Real-time Sensor Data for Efficient Localisation Employing a Weightless neural system

Real-time floor and geometric data acquisition from simple sensors

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***Abstract*—Mobile robotic localisation obtained from simple sensor data potentially offers real-time real-world integration. Computationally highly efficient Weightless Neural Networks, when used for location determination, further enhances performance potential. This paper introduces techniques for the identification of rooms or locations in the absence of complex and succinct information. Using simple floor colour and texture, and room geometrics from ranging data, although inherent uncertainties exist, these limited simple fused real-time sensor data can be easily resolved into a room identification criterion using architectures generated by a Genetic Algorithm technique applied to a Weightless Neural Network Architecture.**

Keywords-component; Autonomous navigation, localisation, weightless neural networks, real-time, floor texture and colour.

I. INTRODUCTION

Operating mobile robots within enclosed dynamic environments, such as buildings, requires adaptable location distinguishability. Without the ability to determine the robot's position and orientation within an environment, no trajectory can be generated [1]; therefore no effective action can be taken. The Literature is well versed with regard to mapping and object identification techniques using simple sensors such as sonar or infrared ranging [2, 3]. The simplest methods often suggested for identification, in terms of processing, are either geometric or colour histogram in form [4].

The advantages simple sensors offer to the mobile robotics field are many, in particular cost, both financial and computational, dimension and redundancy. Simple multiple type sensor data which can be fused and processed quickly reduces uncertainties allowing for immediate localisation, yet this data when further processed and stored can permit more accurate application, such as mapping, when required.

Surface texture and colour are two identifying features which can be employed to distinguish between different surfaces. Many rooms may have the same or very similar floor properties throughout, such as in a dwelling, additionally other equally non-volatile potential identifying features exist such as size and shape. Buschka and Saffiotti [3] identify rooms, for example, from length and breadth histograms. When sensor data sets are fused uncertainties in one set of data can be minimized by certainties in another.

We therefore propose in this paper a localisation system using a combination of real-time floor colour and texture data, and noisy ranging data, using simple in-expensive sensors, combined to identify location using an adaptive Weightless Neural Network (WNN). One contribution lies in the adaptability of the system to changing environments: a room profile is stored in look-up tables as WNN training sets hence any small changes, such as carpet stains, and wear and tear can be accommodated by updating the look-up tables, flexibility exists for the system to incorporate other sensor data further improving localisation. Advantages of the system which are significant in a real-world environment are as follows:

- The system is adaptable to change by potentially adding, removing and updating room profiles.
- Efficient use of sensors; a relatively small amount of data is needed in order to identify a room.
- As most indoor robots require a clear floor to traverse selecting floor features for identification reduces susceptibility to occlusion.

The Weightless Neural Network employed requires a heavily modified Genetic Algorithm used to create and control the WNN architectures. This tunes the performance and pattern recognition ability as the system continues to run [5-7] improving room identification.

II. WEIGHTLESS ARTIFICIAL NEURAL ARCHITECTURES

Bledsoe and Browning [8] first proposed Weightless Neural Networks (WNN), i.e. neurons that do not have weight values between the inputs and the nodes, in 1959. Operating on simple binary values, rather than weighted networks which require copious amounts of training and processing to converge, Boolean networks (WNNs/Ram-

Based Neural Networks) can operate on more simplistic hardware. The key difference between WNNs and weighted neural networks is the way WNNs modify stored look-up tables instead of complex weightings. This simplicity does not deter from the excellent pattern recognition ability WNN's possess, such as optical character recognition where data can be easily binarised using thresholding techniques [9]. The comparatively fast testing and training employed by the WNN means it is more efficient to implement on hardware thus ideally suited to application in mobile robotics.

Weightless Neural Network real-time implementation was demonstrated by Nurmaini et al. [10]. Corners, obstacles and corridors were identified from sonar data with an execution time of 0.25 µs on an Atmel AT89x55 with 256 bytes of RAM and a 24.3 MHz clock speed.

