Faculty of Electronic and Computer Engineering

NEUROMORPHIC LEARNING MACHINE BASED ON STOCHASTIC RESERVOIR COMPUTING FOR TIME SERIES DATA PROCESSING AND CLASSIFICATION

Saw Chia Yee

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SAW CHIA YEE

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DECLARATION

I declare that this thesis entitled “Neuromorphic Learing Machine Based on Stochastic Reservoir Computing for Time Series Data Processing and Classification” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature : ....

Name : Saw Chia Yee

Date : 12 Jan 2023

APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Master of Science in Electronic Engineering.

Signature : ....

Name : Assoc. Prof. Dr. Wong Yan Chiew

Date : 12 Jan 2023

DEDICATION

This project is dedicated to my beloved parents and Profesor Madya Dr. Wong Yan Chiew who for their never-ending moral support in my academic life.

ABSTRACT

Neuromorphic computing is a potential alternative to conventional von Neumann computers for specialised sensory-processing or classification applications. Neuromorphic systems replicate the biophysics of neurobiological networks by replicating the information processing mechanism of biological neurons and synapses, resulting in high connection and parallelism on a smaller footprint. These characteristics contribute to the implementation of neuromorphic architectures in hardware development for time series data classification and recognition. However, hardware implementation of neural network suffers from resource constraints because to the typically large number of nodes utilised in RC networks and the high chip area required for each processing node. Moreover, a high number of features in time series data classification introduces computational burden and leads to excessive hardware calculation overhead. In this work, a reservoir computing based stochastic spiking neural network (SSNN) has been proposed for time series data processing and classification, enabling a more efficient hardware implementation with low computation overhead caused by minimum extracted features. The proposed neuron reservoir is implemented in two applications including ventricular heartbeat classification and human activity recognition (HAR). The 43 recordings of Electrocardiogram (ECG) signals that included both normal and arrhythmic beats from MIT-BIH arrhythmia database obtained from Physio-Net were used in this work for heartbeat classification. Baseline drift and power line interference that are frequently emphasized in ECG readings are minimized by signal denoising. The single feature, QRS complexes, was extracted and fed into the neural reservoir with 20 neurons in cyclic topology for arrhythmias' similarity calculation and classification. The HAR is evaluated in order to further validate the proposed SSNN approach. This work proposes feature extraction based on subcarrier correlation and pseudocolor variations caused by human movements depicted in the images using convolution neural network (CNN) without preprocessing applied and enabling low computational complexity and visual observation of entire pattern changes. The extracted features are fed into the neural reservoir for activities recognition. A two-input stochastic neuron is developed for complex machine learning using the stochastic computing (SC) theory. The 20 stochastic neurons are then arranged into a simple cycle reservoir (SCR) architecture to create the SSNN. The proposed system has been implemented in Xilinx Zynq-7000 field-programmable gate array (FPGA) to demonstrate the hardware efficiency leads by the minimum feature size used. The proposed stochastic spiking reservoir achieves an accuracy of 96.91% in heartbeat classification and 92.94% and 93.91% for features based on subcarrier correlation and pseudocolor plot in HAR, demonstrating that the system is accurate and effective at classifying time series data.

MESIN PEMBELAJARAN NEUROMORFIK BERASASKAN PENGKOMPUTERAN TAKUNGAN STOKASTIK UNTUK PEMPROSESAN DAN PENGELASAN DATA SIRI MASA

