Some applications with FGs

- Autonulling amplifier (Hasler et al 2001, Rahimi et al 2002)
- Learning with probabilities (Hsu)
- Mismatch reduction (Mitros)
- Automaximizing bump circuit, and learning the means of a mixture of Gaussians (Hsu)

Autonulling Amplifier



- AC coupled with a ~0.1Hz corner
 - Tunneling/IHEI sets DC output voltage
 - Capacitive ratio -C1/C2 sets amplifier gain

Ania Mitros, Telluride Neuromorphic Workshop 2003

see Rahimi et al, 2002

Amp Circuit Data and Simulation



• Input: 0.2 Hz, 15mV sinewave superimposed on a 0.012 Hz, 19mV square-wave

see Rahimi et al, 2002

Learning a Conditional Probability

"Learning Spike-Based Correlations and Conditional Probabilities in Silicon" Aaron Shon, Dave Hsu, and Chris Diorio. *In Proc. NIPS 2001*



Circuit data for P(X|Y)

Equilibrium weight versus input statistics



"Learning Spike-Based Correlations and Conditional Probabilities in Silicon" Aaron Shon, Dave Hsu, and Chris Diorio. *In Proc. NIPS 2001*

Learning Correlations



Let V_{tun} be constant (like leakage current). The circuit learns the correlation between X and Y.

$$I_{w} = \left(P(V_{inj})\right)^{s} = \left(P(x, y)\right)^{s}$$

"Learning Spike-Based Correlations and Conditional Probabilities in Silicon" Aaron Shon, Dave Hsu, and Chris Diorio. *In Proc. NIPS 2001*

Learning on handwritten digits

- Simulated Boltzmann machines on handwritten digits
- Hidden layer neurons learn informative features
- Classification results
 - Silicon learning rule: 94.09%
 - Standard Boltzmann rule 93.88%

Hidden layer weights



Mismatch reduction

- Standard techniques for improving mismatch require a lot of die area:
 - dummy transistors
 - common-centroid layout
 - large transistors (or multiple copies)
- Charge on floating gate is equivalent to changing V_{TH} . Floating gates allow use of minimum size transistors and programming away of most of the mismatch as long as mismatch is mainly due to V_{TH} mismatch rather than gain mismatch (true for circuits I've dealt with).

Logarithmic photoreceptors



$$V_{X} \xrightarrow{I_{PH}} C_{B} \xrightarrow{C}_{S}$$

$$V_{PH} = -\log\left(\frac{I_{PH}}{I_0}\right)$$

$$V_{PH} = -2\left(\frac{C_S + C_B}{C_S}\right)\log\left(\frac{I_{PH}}{I_O}\right)$$

Photoreceptor: shifting DC level



The data collection procedure was as follows: 6 tunneling pulses, 1 injection pulse, 6 tun, 1 inj, 6 tun. Several data points were collected between each programming pulse. The plots show data as a function of time. Each upward vertical jump in the data corresponds to the result of a tunneling pulse. Each downward jump corresponds to injection. Colors represent intensity of LCD monitor: Dark blue=0 (darkest), Cyan=21, Green=42, Red=63 (brightest).

Photoreceptor: effect on AC gain

The gain is defined as:

max output (no light) - min output (max light)

The gain varies slightly as a function of the output DC voltage.





Gilbert multiplier



Problems with Gilbert

- Limited range: Must keep all transistors in saturation; distortion
 - Limited output range: Vout < Vmax = K(max(V3,V4)-Vb)</p>
 - Limited input range: similar constraint for inputs V1 and V2
- No good place to put floating gates for adaptation:
 - FG on inputs V1 or V2 results in gain mismatch between inputs
 - Since V3 and V4 go to two transistors each, we would have to have two floating gates to remove offsets between V3 and V4. Total: 3 floating gates are too many.
- Solution: use current mirrors to isolate the V1-V2 diff pairs from V3-V4 pairs. Increase headroom.



Bump circuit

- Computes similarity between inputs V1 and V2
- I_{mid} shaped like a Gaussian



Adaptive bump circuit

- Bump circuit is a 1-D Gaussian distribution in silicon
 - Stores nonvolatile analog value μ
 - Computes Gaussian-like probability, $P(x|\mu)$
 - Adapts μ to increase P(x| μ)
 - In 14 transistors





Adaptive bump circuit



Adaptive bump circuit



Learning Mixture of Gaussians input X bump μ circuits μ $\|\mu_1 - X\|$ $\|\mu_2 - X\|$ Winner-take-all 1/0 1/0 feedback circuitry $\overline{(V_{tun1}, v)}$ $\overline{(V_{tun2}, V_{inj2})}$

Mixture of Gaussians data



The end

Appendices follow

The very basic logarithmic photoreceptor:



Double the impedance, double the gain:



Use a floating gate instead of a bias:



V_X

 V_{PH}

Add AC gain:





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Differential Pair

voltage-current relation in subthreshold:



$$I_1 = I_o e^{(V_s - \kappa V_1)}$$

$$I_2 = I_o e^{(V_s - \kappa V_2)}$$

$$I_{bias} = I_1 + I_2$$

$$= I_o e^{-V_s} \left(e^{\kappa V_1} + e^{\kappa V_2} \right)$$

current split between I_1 and I_2 :

$$I_{1} = I_{bias} \frac{e^{\kappa V_{1}}}{e^{\kappa V_{1}} + e^{\kappa V_{2}}}$$

$$I_{2} = I_{bias} \frac{e^{\kappa V_{2}}}{e^{\kappa V_{1}} + e^{\kappa V_{2}}}$$

$$I_{1} - I_{2} = I_{bias} \frac{e^{\kappa V_{1}} - e^{\kappa V_{2}}}{e^{\kappa V_{1}} + e^{\kappa V_{2}}}$$
multiply by $e^{-(V_{1}+V_{2})/2}$

$$I_1 - I_2 = I_{bias} \frac{e^{\kappa(V_1 - V_2)/2} - e^{\kappa(V_2 - V_1)/2}}{e^{\kappa(V_1 - V_2)/2} + e^{\kappa(V_2 - V_1)/2}} = I_{bias} tanh \frac{\kappa(V_1 - V_2)}{2}$$