The Generalised Convergent Network (GCN) [11] will be employed in this paper. This architecture uses distinctly independently connected layers. The GCN architecture is illustrated in Figure 1 and has the following properties:

- A set of layers is created, each having a set number of neurons equating to the dimensions of the initial input matrix. Essentially this means if the input matrix is n by n then n by n neurons are created.
- A connectivity pattern is used to link matrix elements using neurons within a given layer. This pattern is relative to the location of each neuron which is unique to a particular layer meaning its relative position can be distinguished within the input matrix.
- There are two main groups of layers within the architecture; 'Pre' and 'Main'.
- A merge is then performed on the component layer outputs of each group. This is done on the corresponding neurons within each of the layers and for each position within the layers.
- Output from each merge layer is subsequently delivered, unaltered, into the input of each of the layers in Main-Group.
- The connectivity patterns used for each layer are defined using a Genetic Algorithm creating an 'Architecture'. Connectivity may depend on the networks ability and error rate on a given data set.
- The constituent layers of each group differ in the selection of elements attached to the inputs of their constituent neurons (termed the connectivity pattern).
- Each of the neurons in a single layer is connected in the same way; relative to their location within the parsed code matrix (all have the same connectivity).

For a full description of this architecture, please follow this reference [11]. During the training phase, layers are adjusted independently of each other. The Genetic Algorithm employed governs the number of layers and groups as required.

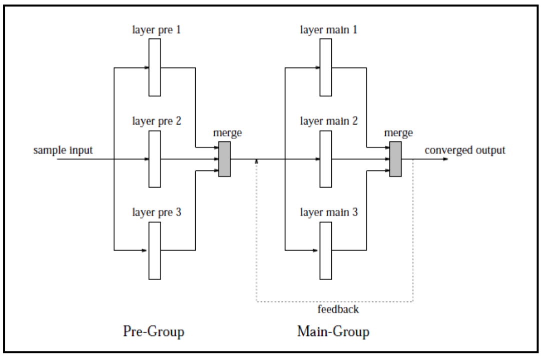

Figure 1. Example of GCN Network Architecture, Howells, Fairhurst and Bisset 1995.

III. Identifying Floor Signatures

The identification of a floor surface can be obtained from incident light. A simple measure of Texture, as shown in Figure 2, may be obtained from incident angle reflectance, and colour from a calibrated parallel light source negating bi-directional reflectance.

- Contrast provides grey level range.
- Average pixel value provides a level of albedo (dark/light).
- Homogeneity or uniformity is a measure of patterning or distinguishable features.
- Colour histogram floor measurement provides a direct method of identification, particularly in the human environment.

We demonstrate in this paper a real-time method of room identification for localisation. Texture and colour histogram information is obtained from simple low cost sensors, potentially allowing implementation on all form mobile robotics platforms.

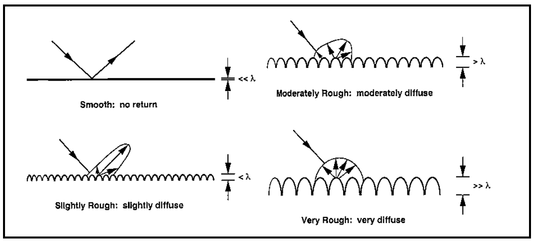

Figure 2. Specular reflectance top left through complex top right to Lambertian bottom right, NASA

A. Sensors

Real-time imagery processing requires complex and expensive hardware. We have therefore chosen an MCS-12086 mainstream, simple small form factor optical mouse sensor. The MCS-12086 contains a 324 pixel Image Acquisition System and a Digital Signal Processor which provides a non-mechanical tracking device for computer human interface; illumination is by an offset red led.

Data registers on the sensor provides various datum information each clock cycle. We are interested in obtaining a form of surface texture therefore we have selected to directly obtain surface feature count from the optical flow algorithm, contrast from pixel intensity variation, reflectance from average pixel intensity and surface roughness due to reflectance incident angle.

Sample	Median pixel values for texture test samples				
	Max Pixel	*Min Pixel*	*Mean*	*Feature Count*	*Contrast*
White Gloss paint	84	39	39	0	45
Dark Gloss paint	5	0	1	0	5
Tight Woven Material	87	13	17	30	74
Buff Paper	91	30	40	0	61
White Paper	102	42	50	0	64
Complex long fibre	53	8	12	25	45

TABLE I. TEXTURE CALIBRATION DATA

A second simple sensor, an ADJD-S311-CR999 surface mount RGB and Clear channel four pixel digital output sensor with filters and a front end analogue-to-digital converter, was used for determining spectral floor identification. Illumination was provided by four white LEDs mounted to provide parallel reflectance from the surface under investigation.

