as Seen by IR Camera*

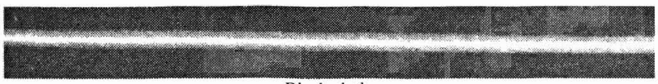
The first experiment was designed to evaluate the theory, proposed in Section II, that the return intensity of an object is due to the surface properties of the object and the angle of incidence of the light. The Hokuyo laser was placed on a desk and directed towards a wall. An infra-red sensitive camera was then placed so that the lens was in close proximately to the light receiving component of the Hokuyo, the focal plane of the camera was aligned so that it was parallel to the wall. Several materials where then placed against the wall and still images showing the reflected light intensity were taken, Fig. 6.



Grey, rough metal



Shiny, smooth metal



Black cloth

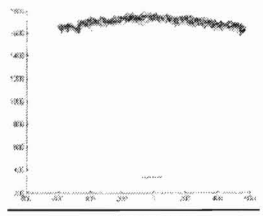
Figure 6. Intensity Images From Infra-Red Camera

As can be seen in the figure, the theory presented in Section II has predicted the actual behavior of the light. In the case of an object with a high amount of surface roughness and low reflectivity (labeled Black cloth in the figure) the intensity of the light return is uniform over the range of angle of incidences. The image shown to the top of the figure, the Grey metal (high surface roughness and high reflectivity), shows the effect of a higher reflectivity. On inspection of the image it can be seen that, as the angle of incidence decreases from 90^o (image centre) the return intensity decreases. The final case shown here shows the Hokuyo light intersecting with shiny, smooth metal (figure centre). As can be seen the return intensity around the range of angle of incidences of $85\text{-}95^o$ is high (due to the high reflectivity of the surface) and as the angle of incidence decreases the return intensity significantly decreases as the highly reflective surface causes little diffusion.

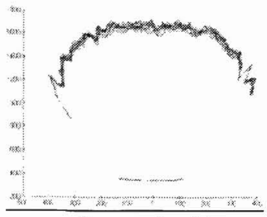
These results clearly demonstrate that the theory presented in Section II and Section III is observable in 'real world' situations and that the variations in the return intensities from various materials are significant and measurable. These results also demonstrate that the Hokuyo Laser Range finder can be used as the light source for the proposed task of light based material type classification.

B. *Hokuyo's Based Classification*

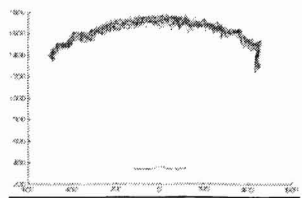
With the aforementioned results reinforcing the feasibility of Hokuyo based material type classification an experiment was designed to determine whether Hokuyo data would be consistent with what was visually observed. A communication link was established between the Hokuyo and MATLAB enabling the sensor to take a single scan on command and return the data to MATLAB. Fig. 7 shows three plots, one each for three different materials: Shiny metal, Grey metal and Black cloth. The plots are in polar co-ordinates with θ being the angle of the Hokuyo's ray and r being the range value (for the flatter line towards the bottom of each of the plots) and intensity value (for the curved line towards the top of the plots). The plots use a *mm* scale for distance for the range line and magnitude for the intensity line. Each of the plots shows range and intensity for twenty single scans. The Hokuyo was sensing a flat surface at a known distance of *350mm*.



Black cloth



Grey, rough metal



Shiny, smooth metal

Figure 7. Hokuyo Scans in MATLAB

As can be seen, the response for the three materials is significantly different and consistent with theory. The return intensity for the Black cloth is relatively uniform across the range of angle of incidences and the return intensity for the Grey and Shiny metals decrease as the angle of incidences decrease. Of note in this result is that the Hokuyo derived range for the section of shiny metal around the range of angle of incidences of $85^o\text{-}95^o$ shows a significant range error.

This result shows that in the case of a highly reflective surface the Hokuyo's auto-gain circuit fails to gain the signal level below saturation and an error in the range measurement is introduced. These results also show that the return data from the Hokuyo is consistent with those seen visually and thus shows that the Hokuyo Laser Range finder can be used as both the light source and return intensity measuring device for the proposed task of light based material type classification.