ABSTRAK

Pengkomputeran neuromorfik ialah alternatif yang berpotensi kepada komputer von Neumann konvensional untuk pemprosesan deria atau aplikasi klasifikasi. Sistem neuromorfik mereplikasi biofizik rangkaian neurobiologi dengan mereplikasi mekanisme pemprosesan maklumat neuron biologi dan sinaps, menghasilkan sambungan yang tinggi dan selari pada jejak yang lebih kecil. Ciri-ciri ini menyumbang kepada pelaksanaan seni bina neuromorfik dalam pembangunan perkakasan untuk pengelasan dan pengecaman data siri masa. Walau bagaimanapun, pelaksanaan perkakasan rangkaian saraf mengalami kekangan sumber kerana bilangan nod yang biasanya besar digunakan dalam rangkaian RC dan kawasan cip tinggi yang diperlukan untuk setiap nod pemprosesan. Selain itu, bilangan ciri yang tinggi dalam klasifikasi data siri masa memperkenalkan beban pengiraan dan membawa kepada overhed pengiraan perkakasan yang berlebihan. Dalam kerja ini, rangkaian neural spiking stokastik (SSNN) berasaskan pengkomputeran takungan telah dicadangkan untuk pemprosesan dan pengelasan data siri masa, membolehkan pelaksanaan perkakasan yang lebih cekap dengan overhed pengiraan rendah disebabkan oleh ciri yang diekstrak minimum. Takungan neuron yang dicadangkan dilaksanakan dalam dua aplikasi termasuk klasifikasi degupan jantung ventrikel dan pengecaman aktiviti manusia (HAR). 43 rakaman isyarat Elektrokardiogram (ECG) yang merangkumi kedua-dua rentak normal dan aritmik daripada pangkalan data aritmia MIT-BIH yang diperoleh daripada Physio-Net telah digunakan dalam kerja ini untuk klasifikasi degupan jantung. Hanyutan garis dasar dan gangguan talian kuasa yang kerap dititikberatkan dalam bacaan ECG diminimumkan dengan penyahtandaan isyarat. Ciri tunggal, kompleks QRS, telah diekstrak dan dimasukkan ke dalam takungan saraf dengan 20 neuron dalam topologi kitaran untuk pengiraan dan klasifikasi persamaan aritmia. HAR dinilai untuk mengesahkan lagi pendekatan SSNN yang dicadangkan. Kerja ini mencadangkan pengekstrakan ciri berdasarkan korelasi subcarrier dan variasi pseudocolor yang disebabkan oleh pergerakan manusia yang digambarkan dalam imej menggunakan rangkaian neural convolution (CNN) tanpa prapemprosesan yang digunakan dan membolehkan kerumitan pengiraan rendah dan pemerhatian visual terhadap keseluruhan perubahan corak. Ciri yang diekstrak dimasukkan ke dalam takungan saraf untuk pengecaman aktiviti. Neuron stokastik dua input dibangunkan untuk pembelajaran mesin yang kompleks menggunakan teori pengkomputeran stokastik (SC). 20 neuron stokastik kemudiannya disusun menjadi seni bina takungan kitaran mudah (SCR) untuk mencipta SSNN. Sistem yang dicadangkan telah dilaksanakan dalam Xilinx Zynq-7000 FPGA untuk menunjukkan kecekapan perkakasan diterajui oleh saiz ciri minimum yang digunakan. Takungan spiking stokastik yang dicadangkan mencapai ketepatan 96.91% dalam pengelasan degupan jantung dan 92.94% dan 93.91% untuk ciri berdasarkan korelasi subcarrier dan plot pseudocolor dalam HAR, menunjukkan bahawa sistem adalah tepat dan berkesan dalam mengklasifikasikan data siri masa..

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LIST OF ABREVIATIONS

ALU	-	Arithmetic and Logic Unit
ANN	-	Artificial Neural Network
ASIC	-	Application-Specific Integrated Circuit
B2P	-	Binary-to-pulse converter
Bi-LSTM	-	Bidirectional Long Short-Term Memory
BNN	-	Binarized Neural Network
BPNN	-	Back propagation neural network
BPTT	-	Backpropagation through time
BW	-	Baseline wander
CDC	-	Centers for Disease Control and Prevention
CMOS	-	Complementary metal-oxide-semiconductor
CNN	-	Convolution neural network
CoNN	-	Continuous neural network
CPU	-	Central processing unit
CI	-	Cumulative statistical index
CSI	-	Channel state information
DLR	-	Delay line reservoir
DLRB	-	Delay line reservoir with feedback
DNN	-	Deep neural network

