

FIELD PROGRAMMABLE GATE ARRAY  
BASED SIGMOID FUNCTION  
IMPLEMENTATION USING DIFFERENTIAL  
LOOKUP TABLE AND SECOND ORDER  
NONLINEAR FUNCTION

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DOCTOR OF PHILOSOPHY

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We hereby declare that We have checked this thesis and in our opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Doctor of Philosophy.

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I hereby declare that the work in this thesis is based on my original work except for quotations and citation which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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## ABSTRAK

Rangkaian neural buatan (ANN) adalah teknik kecerdasan buatan yang digunakan secara meluas dalam menyelesaikan banyak masalah seperti pengkelasan dan pengelompokan di dalam pelbagai bidang. Salah satu masalah yang dihadapi oleh rangkaian saraf buatan ini ialah pemprosesan yang sangat perlahan apabila melibatkan jumlah neuron yang besar. Untuk menyelesaikan masalah ini, rangkaian saraf buatan ini telah diimplementasikan ke dalam perkakasan yang dinamakan *field programmable gate array* (FPGA). Walau bagaimana pun, kaedah penyelesaian ini menghadapi masalah baru iaitu fungsi sigmoid yang biasa digunakan di dalam rangkaian saraf buatan tidak boleh diaplikasikan secara terus ke dalam FPGA. Dengan kepantasan dan ketepatan yang tinggi, *Lookup table* adalah satu teknik yang sering digunakan untuk menggantikan fungsi sigmoid di dalam FPGA. Walau bagaimana pun ketepatan yang tinggi ini memerlukan kos memori yang sangat besar. Sementara itu, fungsi ketidakseragaman ke-dua pula mempunyai kelebihan dari segi keperluan jumlah memori yang kecil. Namun begitu, teknik ini menghadapi isu tentang ketepatan hasil akhir fungsi sigmoid. Dengan menggunakan kelebihan yang ada pada fungsi ketidakseragaman ke-dua dan *lookup table* yang diubahsuai yang dipanggil *differential lookup table*, penyatuan di antara kedua-dua kaedah berkenaan telah dicadangkan untuk mengatasi masalah ini. Perbezaan nilai antara fungsi ketidakseragaman ke-dua berbanding fungsi sigmoid digunakan untuk membina *differential lookup table*. Fungsi ketidakseragaman ke-dua digunakan sebagai langkah pertama untuk menganggarkan nilai fungsi sigmoid dan kemudian ditambah/ditolak dengan nilai yang disimpan di dalam *differential lookup table* sebagai langkah kedua seperti yang ditunjukkan di dalam simulasi. Kaedah yang dicadangkan menghasilkan keputusan yang hampir sama sebagaimana pengiraan yang dilakukan secara simulasi di dalam perisian Matlab. Ujian selanjutnya telah dijalankan untuk menguji ketepatan rangkaian saraf buatan menentukan kedudukan objek di dalam bangunan dengan menggunakan kaedah yang dicadangkan sebagai pengiraan fungsi sigmoid. Hasilnya rangkaian saraf buatan menghasilkan ketepatan yang tinggi seperti mana keputusan daripada perisian. Kaedah penyelesaian yang dicadangkan ini membolehkan rangkaian saraf buatan digunakan di mana-mana bidang yang memerlukan pemprosesan yang cepat dengan ketepatan yang tinggi dari pengiraan fungsi sigmoid.

## ABSTRACT

Artificial neural network (ANN) is an established artificial intelligence technique that is widely used for solving numerous problems such as classification and clustering in various fields. However, the major problem with ANN is a factor of time. ANN takes a longer time to execute a huge number of neurons. In order to overcome this, ANN is implemented into hardware namely field-programmable-gate-array (FPGA). However, implementing the ANN into a field-programmable gate array (FPGA) has led to a new problem related to the sigmoid function implementation. Often used as the activation function for ANN, a sigmoid function cannot be directly implemented in FPGA. Owing to its accuracy, the lookup table (LUT) has always been used to implement the sigmoid function in FPGA. In this case, obtaining the high accuracy of LUT is expensive particularly in terms of its memory requirements in FPGA. Second-order nonlinear function (SONF) is an appealing replacement for LUT due to its small memory requirement. Although there is a trade-off between accuracy and memory size. Taking the advantage of the aforementioned approaches, this thesis proposed a combination of SONF and a modified LUT namely differential lookup table (dLUT). The deviation values between SONF and sigmoid function are used to create the dLUT. SONF is used as the first step to approximate the sigmoid function. Then it is followed by adding or deducting with the value that has been stored in the dLUT as a second step as demonstrated via simulation. This combination has successfully reduced the deviation value. The reduction value is significant as compared to previous implementations such as SONF, and LUT itself. Further simulation has been carried out to evaluate the accuracy of the ANN in detecting the object in an indoor environment by using the proposed method as a sigmoid function. The result has proven that the proposed method has produced the output almost as accurately as software implementation in detecting the target in indoor positioning problems. Therefore, the proposed method can be applied in any field that demands higher processing and high accuracy in sigmoid function output.

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