We implemented both sensors independent and adjacent, using an ATmega328 microcontroller which pre-processes and reads register information from the sensors sending those values to a laptop used to collect, collate and process.

B. Calibration

Colour data channels from the ADJD sensor were calibrated using the clear channel and white paper to give a consistent and stable histogram at each location. The MCS-12086 optical flow algorithm camera data were calibrated using the maximum pixel values obtained over the data range according to Table l. Illumination for both sensors was provided by localised LEDs to maintain constant spectral irradiance of the floor.

Data from the MCS-12086 sensor shown in Table I, although used raw, give good indication of surface texture. The homogeneity of Lambertian and specular reflectance can be identified in the pattern-less feature count of paper and gloss paint, the albedo is given by the mean pixel value across all 324 pixels and contrast obtained from the maximum-minimum pixel differential values.

Location	Location Floor Data						
	R	*G*	*B*	*Max Pixel*	*Mean Pixel*	*Feature Count*	*Contrast*
Lrg Open Office	27	23	18	61	13	8	48
Clear Coridoor	31	25	18	66	20	3	48
Small Foyer	16	12	9	36	8	0	28
Meeting Area	27	30	27	64	18	0	43
Medium Office	7	8	12	28	5	0	20
Small Office	23	20	14	84	10	28	76
Large Foyer	8	7	7	28	8	0	20
Large Complex Area	31	28	24	36	13	0	25
Complex Passage	47	38	31	66	25	0	46
Large Stairwell	53	46	34	84	33	0	56
Balcony	49	40	28	81	33	0	51
Restaurant Area	122	91	67	184	81	23	114
Oblong Atrium	178	178	126	203	99	15	114
Reception Area	16	18	9	38	10	0	28
Medium Foyer	30	24	20	43	10	3	33
Complex Reception	22	14	13	58	18	3	43
Lounge	71	54	56	127	53	15	79
Kitchen	76	58	62	36	13	0	23
Large Bedroom	72	64	54	168	53	84	122
Small Bedroom	75	66	56	160	48	99	119
Bathroom	161	138	114	203	91	15	119

TABLE II. FLOOR TEXTURE DATA

IV. FLOOR DATA

The campus of the University of Kent and a typical house were chosen to provide testing and training data for room identification. Statistical floor colour histogram and texture data were collected from 21 room locations tabulated in Table II. 50 samples were taken at each of 15 different locations within each room to provide 10 sets of testing data and 5 sets of training data for the WNN.

Raw datum values from the MCS-12086 sensor were read every 1.6 milliseconds and smoothed to remove sample noise. The ADJD RGB sensor raw datum values were read every 1.6 milliseconds averaged 4 times, sampling was delayed to synchronise with the MCS-12086 sensor.

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Location	Geometric Room Data					
	Height (m)	*Std.D (m)*	*Area (m^2)*	*Std.D (m^2)*	*Ratio X/y*	*Std.D*
Lrg Open Office	3.89	1.63	116.83	29.89	1.62	0.37
Clear Coridoor	2.71	0.02	32.87	7.27	8.93	1.22
Small Foyer	2.78	0.22	36.32	13.93	1.43	0.26
Meeting Area	2.76	0.19	98.92	48.23	1.80	0.33
Medium Office	2.59	0.01	49.48	9.28	1.13	0.12
Small Office	3.37	1.75	14.13	0.93	1.20	0.10
Large Foyer	2.95	0.51	64.25	20.19	1.35	0.25
Large Complex Area	2.81	0.12	343.75	121.55	1.20	1.50
Complex Passage	2.28	0.01	32.90	34.36	8.23	1.96
Large Stairwell	4.63	1.78	99.02	43.22	1.65	0.57
Balcony	3.18	0.17	155.20	49.21	1.33	0.40
Restaurant Area	2.51	0.01	173.49	93.77	2.15	0.87
Oblong Atrium	6.72	0.01	78.38	18.46	3.39	0.82
Reception Area	2.55	0.07	75.06	33.50	1.85	0.48
Medium Foyer	2.55	0.08	44.80	21.17	1.57	0.71
Complex Reception	2.42	0.15	63.71	50.13	1.34	0.54
Lounge	2.45	0.01	16.43	1.91	1.65	0.11
Kitchen	2.46	0.01	15.79	1.78	1.71	0.16
Large Bedroom	2.36	0.01	10.36	1.01	1.38	0.27
Small Bedroom	2.36	0.01	6.52	0.58	1.10	0.05
Bathroom	2.36	0.01	3.17	0.25	1.07	0.10