DVS	-	Dynamic Vision Sensor
DWT	-	Discrete wavelet transform
DYNAP	-	Dynamic Neuromorphic Asynchronous Processors
ECG	-	Electrocardiogram
ELM	-	Extreme learning machines
EPSPs	-	Excitatory Postsynaptic Potentials
ESN	-	Echo state network
FF	-	Flip-flop
FFNN	-	Feedforward Neural Networks
FN	-	False negative
FNR	-	False negative rate
FP	-	False positive
FPGA	-	Field programable gate array
FPR	-	False positive rate
FSHNN	-	Fully Spiking Hybrid Neural Network
HAR	-	Human activity recognition
HARSSNN	-	Stochastic spiking neural network based human activity recognition
HICANN	-	High Input Count Analog Neural Network
HPF	-	High pass filter
I/O	-	Input/output
ICA	-	Independent component analysis
IPSPs	-	Inhibitory Postsynaptic Potentials
kNN	-	k-Nearest Neighbours
LDPC	-	Low-density parity-check

LFSR	-	Linear-feedback shift register
LIF	-	Leaky-Integrate-and-Fire
LM-SNN	-	Lattice map spiking neural network
LPF	-	Low pass filter
LSTM	-	Long Short-Term Memory
LUT	-	Lookup tables
MAC	-	Multiply-and-accumulate
MIMO	-	Multiple-input-multiple-output
MIoT	-	Medical Internet of Things
MLP	-	Multilayer Perceptron
MNIST	-	Modified National Institute of Standards and Technology
MUX	-	Multiplexer
MWI	-	Moving Window Integration
NOC	-	Network-on-Chip
ODE	-	Ordinary Differential Equation
ODIN	-	Online-learning Digital Spiking Neuromorphic
OFDM	-	Orthogonal frequency division multiplexing
P2B	-	Pulse-to-binary converter
PCA	-	Principal Component Analysis
PPV	-	Positive predictive value
RC	-	Reservoir computing
RNG	-	Random number generator
RNN	-	Recurrent Neural Network
RTL	-	Register Transfer Level
RTRL	-	Real-time recurrent learning

SC	-	Stochastic computing
SCNN	-	Spiking Convolutional Neural Network
SCR	-	Simple cycle reservoir
SDSP	-	Spike-Driven Synaptic Plasticity
SEN	-	Sensitivity
SLP	-	Single Layer Perceptron
SNGs	-	Stochastic Number Generators
SNN	-	Spiking neural network
SNs	-	Stochastic Numbers
SRAM	-	Static Random Access Memory
SSNN	-	Stochastic spiking neural networks
STDP	-	Spike Time-Dependent Plasticity
SVM	-	Support Vector Machines
TN	-	True negative
TP	-	True positive
WiGeR	-	WiFi-based hand gesture recognition device

LIST OF SYMBOLS

φ	-	Activation function
σ	-	Variance
Ø	-	Matrix with empty set
$\delta(.)$	-	Dirac function
ϑ	-	Threshold value
acc	-	Accuracy
b	-	Bias
C	-	Capacitor
I, i	-	Current
f	-	Nonlinear function
$f_{extract}$	-	Extracted features
g	-	Conductance
L	-	Length
M	-	Matrix
N	-	Number of reservoirs
N_c	-	Clock cycles
P	-	Probabilities
r	-	Reservoir
R	-	Resistor

$S(.)$ - Spiking neuron's output

S_{CSI} - CSI's sequential data

$step$ - Step size of window movement

t - Time

T_{eval} - Evaluation duration

T_{clk} - Clock duration

u - Membrane potential

U - Recovery of the membrane

v, V - Variance

ω - Width of sliding window

W, w - Weight vector

$\bar{x}$ - Mean sequential data

x - Input variables

y - Output variables

LIST OF PUBLICATIONS

1. Saw, C.Y., 2022. Neuromorphic Computing based on Stochastic Spiking Reservoir for Heartbeat Classification. *Jordanian Journal of Computers and Information Technology*, 8(2).