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Highly efficient Localisation utilising Weightless neural systems.

Ben McElroy[1], Michael Gillham[2], Gareth Howells[3], Sarah Spurgeon[4], Stephen Kelly[5], John Batchelor[6], Matthew Pepper[7]
1-6 *School of Engineering and Digital Arts, University of Kent*
7 *East Kent Hospitals University Foundation Trust*

Abstract

Efficient localisation is a highly desirable property for an autonomous navigation system. Weightless neural networks offer a real-time approach to robotics applications by reducing hardware and software requirements for pattern recognition techniques. Such networks offer the potential for objects, structures, routes and locations to be easily identified and maps constructed from fused limited sensor data as information becomes available. We show that in the absence of concise and complex information, localisation can be obtained using simple algorithms from data with inherent uncertainties using a combination of Genetic Algorithm techniques applied to a Weightless Neural Architecture.

1 Introduction

Operating mobile robots in enclosed environments, such as buildings, requires an element of distinguishability between locations or rooms to permit consistent localisation and mapping of that environment. Localisation is considered the most important aspect of mobile robotics [1]; without determining the robot's position and orientation within an environment, no trajectory can be generated [1]. Accurate localisation is required in modern manufacturing environments for robust control [2] however in the case of mobile robotics in real-world scenarios, simple sensor information, for example, may suffice to initially localise, particularly in a highly dynamic environment, yet when compounded may still provide adequate environmental mapping [3]. Whilst uncertainties exist using simple single sensors, fusing of different source data can improve the estimation to a desirable level. For example, Neira et al. [4] fused laser range data with reflected intensity to improve estimation, concluding fusing simple sensor data was computationally inexpensive. Dong et al. [5] discuss fusing multi spectral imagery with radar altimetry improving spatial resolution for object identification, reporting self-adaptive Artificial Neural Networks (ANNs) are more powerful tools than traditional for pattern recognition [5].

Buschka and Saffiotti [6] describe identifying a cluttered room using a dimensional histogram, Tardós et al. [7] review geometric mapping using sonar based sensors, and they suggest a new method for detection of line segments successfully combining

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several stochastic maps. Sturm and Visser [8] show that vision based localisation could determine pose and place from discretised colours, for real-time applications. Stone et al. [9] determined that, despite uncertainties in vision based systems, collective data and learning could consistently enable team based robots to behave reactively in real-time. Natural ceiling features provide a visual positioning method suggested by Xu et al. [10] whilst Hyun Chul Roh et al. [111] suggest point pattern matching using ceiling spot lightings; their high degree of accuracy and fast update algorithm suggests suitability for real-time tasks. Jeong et al. [12] propose a quick ceiling vision based technique using a single ceiling vision sensor resolving the rotation and affine transform problems. Nguyen et al. [13] introduced another natural ceiling landmark system using a 360 degree view angle single camera sensor. They all agree that ceiling data generally suffers less from clutter and are seldom occluded.

In this paper, we therefore propose a multi-modal localisation system using a combination of real-time low quality ceiling images and noisy ranging data combined to classify and identify location using an adaptive Weightless Neural Network (WNN). The main contribution is the ability of the system to change and adapt to the data it is being given to better identify and localise the robot. The system possesses the following advantages, which are highly significant in a practical environment.

- The system is able to operate in real time.
- The system is adaptive; potentially modifying performance in dynamic situations.
- Efficient use of Sensor data; few samples are needed in order to identify a room.
- Reduced susceptibility to occlusion due to the camera pointing at the ceiling.

In order to tune the Weightless Neural Network a heavily modified Genetic Algorithm is used to create and control the WNN architectures. This improves the performance and recognition ability of the WNN as it continues to run [14-16].

2 Weightless Artificial Neural Architectures

Weightless Neural Networks (WNN) first conceived by Bledsoe and Browning [17] are not weighted between inputs and nodes; instead they operate on simple binary values. WNNs are trained by modifying look-up tables rather than weights whereas conventional weighted networks need significant training and processing to converge. WNNs are therefore best suited to real-time hardware implementation, particularly pattern recognition, despite their simplicity. They best perform where data samples can be simply thresholded into binary values, such as facial recognition and character recognition [18]. We employ the Generalised Convergent Network (GCN) [19] architecture in this experiment illustrated in Fig. 1 with the following properties:

- Pattern elements are linked to a given neuron within a particular layer, neuron location defined by connectivity pattern relating to input. Layers have unique

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connectivity patterns, thus each neuron distinguished by its position within the input matrix. Created layers are then put into either 'Pre' group or 'Main' group.