TABLE III. STATISTICAL GEOMETRIC DATA FROM VARIOUS LOCATIONS

V. RANGING DATA

We have chosen a standard narrow beam, 15m range, single ultrasonic transmitter/receiver incorporated into a Stanley™ pre-calibrated measuring device. Geometric properties of each location were randomly sampled for width, length and ceiling height to provide a crude ranging data set comprising of only 15 measurements per location. These raw values listed in Table III were used to provide 10 sets of testing data and 5 sets of training data for the WNN.

VI. PARSING INTO THE WEIGHTLESS NEURAL NETWORK

Data must be converted into a binary form to be used in the weightless neural network, therefore some parsing is required. When converting to binary an issue arises in that certain contiguous values will drastically change the binary, rendering it useless when attempting to find patterns in data, as there must be similar distances represented by similar encoded data. To counter this, Gray Code [12] shown in Figure 3 is used which adopts a special binarising technique; this allows contiguous numbers to be represented more equally.

Binary	Gray Code
31: 0 1 1 1 1 1	31: 0 1 0 0 0 0
32: 1 0 0 0 0 0	32: 1 1 0 0 0 0

Figure 3. Difference between Gray Code and normal Binary, Gilbert 1985.

A total of 10 variables shown in Figure 4 will be placed into the binary matrix which the WNN will use. The first three variables are based on the sonar data collected; the Red Green and Blue variables from the colour samples and the last 4 variables are gathered from the texture sensor. All the variables have been normalized between 0 and 254, each variable requiring 8 bits in order to represent the value in Gray Code.

Variable	Value	Gray Code
Height	104	0 1 0 1 1 1 0 0
Area	15	0 0 0 0 1 0 0 0
Ratio	182	1 1 1 0 1 1 0 1
Red	59	0 0 1 0 0 1 1 0
Green	47	0 0 1 1 1 0 0 0
Blue	48	0 0 1 0 1 0 0 0
Max Pix	154	1 1 0 1 0 1 1 1
Min Pix	66	0 1 1 0 0 0 1 1
Average	50	0 0 1 0 1 0 1 1
Feature Count	93	0 1 1 1 0 0 1 1

Figure 4. Converting variables to Gray Code

The result of this parsing is an 8x10 binary matrix, Fig 4, giving rise to a 21x10 training set and a 21x5 testing set. This can now be used by the WNN to determine best fit identifying location using these characteristics.

VII. WEIGHTLESS NEURAL NETWORK OUTPUTS

The results from the WNN are shown in Table IV, five test iterations have been compiled for each location using the best fit architecture within a given period. Mean values are tabulated to show the percentage of correct localisations for each room and all rooms for the five random test samples. Although rooms of very similar characteristics can be seen to have lower prediction accuracy most locations were however easily and repeatedly identified some 13 out of the 21 rooms better than 95% over all five tests.

It should be noted that all the rooms which were not well identified had highly irregular unusual ceilings and complex structural features.

Location	WNN Accuracy Percentage (%)					
	Test 1	*Test 2*	*Test 3*	*Test 4*	*Test 5*	*Mean*
Lrg Open Office	0	100	0	100	100	**60**
Clear Coridoor	100	100	100	100	100	**100**
Small Foyer	100	100	45	100	100	**89**
Meeting Area	100	100	100	100	100	**100**
Medium Office	20	100	35	0	0	**31**
Small Office	100	100	100	100	100	**100**
Large Foyer	100	100	100	45	100	**89**
Lrg Complex Area	100	100	100	100	100	**100**
Complex Passage	100	100	100	100	100	**100**
Large Stairwell	100	100	100	100	100	**100**
Balcony	100	80	100	100	100	**96**
Restaurant Area	100	100	100	100	100	**100**
Oblong Atrium	0	100	0	0	100	**40**
Reception Area	0	0	100	65	55	**44**
Medium Foyer	100	100	100	100	100	**100**
Complex Reception	100	0	100	0	63	**52.6**
Lounge	100	0	100	100	100	**80**
Kitchen	100	100	100	100	83	**96.6**
Large Bedroom	100	100	100	100	100	**100**
Small Bedroom	100	100	100	100	100	**100**
Bathroom	100	100	100	100	100	**100**
Mean	**81.9**	**84.8**	**84.8**	**81.4**	**90.5**	**84.7**

