lae which include the amount of charge on the gate. The calculation was stepped in time to determine threshold voltage shifts. A flow chart of the entire EPROM programming simulation is shown in Fig. 1.
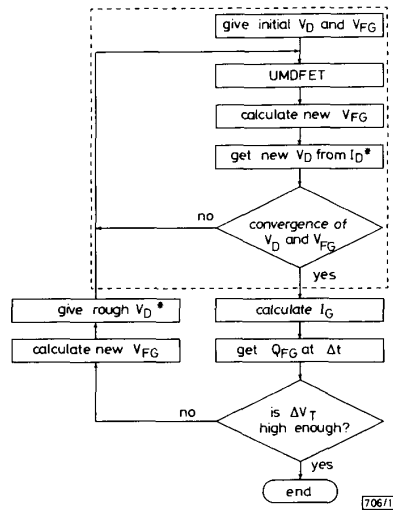

Fig. 1 *Flow chart of EPROM programming simulation*

☐ for I–V characteristics
＊ with R_L only

Results: We simulated EPROM devices with one–two micron channels and drain/gate voltages up to 17/13 V on a Sun 3/60, using the methods described above. Calculation results are compared with experimental data for the programming of 1·25 micron channel EPROMs in Fig. 2, for programming (control gate) voltages of 7, 8, and 9 V. The calculated threshold voltage shift agrees with the experimental result, even though only one adjustable parameter (optical phonon scattering probability in the energy transport simulation) was available for the energy calculation.
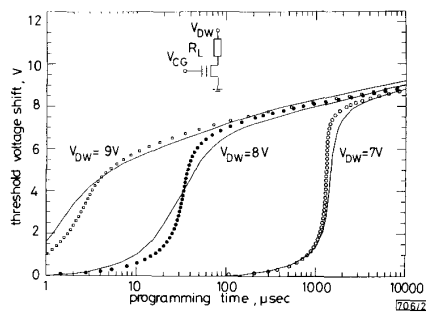

Fig. 2 *Threshold voltage shift against programming time*

$V_{CG} = 17.5 \text{V}$; $L = 1.25 \mu m$; $W = 2.75 \mu m$; $T_{ax} = 350 \text{Å}$; $d_1 = 330 \text{Å}$; $R_L = 1 \text{k}\Omega$
☐●○ calculated
——— experimental

Conclusions: The method demonstrated is simple enough to be made available to design engineers at individual work stations, and can be applied to the efficient determination of the effects of varying design parameters on EPROM programming times. Alternative methods, such as those based on 'lucky electron' models or those that use the Monte Carlo

method, are either much too approximate or much too expensive for this purpose, respectively.

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EXPONENTIAL BIDIRECTIONAL ASSOCIATIVE MEMORIES

Indexing term: Memories

A bidirectional associative memory (BAM) with an exponential nonlinearity is presented. This method has the advantage of exponential strategy. It improves the performance of the BAM. An energy function that decreases as the memory state changes can be defined, ensuring the stability of the system.

Introduction: The bidirectional associative memory (BAM) proposed by Kosko[1,2] produces a two way associative search for stored associations (X^i, Y^i). The BAM has been successfully applied to classification problems. The storage capacity of the BAM is limited by the number of neurons. Tai[3] et al. have described an encoding scheme for a BAM with a high order nonlinearity (HOBAM) which improves the storage capacity and error correcting capability of the BAM. It has been reported[4] that the exponential nonlinearity content addressable memory has a storage capacity exponentially scaled with the number of bits and has a higher error correcting capability. The exponential nonlinearity is suitable for VLSI implementation. We present a neural network for the BAM with exponential nonlinearity (EBAM). The EBAM possesses the advantages of exponential strategy. An energy (Liapunov) function for the EBAM, which decreases as neurons states change is also described.

Exponential bidirectional associative memory: Assume there are m stored data pairs (X^i, Y^i), $i = 1, 2, \ldots, m$, where $X^i \in \{-1, 1\}^n$ and $Y^i \in \{-1, 1\}^p$. The bidirectional recall process of the EBAM in one cycle is

$$Y = f(X) = \text{sgn} \left\{ \sum_{i=1}^{m} Y^i \alpha^{\langle X^i, X \rangle} \right\} \qquad (1)$$

$$X' = g(Y) = \text{sgn} \left\{ \sum_{i=1}^{m} X^i \alpha^{\langle Y^i, Y \rangle} \right\} \qquad (2)$$

where $\langle A, B \rangle$ denotes the inner product of vectors A and B, α is a number greater than unity, and $\text{sgn}(x) = 1$ if $x \geq 0$ and $\text{sgn}(x) = -1$ otherwise.

If we present the EBAM with the stored pattern X^t, we obtain the signal noise expansion

$$Y = \text{sgn} \left\{ \sum_{i=1}^{m} Y^i \alpha^{\langle X^i, X^t \rangle} \right\}$$

$$= \text{sgn} \left\{ \alpha^n Y^t + \sum_{i \neq t}^{m} Y^i \alpha^{\langle X^i, X^t \rangle} \right\} \quad (3)$$

With $\alpha > 1$, the exponential nonlinearity will enhance the similarity of the input with a selected stored pattern pair (X^t, Y^t) and reduce the interference of the other terms. The EBAM has a large storage capacity and a high error correcting capability, demonstrated by computer simulations. The continuity of the association assumption for reliable recalls of BAM can be relaxed.