- Component layer outputs of each group are then combined in a single merge layer. Merge is performed within group for corresponding positions within each layer. Layers within each group are connectively bound to each merge operation. Output of each merge is feedback into inputs of each layer in each group.
- Neuron connectivity and layer numbers within group, defined by the Genetic Algorithm, depend on network performance of the given data. The constituent layers of group differ in selecting elements attached to the neuron inputs.
- Each of the neurons in a single layer is connected in the same way, relative to their location within the parsed code matrix.

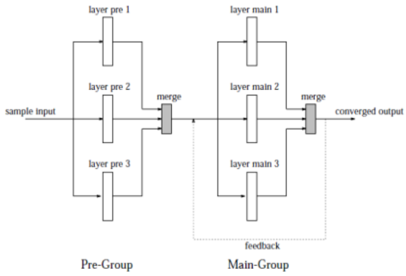

Figure 1: Example of GCN Network Architecture, Howells, Fairhurst and Bisset 1995 [16]

3 Identifying room signatures

Many potential identifying features exist to uniquely identify a room: clutter, colour, texture, size, shape, fixtures and fittings. Benet et al. [20] use sonar return signal amplitude to identify corners; Buschka and Saffiotti [6] identify rooms from length and breadth histograms. We propose to identify and fuse simple unique characteristics for better decision making in a computationally fast neural network for real-time autonomous robotic application. Nurmaini et al. [21] demonstrate real-time identification of corridors, corners and obstacles using sonar data and a Weightless Neural Network, demonstrating a 0.25μs execution time on a small microprocessor.

We chose a narrow beam, 15m range, single ultrasonic transmitter/receiver for measuring geometric properties at each location, X, Y and Z dimensions were sampled at various translations without regard for fixtures and clutter. The second data collection used a single fisheye lens 360 degree camera, pointed at the ceiling, 3 images were taken at each position and up to 4 positions within a room, dependent on size. Images were formatted to 180 x 180 pixels; and a 45 pixel radius core was removed to leave an iris shaped image, as shown in Fig. 2 left image. Subsequent to being formatted correctly, the data was processed using a parsing algorithm. This algorithm quantized the image and split the image into 48 equal sections in a manner similar to that shown in Fig. 2 right image.

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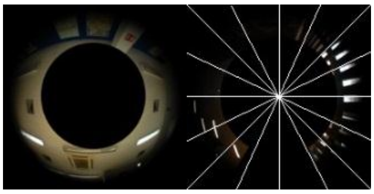

Figure 2: Typical cropped and formatted camera image left, sectioned image right

Images were normalised by subtracting the greyscale from each colour channel, leaving those pixels more distinctive in colour. The number of sections was chosen so that small objects with unique colours could be identified. Median pixel values for each section were obtained and a resultant channel ratio found.

3 Data collection

Various locations around the campus of the University of Kent and at a typical house were sampled to provide sufficient data to recognize unique signatures for room identification. Training data comprised of 10 sets of data and testing data was collected on a different day and time comprising of 5 sets of data from all locations.

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: The difference between Gray Code and normal Binary

The statistical colour histogram data collected from twenty one locations is tabulated in Table 1: Thirty raw measurements, ten room lengths (y), ten room breadths (x) and ten room heights (z) from each of the locations were also collected. Data from sonar and the camera parsing algorithms were collated and binarised, to create a binary matrix. Regular binary suffers from large changes at certain values, as shown in Fig 3. Gray Code removes this weakness and provides a much smoother change in bits from one value to the next [22] serving as the input to the neural network.

4 Weightless Neural Network Outputs

The WNN will self-improve until a point is reached where it is no longer able to; the results are shown in Table 2. A 70.4% recognition rate was obtained in the final test. Some locations were easier to identify than others, for example highly non-geometric rooms with complex ceilings. Although only 10 training data sets were used for each room with high degrees of variance between them.

