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Brain-Machine Interface

Circuits and Systems

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To my son Viggo Alan and
my daughter Emma

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About the Author

Amir Zjajo received the M.Sc. and DIC degrees from the Imperial College London, London, UK, in 2000 and the Ph.D. degree from Eindhoven University of Technology, Eindhoven, The Netherlands in 2010, all in electrical engineering. In 2000, he joined Philips Research Laboratories as a member of the research staff in the Mixed-Signal Circuits and Systems Group. From 2006 to 2009, he was with Corporate Research of NXP Semiconductors as a Senior Research Scientist. In 2009, he joined Delft University of Technology as a Faculty member in the Circuit and Systems Group.

Dr. Zjajo has published more than 70 papers in referenced journals and conference proceedings, and holds more than ten US patents or patent pending. He is the author of the books, *Low-Voltage High-Resolution A/D Converters: Design, Test and Calibration* (Springer 2011, Chinese translation 2015), and *Stochastic Process Variations in Deep-Submicron CMOS: Circuits and Algorithms* (Springer 2014). He serves as a member of Technical Program Committee of IEEE Design, Automation and Test in Europe Conference, IEEE International Symposium on Circuits and Systems, IEEE International Symposium on VLSI, IEEE International Symposium on Nanoelectronic and Information Systems, and IEEE International Conference on Embedded Computer Systems.

His research interests include power-efficient mixed-signal circuit and system design for health and mobile applications and neuromorphic electronic circuits for autonomous cognitive systems. Dr. Zjajo won the best paper award at BIODEVICES 2015 and DATE 2012.

Abbreviations

A/D	Analog to Digital
ADC	Analog-to-Digital Converter
ANN	Artificial Neural Network
AP	Action Potentials
BDF	Backward Differentiation Formula
BMI	Brain Machine Interface
BSIM	Berkeley Short-Channel IGFET Model
CAD	Computer-Aided Design
CDF	Cumulative Distribution Function
CMOS	Complementary MOS
CMRR	Common-Mode Rejection Ratio
D/A	Digital to Analog
DAC	Digital-to-Analog Converter
DAE	Differential Algebraic Equations
DFT	Discrete Fourier Transform
DIBL	Drain-Induced Barrier Lowering
DNL	Differential Nonlinearity
DR	Dynamic Range
DSP	Digital Signal Processor
DTFT	Discrete Time Fourier Transform
EM	Expectation Maximization
ENOB	Effective Number of Bits
ERBF	Exponential Radial Basis Function
ERBW	Effective Resolution Bandwidth
FFT	Fast Fourier Transform
GBW	Gain–Bandwidth Product
IC	Integrated Circuit
IEEE	Institute of Electrical and Electronics Engineers
INL	Integral Nonlinearity

ITDFT	Inverse Time Discrete Fourier Transform
KCL	Kirchhoff' Current Law
KKT	Karush–Kuhn–Tucker
LFP	Local Field Potentials
LNA	Low Noise Amplifier
LSB	Least Significant Bit
MNA	Modified Nodal Analysis
MOS	Metal Oxide Semiconductor
MOSFET	Metal–Oxide–Semiconductor Field-Effect Transistor
MSB	Most Significant Bit
NA	Nodal Analysis
NMOS	Negative doped MOS
ODE	Ordinary Differential Equation
OTA	Operational Transconductance Amplifier
PDE	Partial Differential Equation
PDF	Probability Density Function
PGA	Programmable Gain Amplifier
PMOS	Positive doped MOS
PPA	Power per Area
PSD	Power Spectral Density
PSRR	Power Supply Rejection Ratio
QP	Quadratic Problem
QPO	Quadratic Program Optimization
RBF	Radial Basis Function
RTL	Register Transfer Level
S/H	Sample and Hold
SAR	Successive Approximation Register
SC	Switched Capacitor
SDE	Stochastic Differential Equation
SFDR	Spurious-Free Dynamic Range
SINAD	Signal-to-Noise and Distortion
SNDR	Signal-to-Noise plus Distortion Ratio
SNR	Signal-to-Noise Ratio
SPICE	Simulation Program with Integrated Circuit Emphasis
SRAM	Static Random-Access Memory
STI	Shallow Trench Isolation
SVD	Singular Value Decomposition
SVM	Support Vector Machine
T/D	Time to Digital
T/H	Track and Hold
TDC	Time-to-Digital Converter
THD	Total Harmonic Distortion
V/I	Voltage to Current
VCCS	Voltage-Controlled Current Sources