We discuss the stability of the EBAM. Similar to the proof of the stability of the Kanerva and BMW memories,[5] let us define $2m$ sets of vectors $\{U_0^i, \ldots, U_n^i\}$ and $\{V_0^i, \ldots, V_p^i\}$, $i = 1, 2, \ldots, m$, for which the Hamming distances between the vector pairs (X^i, U_k^i) and (Y^i, V_k^i) are k. For a pair of vectors (X, Y), the energy function is defined as

$$E(X, Y) = \sum_{i=1}^{m} \sum_{k=0}^{d_{xi}} \alpha^{\langle Y^i, f(U_k^i) \rangle} + \sum_{i=1}^{m} \sum_{k=0}^{d_{yi}} \alpha^{\langle X^i, g(V_k^i) \rangle} \quad (4)$$

where d_{xi} and d_{yi} are the Hamming distances between the vector pairs (X^i, X) and (Y^i, Y), respectively. Let $\Delta E_x = E(X', Y) - E(X, Y)$ be the difference between the energies of the current state (X, Y) and the next state (X', Y). With the assumption that $\langle Y^i, f(X) \rangle$ depends only on $\langle X^i, X \rangle$ (a similar assumption was made in Reference 5), it can be shown that

$$\Delta E_x \leq \sum_{i=1}^{m} \alpha^{\langle Y^i, f(X) \rangle} * (d'_{xi} - d_{xi})$$

$$= \frac{-1}{2} \sum_{k=1}^{n} \left\{ \left[\sum_{i=1}^{m} \alpha^{\langle Y^i, f(X) \rangle} * x_k^i \right] (x'_k - x_k) \right\} \quad (5)$$

In eqn. 5 d'_{xi} is the Hamming distance between (X^i, X'), and x_k^i, x_k and x'_k are the kth components of X^i, X and X', respectively. From the recall process given by eqn. 2, eqn. 5 ensures that $\Delta E_x < 0$. It can be shown that ΔE_y, the difference between the energies of the current state (X, Y) and next state (X, Y'), is negative. Since $E(X, Y)$ is bounded by $0 \leq E(X, Y) \leq m(n\alpha^n + p\alpha^p)$ for all X and Y, the EBAM converges to a stable point where the energy is a local minimum.

Computer simulations are performed to examine the storage capacity and the error correcting capability of EBAM with $\alpha = e$, 3rd and 4th order HOBAM and BAM. Fig. 1 shows the storage capacity with $n = p = 16$. Results are obtained from one hundred sets of randomly selected association pairs. Fig. 2 shows the error correcting capability with
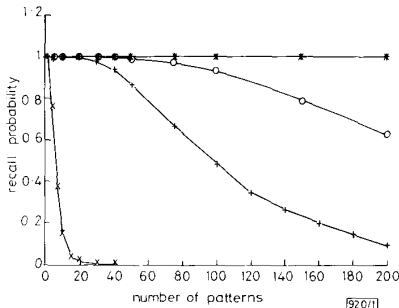

Fig. 1 *Storage capacity*

$n = p = 16$
$\times$ BAM
$+$ 3rd order HOBAM
$\bigcirc$ 4th order HOBAM
$*$ EBAM ($\alpha = e$)

718

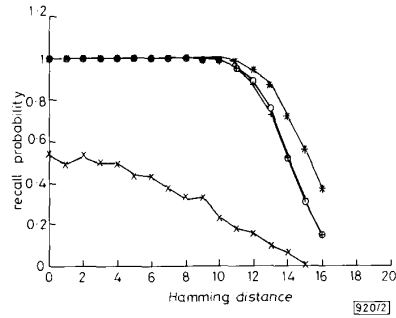$n = p = 40$. One hundred sets of ten randomly selected stored pairs are utilised for the simulation.

Fig. 2 *Recall probability against Hamming distance*

$n = p = 40$
$\times$ BAM
$+$ 3rd order HOBAM
$\bigcirc$ 4th order HOBAM
$*$ EBAM ($\alpha = e$)

Conclusion: The EBAM employs an exponential scheme of information flow to exponentially enhance the similarity between the input pattern and its nearest stored pattern. It improves the storage capacity and error correcting capability of the BAM. The EBAM also has a good convergence property.

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FILTERING WITH THE FAST T TRANSFORM

Indexing terms: Signal processing, Transforms, Algorithms

The T transform is an intermediate transform from which the multidimensional Fourier and Hartley transforms can be calculated. The T transform can be used in place of these two transforms, accelerating the execution times of applications such as filtering of projections and volumes in 3D reconstruction.

Introduction: The two dimensional discrete Hartley transform (2D-DHT) of a set of $M \times N$ points of a real function $s(x, y)$ is defined as[1-3]

$$H[s(x, y)](u, v) = H(u, v)$$

$$= \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} s(x, y)$$

$$\times \text{cas} \left[2\pi(ux/M + vy/N) \right] \quad (1)$$