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Location	Median				Standard Deviation			
	R	G	B	None	R	G	B	None
EDA Lab	8	1	19.5	22	2.514403	1.8135294	5.797509	8.0718991
EDA Corridors	4.5	0.5	6	35.5	2.2010099	1.0327956	4.2176876	4.8085572
EDA Downstairs	13	1.5	6.5	27.5	4.9888765	2.9230882	3.1989582	7.4654761
EDA Back Door	12	1	14.5	21	2.3781412	0.6749486	2.7182511	4.0565448
Physics Building	21.5	0	12	13.5	5.7927157	0.4830459	5.9898062	2.8596814
Octagon Building	12	1	9	24	6.7032331	2.3309512	3.7178249	7.202623
Back of Registry Building	11	0.5	19.5	20.5	4.2373996	0.9189366	7.6310768	4.9227364
Front of Registry Building	16.5	0	7.5	24	6.3595947	4.4484704	4.0496913	8.5277325
Entrance to Darwin	5.5	0.5	16	25	6.6298986	1.1005049	8.3426614	10.339246
Outside Origins Bar	6.5	0.5	10	31	8.0863396	1.3333333	4.976612	12.020353
Origins Bar	18	0	3.5	25	7.1211734	0.6992059	4.5264654	9.6401936
Rutherford Quad	3	0	6	39	1.9364917	3.7178249	1.8708287	2.7131368
Law School Reception	9.5	1	15	20.5	3.6270588	1.2692955	4.2478753	6.8968592
Architecture Social Area	8	2.5	14.5	21	2.9458068	1.8378732	7.7753171	8.819171
Audio/Visual Lab	7	0.5	4.5	34	3.7058512	0.6992059	3.7058512	5.6999025
EDA Lab Meeting Room	5.5	0	11.5	31.5	4.8488257	0.421637	7.3703611	8.9845546
House Lounge	1	0	8.5	38	1.1352924	0.3162278	3.6270588	3.9171985
House Kitchen	0.5	0	7.5	38	0.6992059	0.843274	2.6583203	2.2705848
House Bathroom	2	0	9.5	36.5	1.8135294	0	1.3498971	1.3984118
House Bedroom (Large)	0	0	6.5	41	0.6749486	0	2.5905812	2.8067379
House Bedroom (Small)	0	0	5.5	42.5	0.421637	0	3.3015148	3.2128215

Table 1: Statistical camera data from various locations

Room	Test 1	Test 2	Test 3	Test 4	Mean
EDA Lab	20.0%	0.0%	7.6%	0.0%	6.9%
EDA Corridors	100.0%	95.8%	100.0%	100.0%	99.0%
EDA Downstairs	62.0%	45.2%	60.0%	60.0%	56.8%
EDA Back Door	60.0%	75.8%	71.0%	88.8%	73.9%
Physics Building	26.8%	20.6%	33.6%	40.0%	30.3%
Octagon	30.0%	42.4%	34.4%	47.2%	38.5%
Back of Registry	21.4%	31.0%	1.6%	20.0%	18.5%
Front of Registry	88.6%	99.0%	51.2%	100.0%	84.7%
Entrance to Darwin	20.0%	34.2%	40.0%	40.0%	33.6%
Outside Origins Bar	100.0%	73.0%	57.8%	100.0%	82.7%
Origins Bar	80.0%	80.0%	62.0%	80.0%	75.5%
Rutherford Quad	100.0%	100.0%	100.0%	100.0%	100.0%
Law School Reception	69.8%	59.4%	60.0%	65.4%	63.7%
Architecture Social Area	50.0%	73.2%	60.0%	60.6%	61.0%
Audio/Visual Lab	42.6%	73.0%	63.0%	76.4%	63.8%
EDA Lab Meeting Room	100.0%	50.2%	96.2%	60.0%	76.6%
House Lounge	60.0%	60.0%	60.0%	60.0%	60.0%
House Kitchen	80.0%	88.4%	80.0%	80.0%	82.1%
House Bathroom	100.0%	100.0%	100.0%	100.0%	100.0%
House Bedroom (Large)	100.0%	100.0%	84.4%	100.0%	96.1%
House Bedroom (Small)	100.0%	100.0%	100.0%	100.0%	100.0%
Mean	67.2%	66.7%	62.9%	70.4%	66.8%

Table 2: Weightless Neural Network location identification results

5 Conclusions

The paper has introduced a novel neural architecture which is able to address the significant practical problems associated with indoor robot localisation in real time with reduced sensor data and within a noisy or cluttered environment. The system has employed a Weightless Neural Architecture using simple one shot learning which allows environmental changes and variable conditions to be easily updated in the stored training data, an example may be to store different data sets for night and day ceiling illumination or peak human occupancy and low occupancy.

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