

US00RE41658E

(19) **United States**  
(12) **Reissued Patent**  
**Fabrizio et al.**

(10) **Patent Number:** **US RE41,658 E**  
(45) **Date of Reissued Patent:** **Sep. 7, 2010**

(54) **LOW-VOLTAGE, VERY-LOW-POWER CONDUCTANCE MODE NEURON**  
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(21) Appl. No.: **10/631,323**  
(22) Filed: **Jul. 31, 2003**

EP 0 349 007 1/1990  
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Reissue of:

(64) Patent No.: **6,269,352**  
Issued: **Jul. 31, 2001**  
Appl. No.: **09/461,674**  
Filed: **Dec. 14, 1999**

Benson, R. et al., "UV-Activated Conductances Allow for Multiple Time Scale Learning," *IEEE Trans. on Neural Networks*4(3):434-440, May 1993.

(Continued)

U.S. Applications:

(63) Continuation of application No. 08/731,426, filed on Oct. 15, 1996, now Pat. No. 6,032,140.

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(30) **Foreign Application Priority Data**

Oct. 13, 1995 (EP) ..... 95830433

(57) **ABSTRACT**

(51) **Int. Cl.**  
**G06G 7/00** (2006.01)  
**G06N 3/00** (2006.01)  
**G06N 3/02** (2006.01)  
**G06E 1/00** (2006.01)  
**G06E 3/00** (2006.01)  
**G06F 15/16** (2006.01)

A neural network including a number of synaptic weighting elements, and a neuron stage; each of the synaptic weighting elements having a respective synaptic input connection supplied with a respective input signal; and the neuron stage having inputs connected to the synaptic weighting elements, and being connected to an output of the neural network supplying a digital output signal. The accumulated weighted inputs are represented as conductances, and a conductance-mode neuron is used to apply nonlinearity and produce an output. The synaptic weighting elements are formed by memory cells programmable to different threshold voltage levels, so that each presents a respective programmable conductance; and the neuron stage provides for measuring conductance on the basis of the current through the memory cells, and for generating a binary output signal on the basis of the total conductance of the synaptic elements.

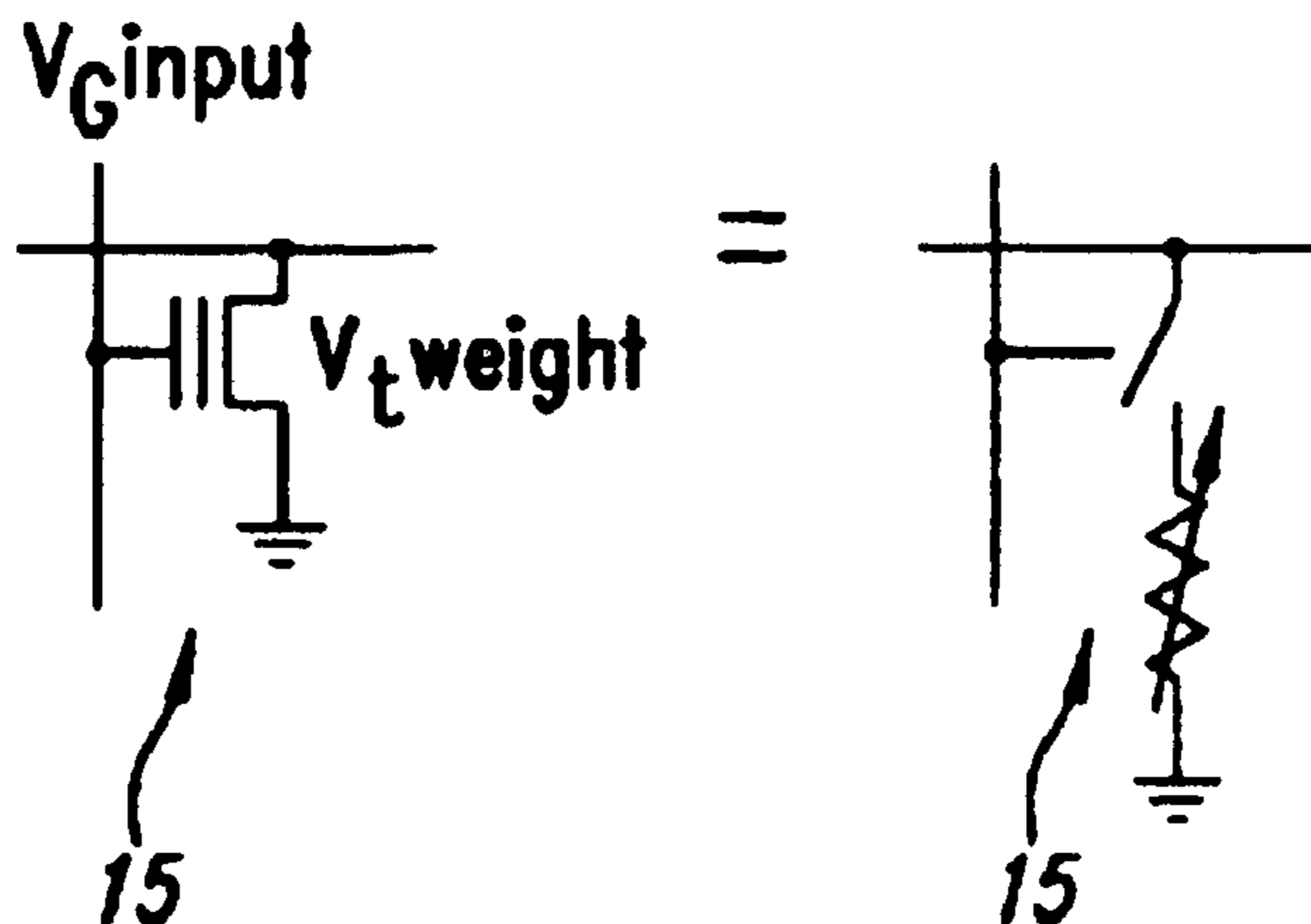
(52) **U.S. Cl.** ..... **706/39; 706/15**  
(58) **Field of Classification Search** ..... **706/15, 706/39**  
See application file for complete search history.

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**24 Claims, 8 Drawing Sheets**