VGA	Variable Gain Amplifier
VTC	Voltage-to-Time Converter
WCD	Worst Case Design
WSS	Wide Sense Stationary

Symbols

a	Elements of the incidence matrix A, bounds
A	Amplitude, area, constant singular incidence matrix
A_f	Voltage gain of feedback amplifier
A_{fmb}	Mid-band gain of amplifier
b	Number of circuit branches, vector of biases, bounds
B_i	Number of output codes
B	Bit, effective stage resolution
B_n	Noise bandwidth
BW	Bandwidth
c_i	Class to which the data x_i from the input vector belongs
c_{xy}	Process correction factors depending upon the process maturity
C^*	Neyman–Pearson Critical region
C	Capacitance, covariance matrix
C_C	Compensation capacitance, cumulative coverage
C_{eff}	Effective capacitance
C_G	Gate capacitance, input capacitance of the operational amplifier
C_{GS}	Gate-Source capacitance
C_{in}	Input capacitance
C_L	Load capacitance
C_{out}	Parasitic output capacitance
C_{ox}	Gate-oxide capacitance
C_{par}	Parasitic capacitance
C_{tot}	Total load capacitance
C_Q	Function of the deterministic initial solution
$C_{\Xi\Xi}$	Autocorrelation matrix
$C_{\varsigma\varsigma}$	Symmetrical covariance matrix
d_i	Location of transistor i on the die with respect to a point of origin
D_i	Multiplier of reference voltage
D_{out}	Digital output
e	Noise, error, scaling parameter of transistor current

e_q	Quantization error
e^2	Noise power
$E\{.\}$	Expected value
E_{conv}	Energy per conversion step
f_{clk}	Clock frequency
f_{in}	Input frequency
$f_{p,n}(d_i)$	Eigenfunctions of the covariance matrix
f_S	Sampling frequency
f_{sig}	Signal frequency
f_{spur}	Frequency of spurious tone
f_T	Transit frequency
$f(x,t)$	Vector of noise intensities
F_Q	Function of the deterministic initial solution
g	Conductance
g_m	Transconductance
G_i	Interstage gain
G_m	Transconductance
h	Numerical integration stepsize, surface heat transfer coefficient
i	Index, circuit node, transistor on the die
$i_{\max}$	Number of iteration steps
I	Current
I_{amp}	Total amplifier current consumption
I_{diff}	Difussion current
I_D	Drain current
I_{DD}	Power supply current
I_{ref}	Reference current
j	Index, circuit branch
J_0	Jacobian of the initial data z_0 evaluated at p_i
k	Boltzmann's coefficient, error correction coefficient, index
K	Amplifier current gain, gain error correction coefficient
$K(t)$	Variance–covariance matrix of $\lambda(t)$
L	Channel length
L_i	Low-rank Cholesky factors
$L(\theta \vert T_X)$	Log-likelihood of parameter θ with respect to input set T_X
m	Index
M	Number of terms, number of channels in BMI
n	Index, number of circuit nodes, number of bits
N	Number of bits
N_{aperture}	Aperture jitter limited resolution
P	Power
p	Process parameter
$p(d_i,\theta)$	Stochastic process corresponding to process parameter p
$\mathrm{p}_{X\vert\Theta}(x \vert \theta)$	Gaussian mixture model
p^*	Process parameter deviations from their corresponding nominal values