TABLE IV. LOCALISATION ACCURACY PERCENTAGE RESULTS

VIII. CONCLUSIONS

Our previous experiment [13] resulted in a lower room recognition rate when using a camera to obtain a colour histogram of the ceiling. Although not suffering from occlusion the ceiling has a considerable variation in colour due to irregular illumination and emissions. Flooring however tends to be more homogeneous in both colour and texture and more particularly illumination can be carefully controlled. Ceiling height and room size however continue to be consistent and highly desirable characterising features.

Colour data from the simple sensor was found to be very stable over the entire range and texture data although noisy is clearly obtainable from a simple low cost sensor in raw format. The Genetic Algorithm continuously updates the system localisation identification mechanism, although not running in real-time, therefore potentially allowing the system to build room localisation 'profiles' which can be updated each new visit; hence an adaptable system. Coarse localisation within individual rooms may therefore also be possible.

We have shown adequate sensitivity of the simple instruments, sufficient to uniquely identify individual locations, and the ability of the WNN to successfully use raw data. Our method of localisation using simple robust low cost sensors potentially allows dynamic changes to room layout, content, and floor degradation to be incorporated into an adaptable localisation and path planning system.

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REFERENCES

[1] M. Betke and L. Gurvits, "Mobile robot localization using landmarks," *Robotics and Automation, IEEE Transactions on,* vol. 13, pp. 251-263, 1997.

[2] A. Elfes, "Sonar-based real-world mapping and navigation," *Robotics and Automation, IEEE Journal of,* vol. 3, pp. 249-265, 1987.

[3] P. Buschka and A. Saffiotti, "A virtual sensor for room detection," in *Intelligent Robots and Systems, 2002. IEEE/RSJ International Conference on,* 2002, pp. 637-642 vol.1.

[4] J. Neira, J. D. Tardos, J. Horn and G. Schmidt, "Fusing range and intensity images for mobile robot localization," *Robotics and Automation, IEEE Transactions on,* vol. 15, pp. 76-84, 1999.

[5] B. McElroy and G. Howells, "Adaptive Meta-Network Design Employing Genetic Algorithm Techniques," *Artificial Intelligence and Soft Computing,* 2011.

[6] B. McElroy and G. Howells, "Automated adaptation of input and output data," *International Journal of Database Theory and Application,* vol. 4, 2011.

[7] B. McElroy and G. Howells, "Improved Adaptive Meta-Network Design Employing Genetic Algorithm Techniques," *ICINCO 8th International Conference on Informatics in Control, Automation and Robotics,* 2011.

[8] A. Bledsoe and A. Browning , "Pattern recognition and reading by machine," in *IRE-AIEE-ACM Computer Conference,* Boston, 1959, .

[9] B. McElroy and G. Howells, "Evaluating the application of simple weightless networks to complex patterns," in *Emerging Security Technologies (EST), 2010 International Conference on,* 2010, pp. 67-70.

[10] S. Nurmaini, S. Zaiton, M. Hashim and D. Jawawi, "Modular Weightless Neural Network Architecture for Intelligent Navigation," *Int. J. Advance. Soft Comput,* vol. 1, 2009.

[11] G. Howells, M. C. Fairhurst and D. L. Bisset, "GCN: The generalised convergent network," in *Fifth International Conference on Image Processing and its Applications,* Edinburgh, 1995, .

[12] E. Gilbert, "Gray Codes and Paths on the n-Cube," *The Bell System Technical Journal,* vol. 37, pp. 815-826, 1958.

[13] B. McElroy, M. Gillham, G. Howells, S. Spurgeon, S. Kelly, J. Batchelor, M. Pepper, "*Highly Efficient Localisation Utilising Weightless Neural Systems" ESANN (2012).*