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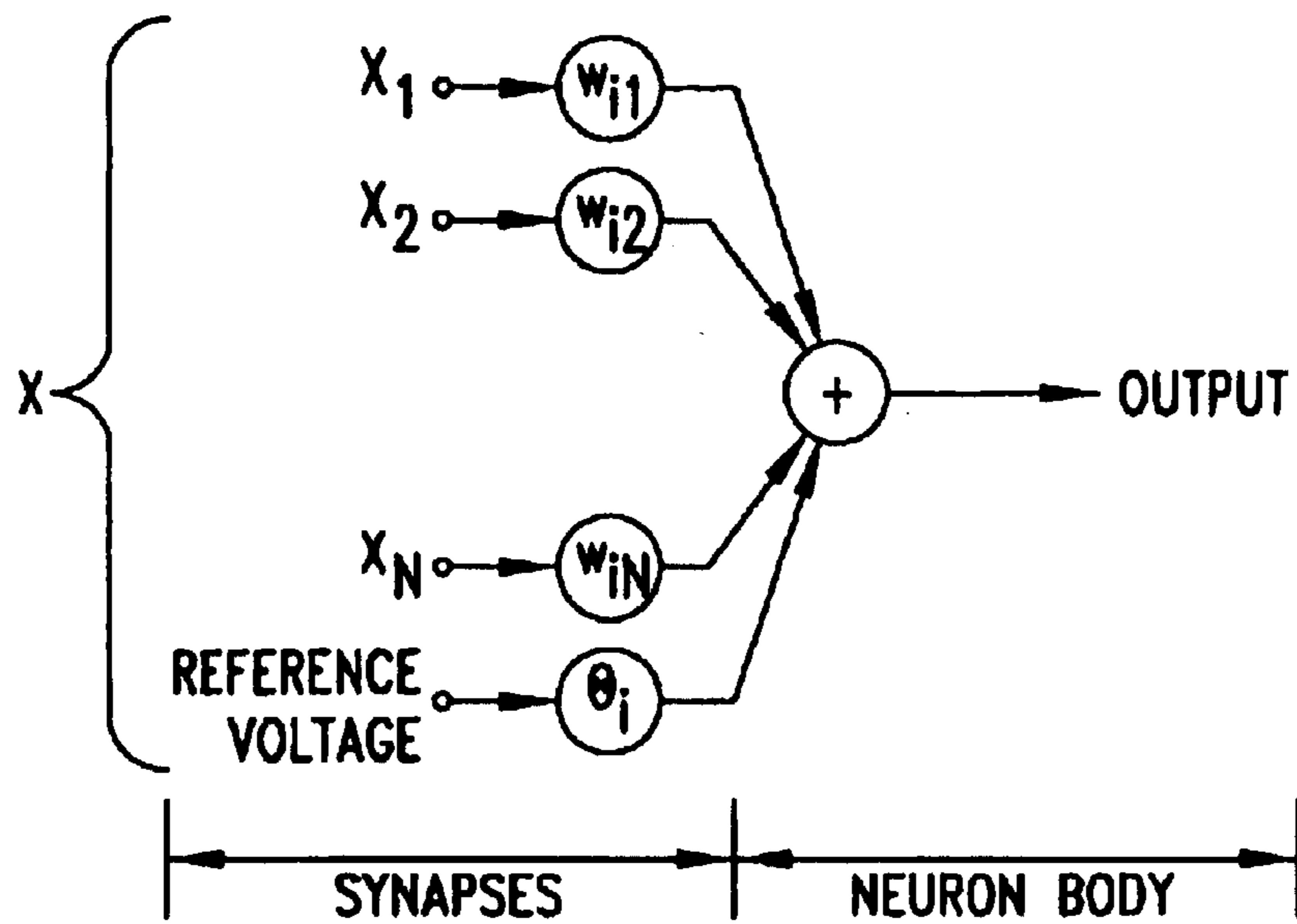
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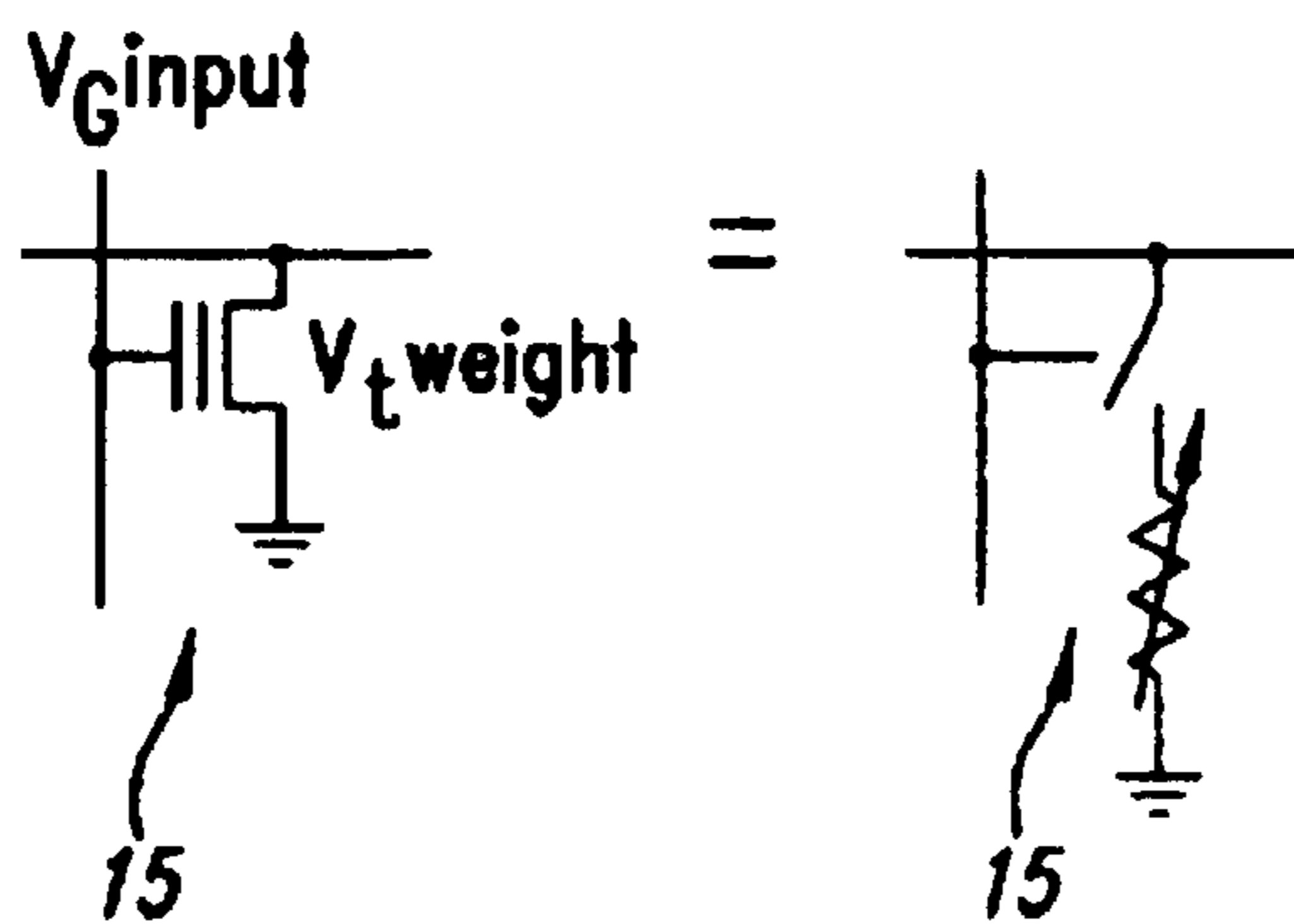
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*Fig. 1*  
*(Prior Art)*