p_1	Dominant pole of amplifier
p_2	Nondominant pole of amplifier
q	Channel charge, circuit nodes, index, vector of state variables
r	Circuit nodes, number of iterations
R	Resistance
r_{ds}	Output resistance of a transistor
R_{eff}	Effective thermal resistance
R_{on}	Switch on-resistance
R_{n-1}	Process noise covariance
r_{out}	Amplifier output resistance
S_i	Silicon
S_n	Output vector of temperatures at sensor locations
s	Scaling parameter of transistor size, score
t	Time
T	Absolute temperature, transpose, time, transistor
t_{ox}	Oxide thickness
t_S	Sampling time
v_f	Fractional part of the analog input signal
v_n	Input-referred noise of the amplifier
u_n	Gaussian sensor noise
V	Voltage
V_{CM}	Common-mode voltage
V_{DD}	Positive supply voltage
V_{DS}	Drain-source voltage
$V_{\mathrm{DS,SAT}}$	Drain-source saturation voltage
V_{FS}	Full-scale voltage
V_{GS}	Gate-source voltage
V_{in}	Input voltage
V_{LSB}	Voltage corresponding to the least significant bit
V_{off}	Offset voltage
V_{ref}	Reference voltage
V_T	Threshold voltage
U_T	Thermal voltage
w	Normal vector perpendicular to the hyperplane, weight
w_i	Cost of applying test stimuli performing test number *i*
W	Channel width, Wiener process parameter vector, loss function
W^*, L^*	Geometrical deformation due to manufacturing variations
x	Vector of unknowns
x_i	Vectors of observations
$x(t)$	Analog input signal
X	Input, observability Gramian
y_0	Arbitrary initial state of the circuit
$y[k]$	Output digital signal
y	Yield

Y Output, controllability Gramian
z_0 Nominal voltages and currents
$z_{(1-\alpha)}$ (1-α)-quantile of the standard normal distribution Z
z[k] Reconstructed output signal
Z Low rank Cholesky factor
α Neyman–Pearson significance level, weight vector of the training set
β Feedback factor, transistor current gain, bound
γ Noise excess factor, measurement correction factor, reference errors
γ_i Iteration shift parameters
δ Relative mismatch
ε Error
ζ Distributed random variable, forgetting factor
η Random vector,
θ Die, unknown parameter vector, coefficients of mobility reduction
$\vartheta_{p,n}$ Eigenvalues of the covariance matrix
κ Converter transition code, subthreshold gate coupling coefficient
λ Threshold of significance level α, white noise process
λ_κ Central value of the transition band
μ Carrier mobility, mean value, iteration step size
ν Fitting parameter estimated from the extracted data
ξ Yield bound
$\xi(t)$ Vector of independent Gaussian white noise sources
ξ_i Degree of misclassification of the data x_i
$\xi_n(\theta)$ Vector of zero-mean uncorrelated Gaussian random variables
ρ Correlation parameter reflecting the spatial scale of clustering
ς_p Random vector accounting for device tolerances
σ Standard deviation
U_n Measurement noise covariance
τ Time constant
ω Matrix of normal vectors
Φ Set of all valid design variable vectors in design space
φ Clock phase, Mercer kernel
ϕ_T Thermal voltage at the actual temperature
χ Circuit performance function
$\Gamma_{r,f}[.]$ Probability function
Δ Relative deviation, yield constraint violation
Ξ_r Boundaries of voltage of interest
Σ Covariance matrix
Ω Sampling space