At this stage, as the primary research goal of this work is not to develop a classifier, a simple classifier was developed as a means to evaluate the potential of the Hokuyo for delivering data which can be used to classify material type. The simple classifier is detailed in Section III. This is shown for the three materials, one in each of the rows of Fig. 8. As can be appreciated from Fig. 8, whilst the mean squared error for the Black cloth intensity curve will be low (the second-order polynomial fit will be good) the mean square error for the intensity curve of the Grey metal will be high (the second-order polynomial fit will be poor). Fig. 8 shows that the residuals for each of the cases and mean squared errors are significantly different for the materials.

From this result, six mean squared error range bands where derived; where a pair represents a material. The classifier was set to output a material type based on the bands that the mean squared errors were in. The data collected and displayed in Fig. 7 was then used as an input to the classifier and the classifier return was compared to the known material type of the sensed object, shown in Table I. As can be seen from the table, classifying between Grey metal, Shiny metal and Black cloth is done by the LRC with a high level of confidence. Errors will be introduced when the LRC attempts to classify from a less limited set or with 'looser' orientation constraints on the laser.

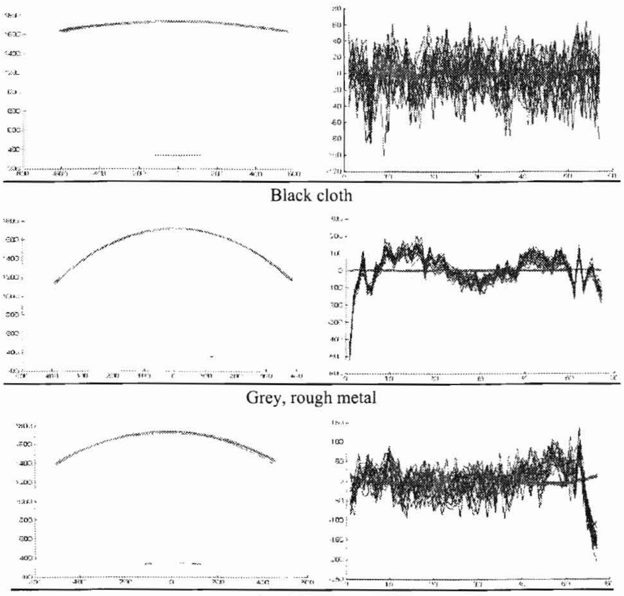


Figure 8. Hokuyo Classifier Operation

TABLE I. LRC - CLASSIFIER RESULTS

Material	Correct (%)	Incorrect (%)	Unknown (%)
Shiny Metal	100	0	-
Grey Metal	100	0	-
Black Cloth	100	0	-

C. Determining Constraints on Hokuyo-Surface Placement

The next experiment was designed to roughly evaluate what range of angle of incidence the Hokuyo's 0^o ray could have with the surface and for what Hokuyo-object distance the classifier would correctly classify over; the plane of the scanner's rays was 90^o to the surface. MATLAB was configured to read data from the Hokuyo at 5Hz and then to the process the data and classify the sensed object. The MATLAB algorithm was told a priori the material type of the object being sensed. The Hokuyo was then manually moved towards and away from the object and rotated and the MATLAB algorithm plotted the input data that resulted in correct classifications only, shown in Fig. 9. As only the input data from correct classifications is shown in the plots it is possible to determine the range of sensor movement and alignment that did not affect the classifiers performance. As can be seen from the figure the Hokuyo could be moved approximately ±100mm and rotated approximately $\pm 20^o$ with successful classification still possible.

This result clearly demonstrates that the LRC produces data that can be used as an input to a classifier and that the quality of the data (with respect to the ability to classify based upon it) is robust against errors in position and orientation of the sensor. Determining the exact angular range and Hokuyo-object distance that the LRC can function under and expanding the classifier to make adjustments for the orientation and the Hokuyo-object range is planned for future work.