*Fig. 2*

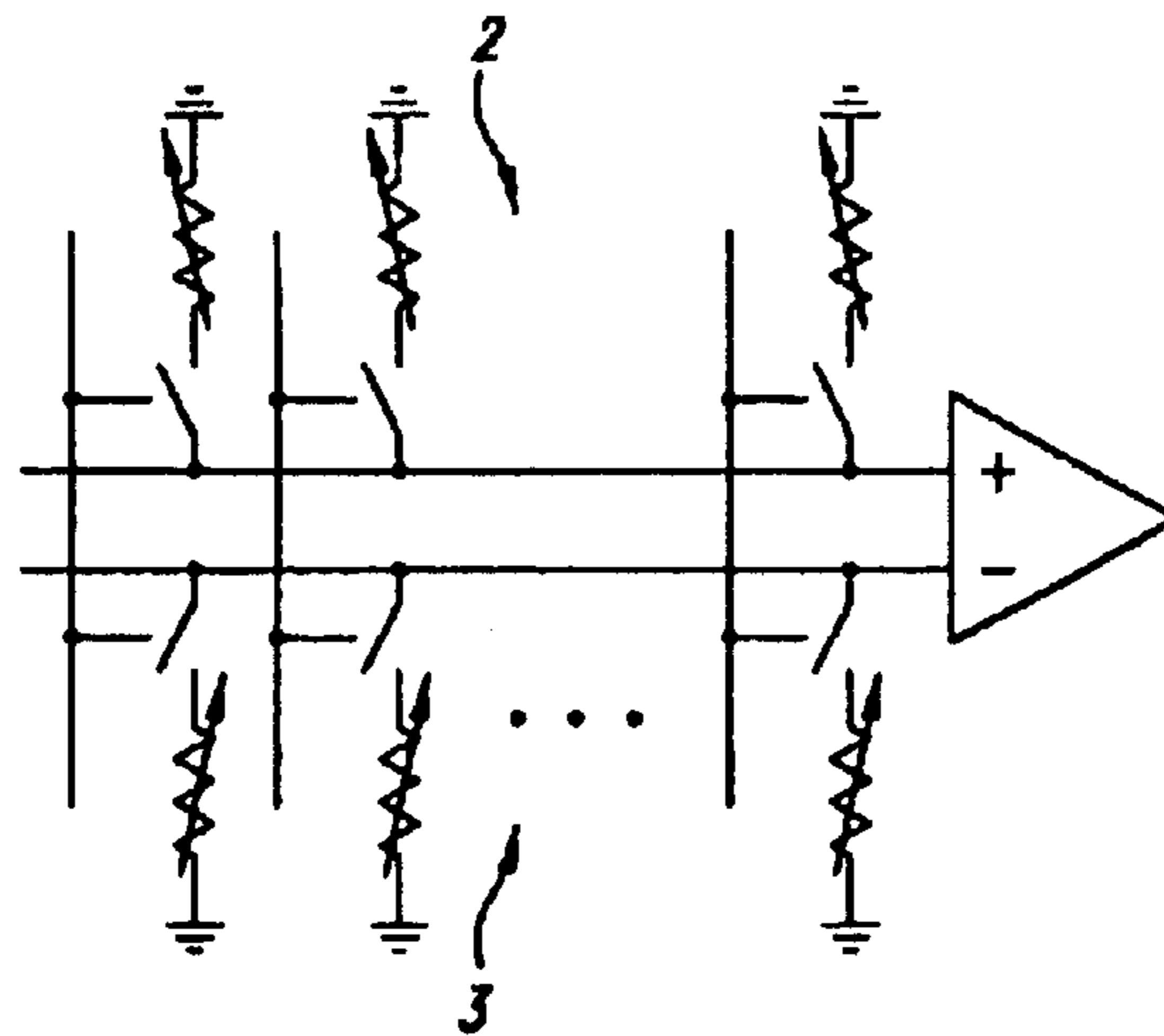


Fig. 3

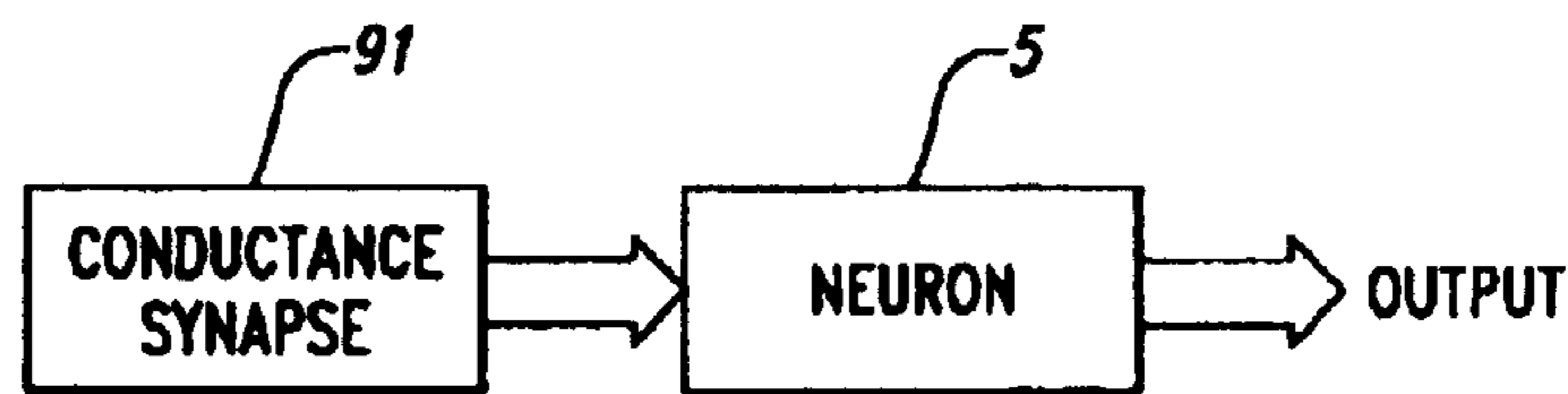


Fig. 4A

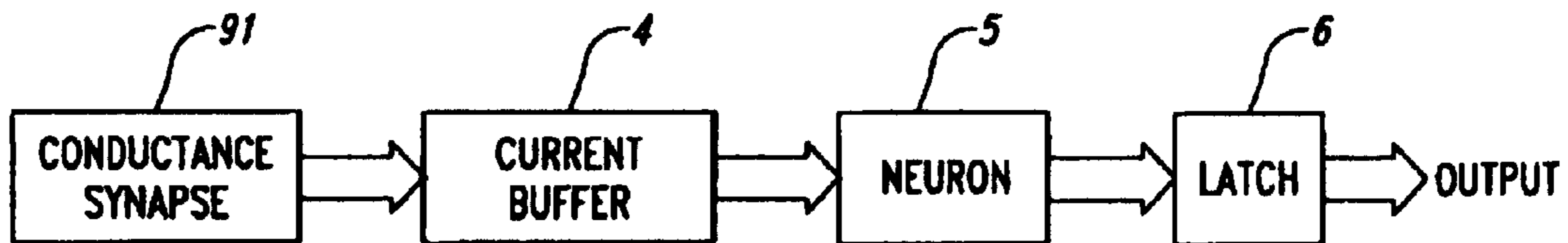