Chapter 1
Introduction

Abstract Continuous monitoring of physiological parameters (e.g., the monitoring of stress and emotion, personal psychological analysis) enabled by brain–machine interface (BMI) circuits is not only beneficial for chronic diseases, but for detection of the onset of a medical condition and the preventive or therapeutic measures. It is expected that the combination of ultra-low power sensor- and ultra-low power wireless communication technology will enable new biomedical devices that will be able to enhance our sensing ability, and can also provide prosthetic functions (e.g., cochlear implants, artificial retina, motor functions). Practical multichannel BMI systems are combined with CMOS electronics for long term and reliable recording and conditioning of intra-cortical neural signals, on-chip processing of the recorded neural data, and stimulating the nervous system in a closed-loop framework. To evade the risk of infection, these systems are implanted under the skin, while the recorded neural signals and the power required for the implant operation is transmitted wirelessly. This migration, to allow proximity between electrodes and circuitry and the increasing density in multichannel electrode arrays, is, however, creating significant design challenges in respect to circuit miniaturization and power dissipation reduction of the recording system. Furthermore, the space to host the system is restricted to ensure minimal tissue damage and tissue displacement during implantation. In this book, this design problem is addressed at various abstraction levels, i.e., circuit level and system level. It therefore provides a broad view on the various solutions that have to be used and their possible combination in very effective complementary techniques. Technology scaling, circuit topologies, architecture trends, (post-silicon) circuit optimization algorithms and yield-constrained, power-per-area minimization framework specifically target power-performance trade-off, from the spatial resolution (i.e., number of channels), feasible wireless data bandwidth and information quality to the delivered power of implantable batteries.

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1.1 Brain–Machine Interface: Circuits and Systems

Best way to predict the future is to invent it. Medicine in the twentieth century relied primarily on pharmaceuticals that could chemically alter the action of neurons or other cells in the body, but twenty-first century health care may be defined more by electroceuticals: novel treatments that will use pulses of electricity to regulate the activity of neurons, or devices that interface directly with our nerves. Systems such as brain–machine interface (BMI) detect the voltage changes in the brain that occur when neurons fire to trigger a thought or an action, and they translate those signal into digital information that is conveyed to the machine, e.g., prosthetic limb, speech prosthesis, a wheelchair.

Recently, many promising technological advances are about to change our concept about healthcare, as well as the provision of medical cares. For example, the telemedicine, e-hospital, and ubiquitous healthcare are enabled by emerging wireless broadband communication technology. While initially becoming main-stream for portable devices such as notebook computers and smart phones, wireless communication (e.g., wireless sensor network, body sensor network) is evolving toward wearable and/or implantable solutions. The combination of two technologies, ultra-low power sensor technology and ultra-low power wireless communication technology, enables long-term continuous monitoring and feedback to medical professionals wherever needed.

Neural prosthesis systems enable the interaction with neural cells either by recording, to facilitate early diagnosis and predict intended behavior before undertaking any preventive or corrective actions, or by stimulation, to prevent the onset of detrimental neural activity. Monitoring the activity of a large population of neurons in neurobiological tissue with high-density microelectrode arrays in multichannel implantable BMI is a prerequisite for understanding the cortical structures and can lead to a better conception of stark brain disorders, such as Alzheimer's and Parkinson's diseases, epilepsy and autism [1], or to reestablish sensory (e.g., hearing and vision) or motor (e.g., movement and speech) functions [2].

Metal-wire and micro-machined silicon neural probes, such as the Michigan probe [3] or the Utah array [4], have aided the development of highly integrated multichannel recording devices with large channel counts, enabling study of brain activity and the complex processing performed by neural systems in vivo [5–7]. Several studies have demonstrated that the understanding of certain brain functions can only be achieved by monitoring the electrical activity of large numbers of individual neurons in multiple brain areas at the same time [8]. Consequently, real-time acquisition from many parallel readout channels is thus needed both for the successful implementation of neural prosthetic devices as well as for a better understanding of fundamental neural circuits and connectivity patterns in the brain [9].

One of the main goals of the current neural probe technologies [10–21] is to minimize the size of the implants while including as many recording sites as possible, with high spatial resolution. This enables the fabrication of devices that match the feature size and density of neural circuits [22], and facilitates the spike