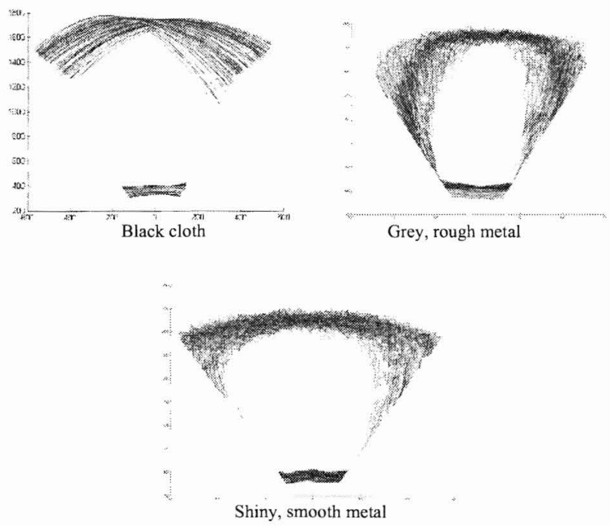


Figure 9. Hokuyo Classifier Various Alignments and Object ranges

D. In-motion Classifcation

The final experiment presented here saw the Hokuyo fitted to the end-effector of a 6-DOF anthropomorphic robotic arm and the LRC's ability to classify a variety of materials whilst the robot was in-motion was evaluated, the setup is shown in Fig. 10. The robot was programmed to moved between the five materials shown in the figure (Grey metal, Shiny metal, Wood, Black cloth and Concrete) and during periods when the Hokuyo was within the limits for successful classification (as determined by the previous experiment) the LRC attempted to classify the object. Approximately one hundred scans were taken within these limits and for each of the materials. The classifier was not altered from the previous tests and was not trained for Concrete or Wood: possible outputs were: Shiny metal, Grey metal, Black cloth and Unknown.

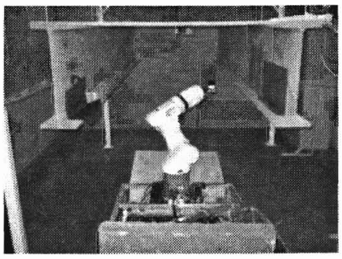


Figure 10. Hokuyo Classifier In-Motion on Robotic Arm

As can be seen from the results, Table II, the LRC was able to successfully classify Shiny metal, Grey Metal and Black cloth without error. The results also show that without reference values for the additional materials the *unknown* materials were incorrectly classified rather than classified correctly as unknown. This highlights the need to develop a more sophisticated classifier, planned for future work.

TABLE II. LRC – IN-MOTION CLASSIFIER RESULTS

Material	Correct (%)	Incorrect (%)	Most Common Error
Shiny Metal	100	0	-
Grey Metal	100	0	-
Wood	0	100	B-Cloth
Black Cloth	100	0	-
Concrete	0	100	B-Cloth

The results presented in Table II demonstrate the LRC's ability to classify various materials whilst fitted to an in-motion robotic arm, thus demonstrating the feasibility of using the LRC during the mapping phase of the proposed application. Further to this, as metal is the only material intended to be sandblasted and as metal has proved to be reliably classifiable by the LRC these results demonstrate the technologies suitability for the intended application.

V. CONCLUSIONS AND FUTURE WORK

This paper has presented the LRC which has been designed to provide material type data for objects in the sensing field simultaneously with providing three-dimensional mapping data. The LRC is intended to be used to develop environmental awareness during the mapping phase of an autonomous sandblasting robotic system.

Experiments have demonstrated the LRC's ability to classify material type from a set of known materials common to sandblasting environments without error (under alignment and orientation constraints). The results presented here have clearly demonstrated that the LRC can yield material type information during use in our stated application and thus the technology will be pursued.

Future work will focus on a method of *relaxing* the alignment and orientation constraints required for successfully classification and in developing a sophisticated classifier.

ACKNOWLEDGMENT

This work is proudly supported by the ARC Centre of Excellence for Autonomous Systems (CAS), a University of Technology, Sydney (UTS) partnership grant with the Roads and Traffic Authority (RTA), the Australian Research Council (ARC) and the New South Wales State Government.

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