Fig. 4B



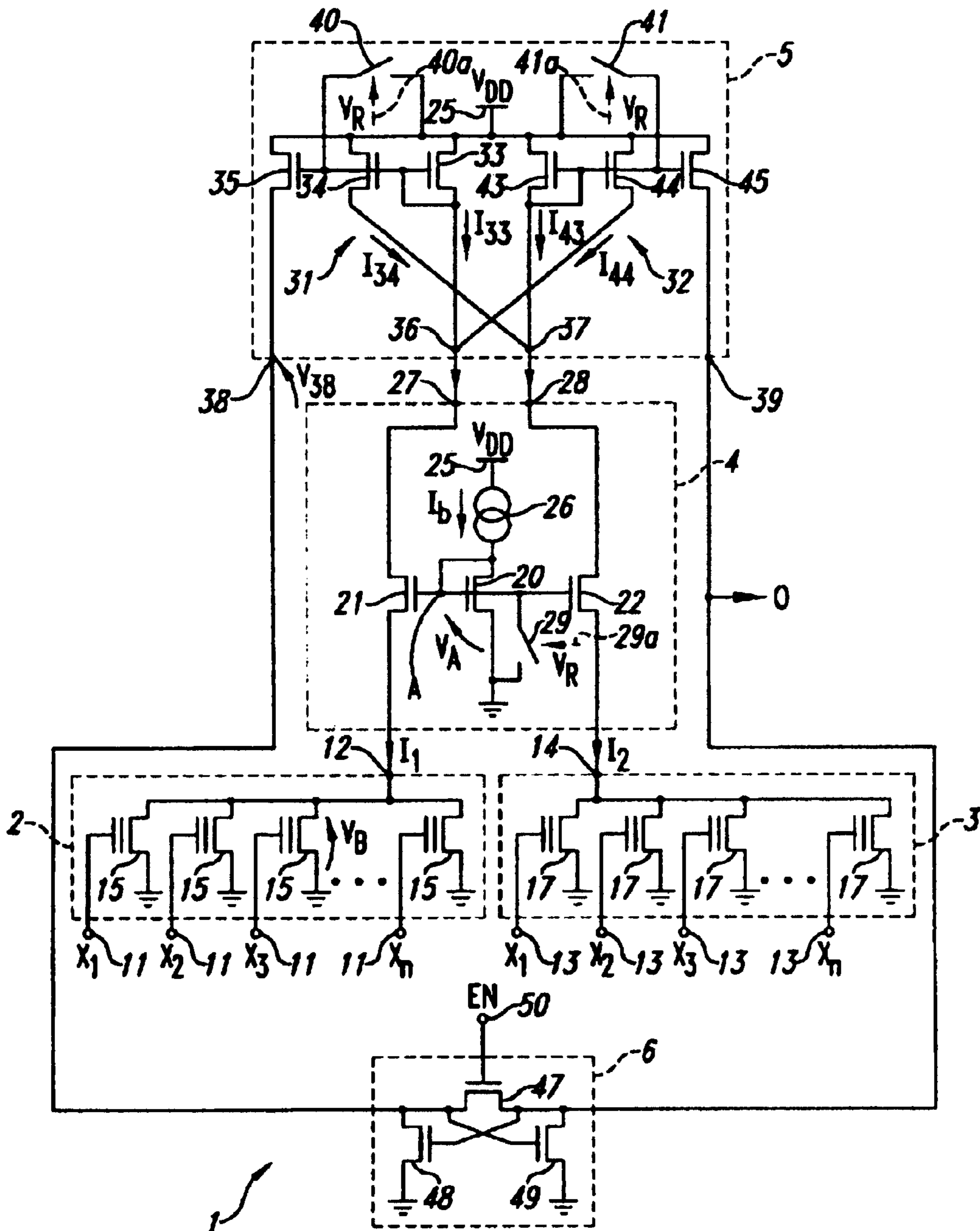


Fig. 4C

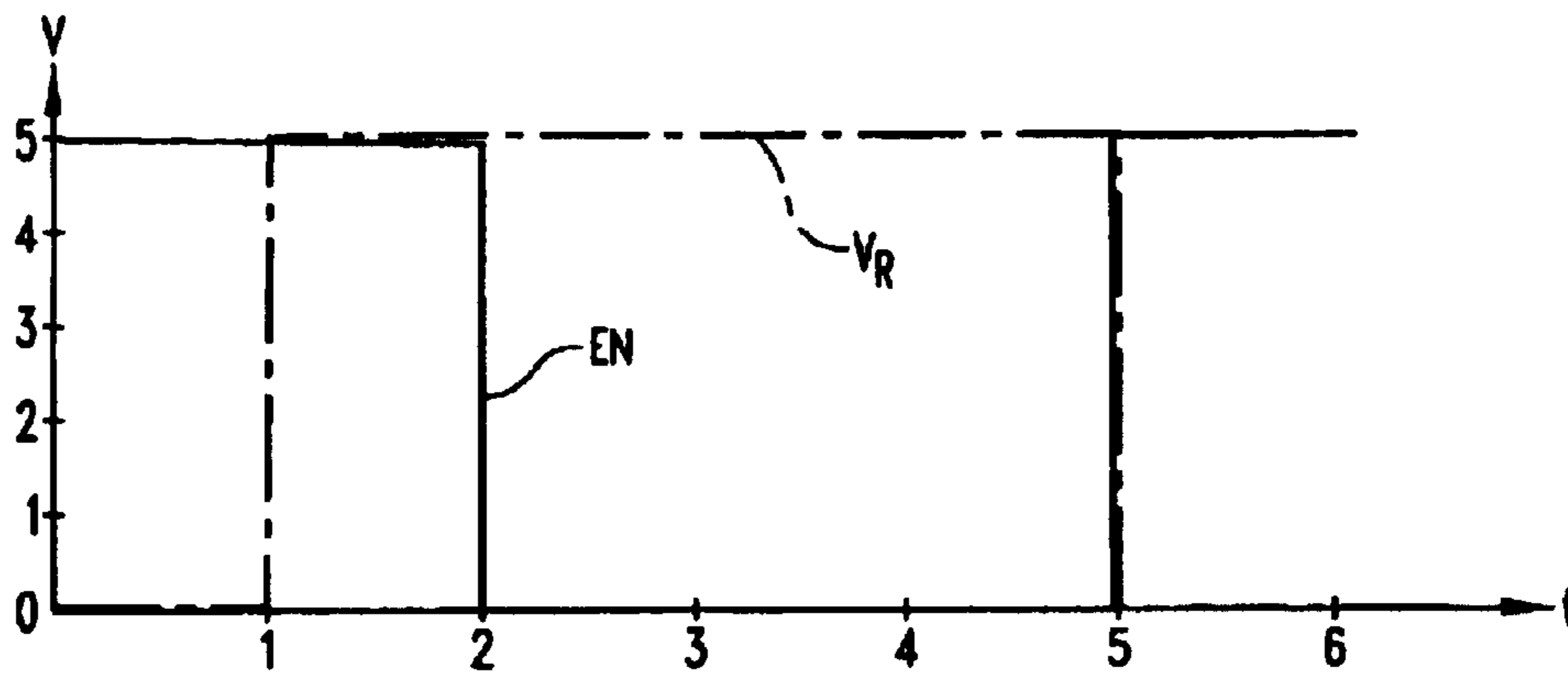


Fig. 5

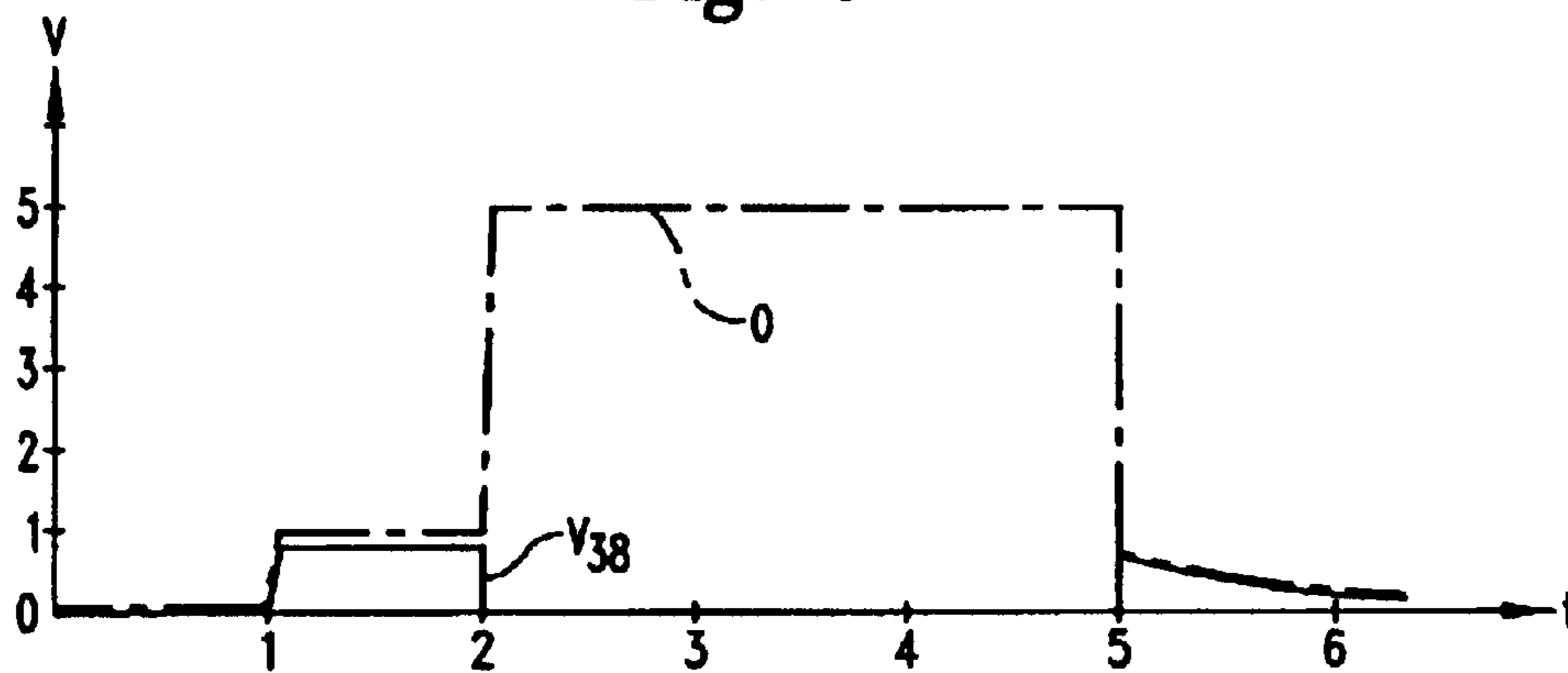


Fig. 6

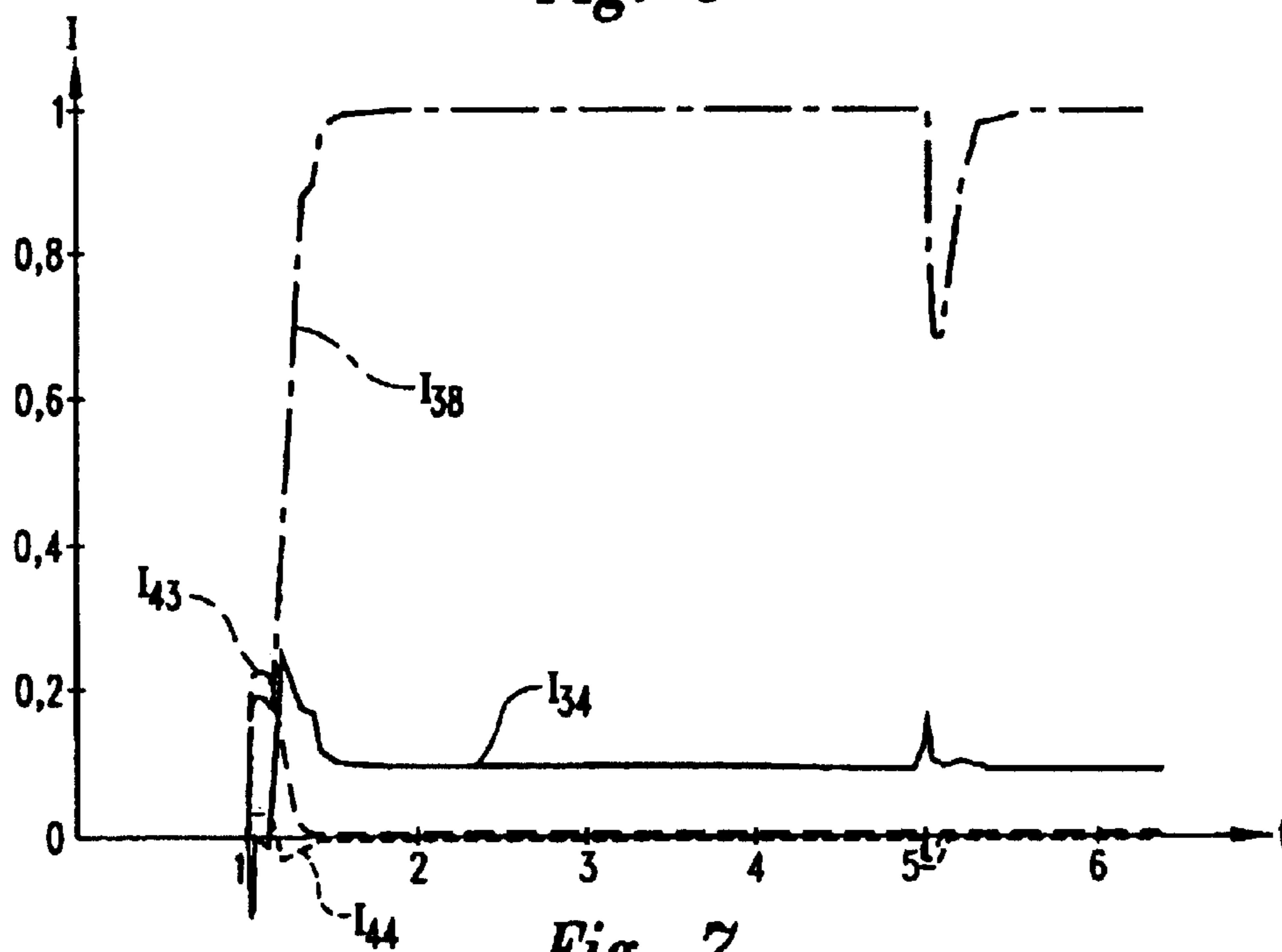
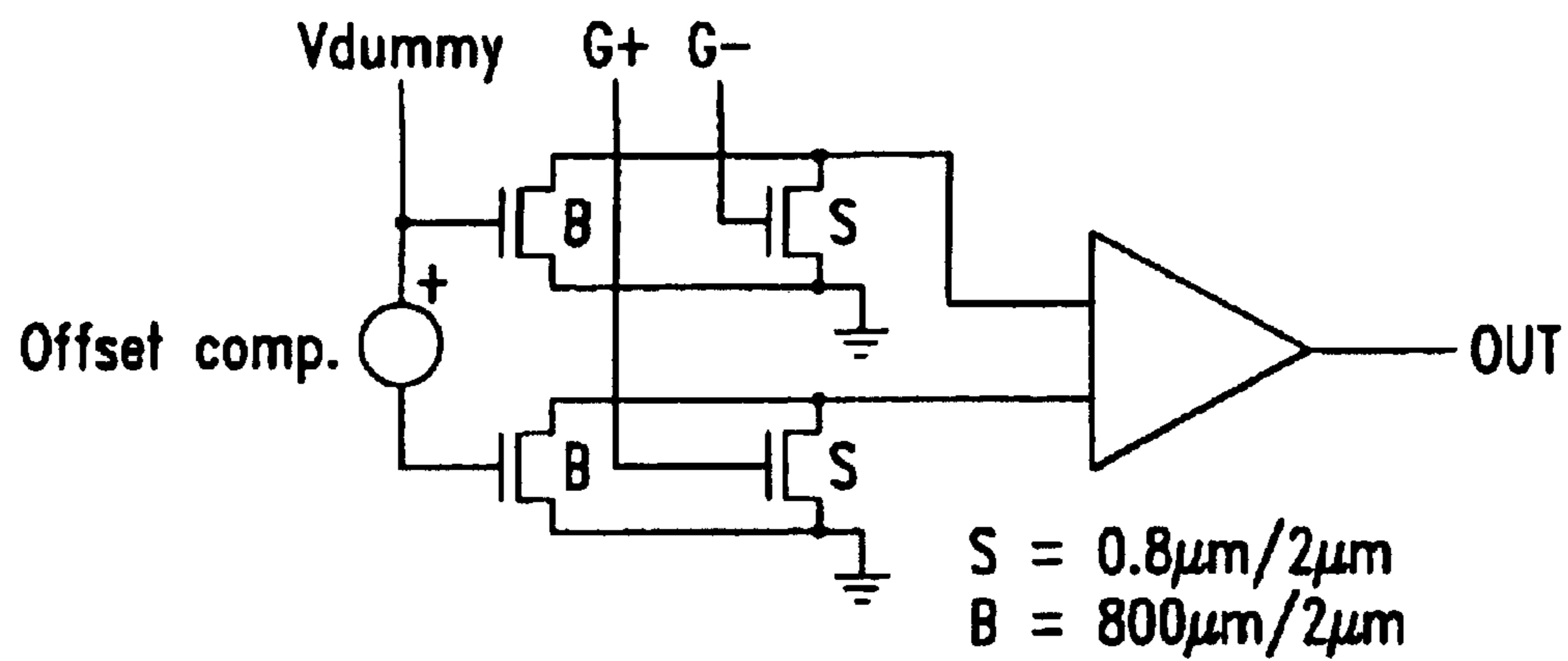
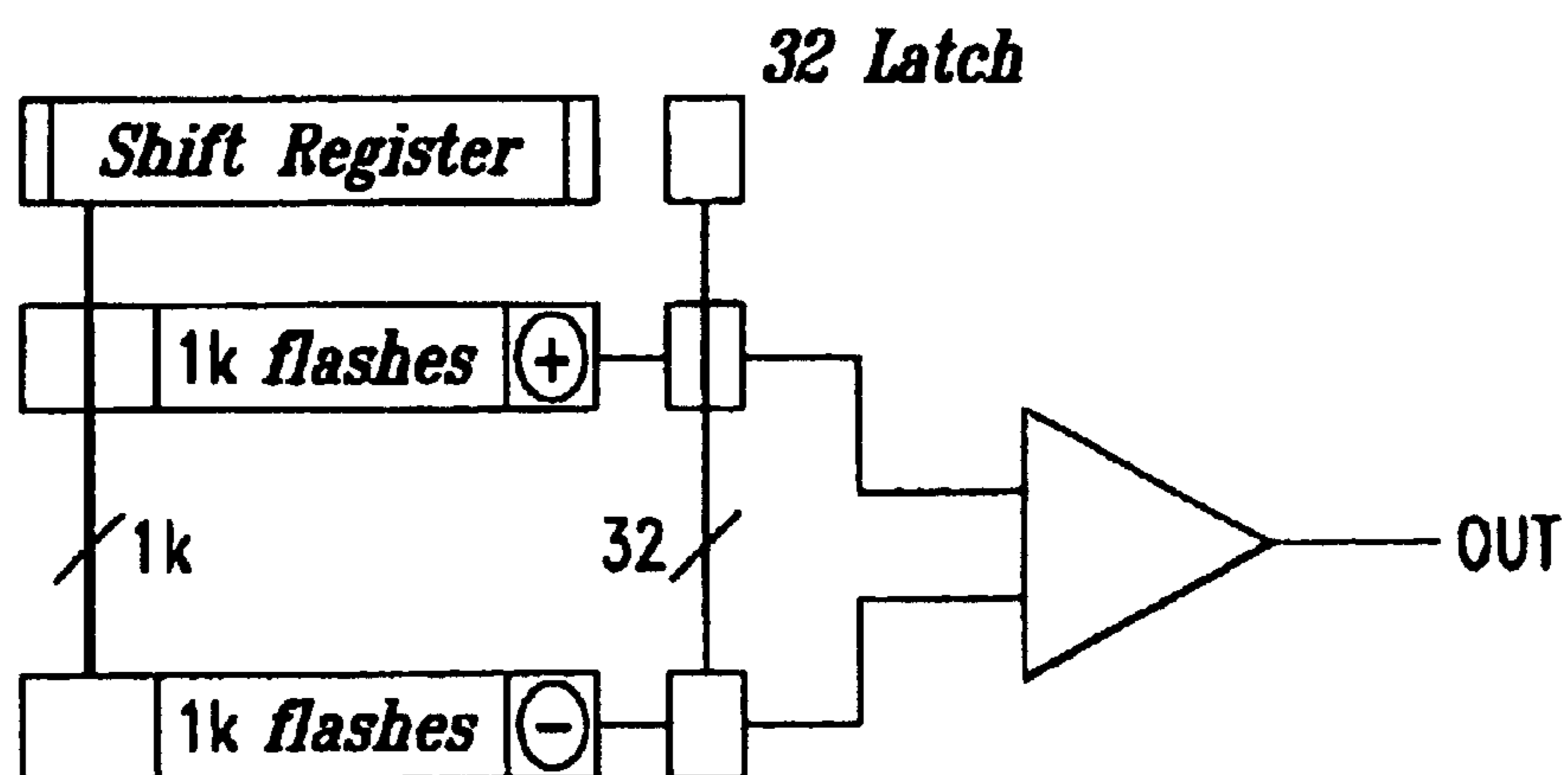


Fig. 7



*Fig. 8*



*Fig. 9*

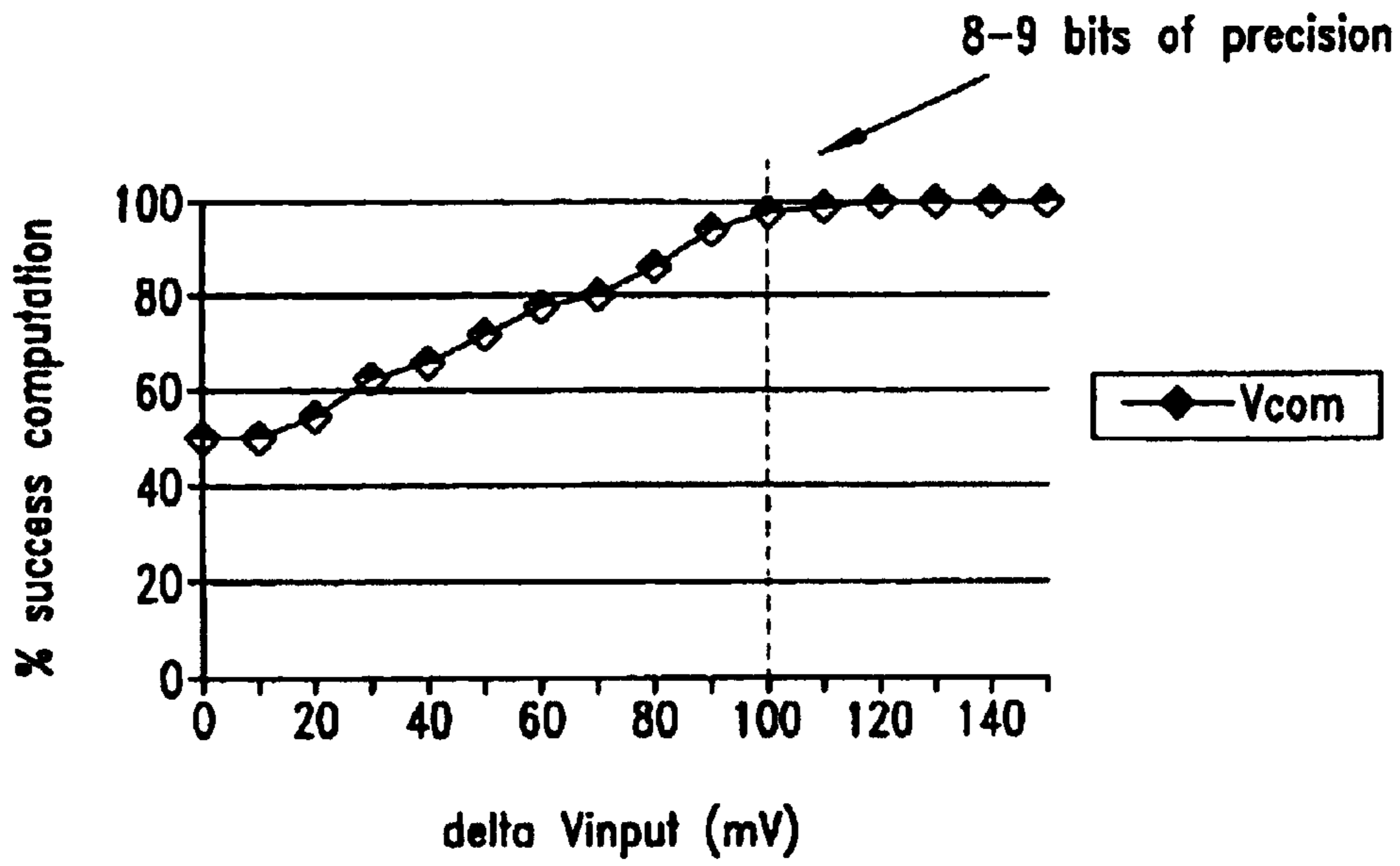


Fig. 10

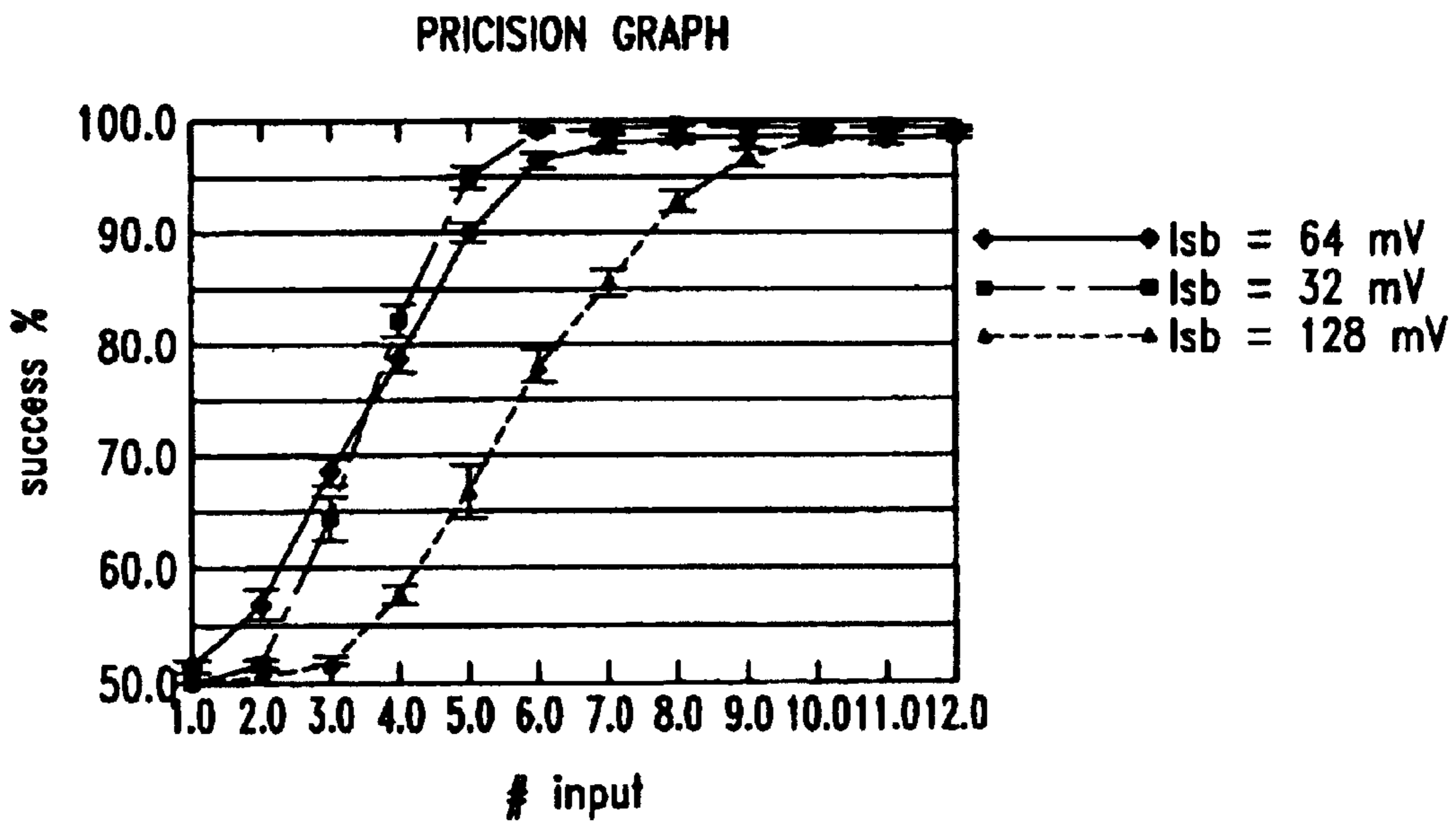
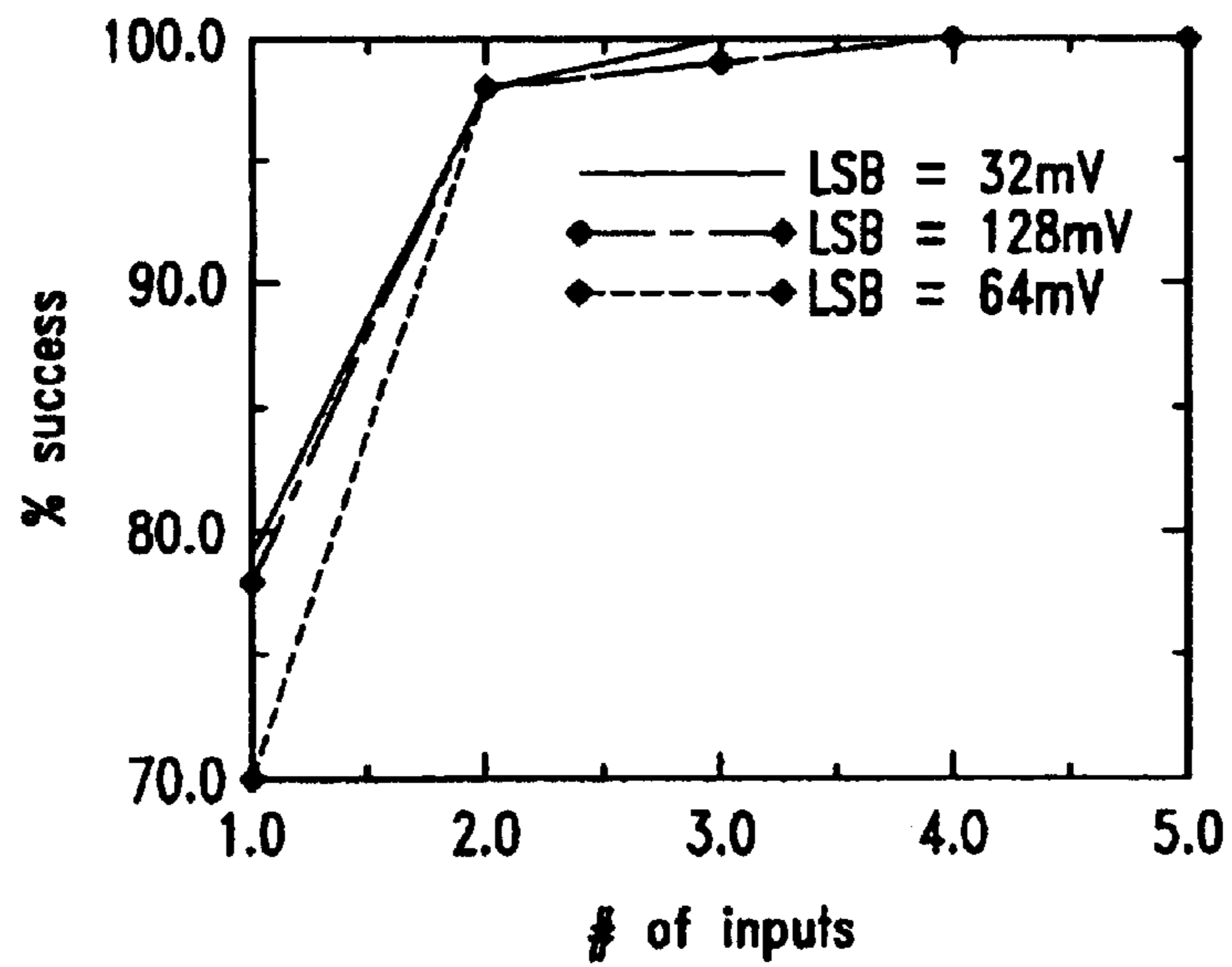
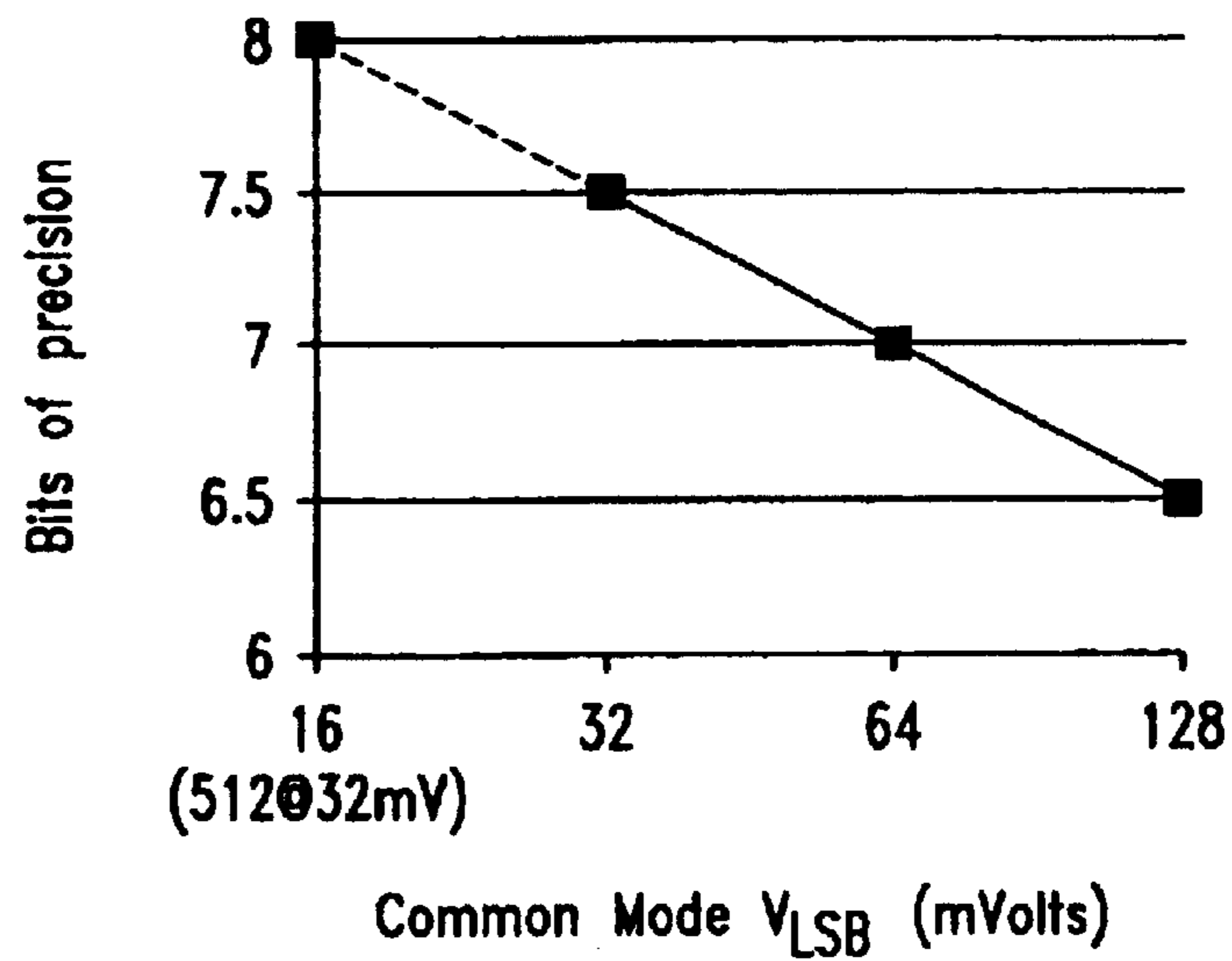


Fig. 11





*Fig. 12*



*Fig. 13*

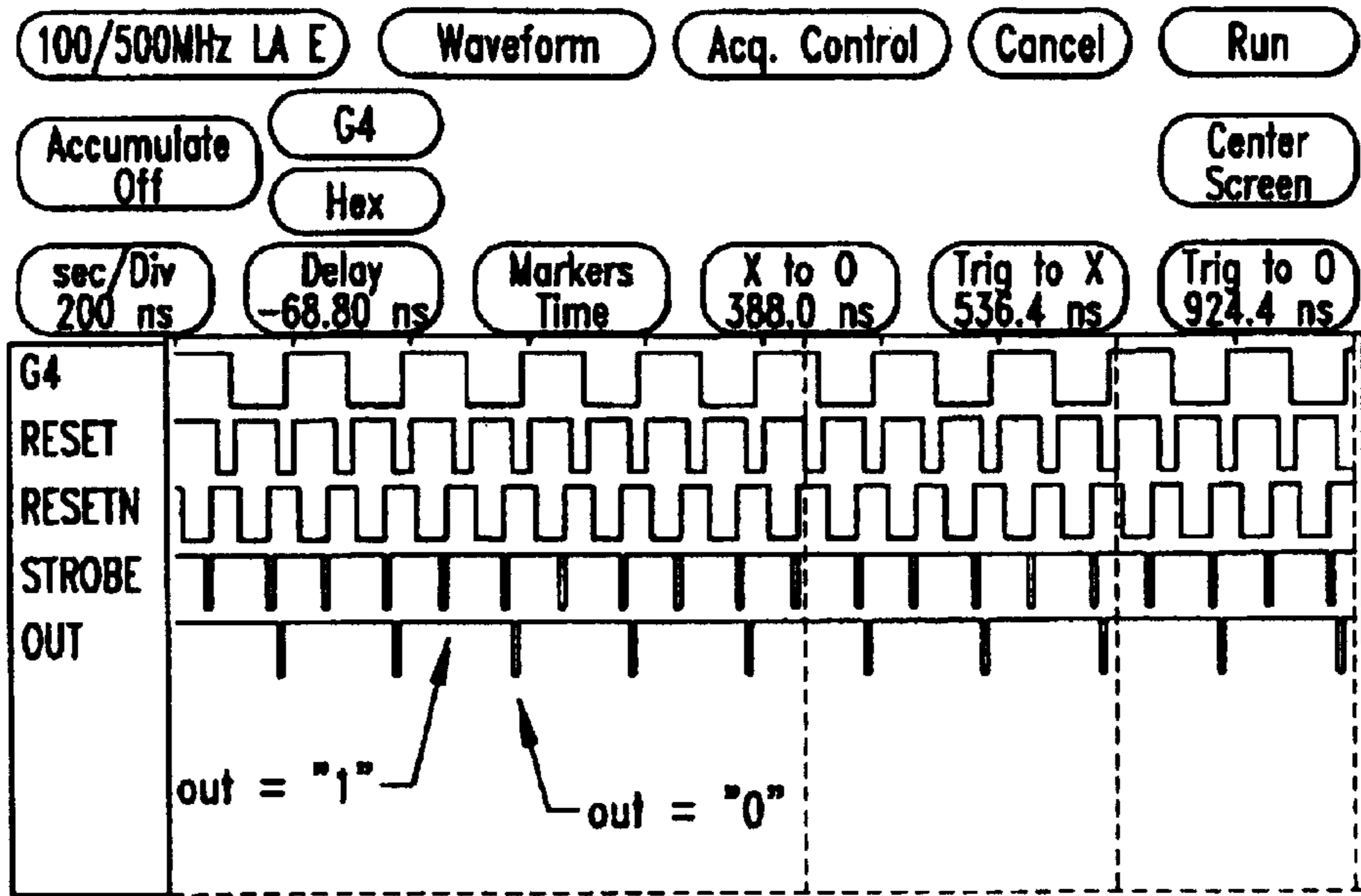


Fig. 14

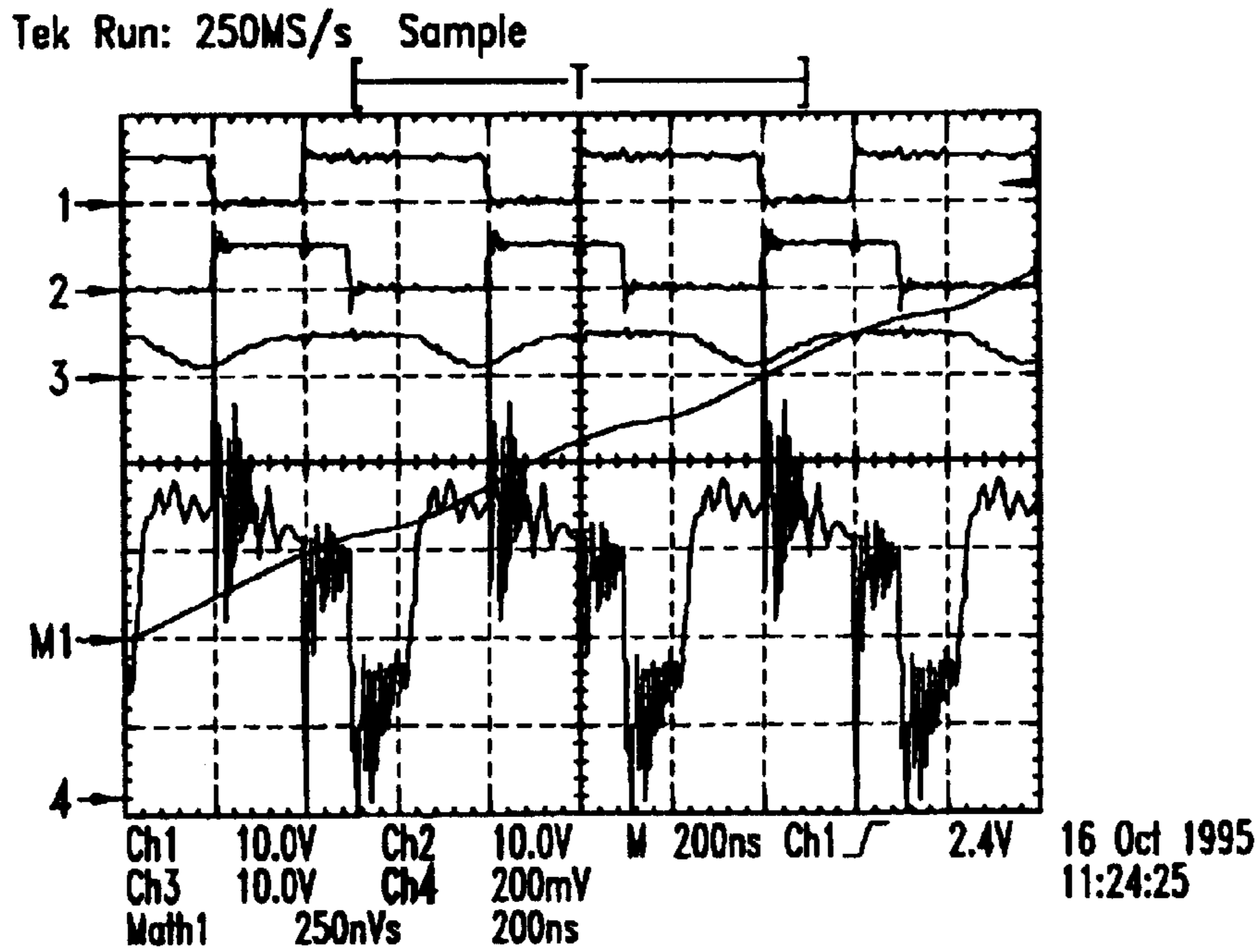


Fig. 15



## LOW-VOLTAGE, VERY-LOW-POWER CONDUCTANCE MODE NEURON

**Matter enclosed in heavy brackets [ ] appears in the original patent but forms no part of this reissue specification; matter printed in italics indicates the additions made by reissue.**

### CROSS-REFERENCE TO RELATED APPLICATION

This application is a continuation of U.S. patent application Ser. No. 08/731,426 filed Oct. 15, 1996 and allowed Sep. 13, 1999 now U.S. Pat. No. 6,032,140.

### TECHNICAL FIELD

The present invention relates to a low-voltage, very-low-power conductance mode neuron.

### BACKGROUND OF THE INVENTION

As is known, artificial intelligence systems feature neural networks for performing complex tasks, in particular, for texture analysis, morphological kernel filtering in facsimile transmission, vehicle tracking systems, pattern recognition, hardware simulation in neural CAD systems, and preprocessing in optical character recognition applications.

Neural networks employ components known as neurons, similar to the biological elements of the same name and based on the addition and subtraction of appropriately weighted inputs, and for which various mathematical formalisms have been devised. Reference is made in the present invention to binary neurons according to the McCulloch-Pitts model, which stands out for the precision and elegance of its mathematical definition, and according to which, the output may assume only two binary values "0" and "1" and operates under a discrete time assumption, with predetermined neuron thresholds and weights. Each neuron comprises a processing element with a number of synaptic input connections and one output; and input and output signal flow is considered one-way.

In the classification phase neural network parameters are fixed and the neural network executes the recognition or the analysis starting from the information contained in the topology and in the weights of the neural network. FIG. 1 shows a symbolic representation of the McCulloch-Pitts model, in which  $x_1, x_2, \dots, x_i$  are the inputs,  $w_1, w_2, \dots, w_i$  the weights, and  $O$  the output. The neuron is represented by a node defining function  $f$ , which, when applied to the weighted inputs, supplies the output according to the equation:

$$O = f(\sum w_i * x_i)$$

Typically, the  $f$  function compares the sum of the weighted products of the inputs with a threshold, and, depending on the outcome of the comparison, determines the binary value of the output.

Various solutions are known for implementing neural networks, as described for example in S. Satyanarayana et al., "A Reconfigurable VLSI Neural Network," IEEE Journal of Solid-State Circuits 27:1, January 1992; B. E. Boser et al., "An Analog Neural Network Processor with Programmable Topology," IEEE Journal of Solid-State Circuits 26:12, December 1991; and A. Kramer et al., "EEPROM Device As a Reconfigurable Analog Element for Neural Networks," IEDM, 1989, pp. 259-262.

All known solutions, however, involve a trade-off between power consumption and precision, require a large integration area, and are complex in design. Moreover, all known prior art solutions make it necessary to choose between solutions designed for high speed but requiring high power (current mode computation) and solutions designed for low power but operating at low speed (charge computation mode).

Analog implementations of Neural Network Architectures provide a framework for computation which is more efficient than standard digital techniques for certain problems. Typically, implementations of analog neural networks have been based on the use of either current or charge as the variable of computation.

### SUMMARY OF THE INVENTION

The present invention provides a new class of analog neural network circuits based on the concept of conductance-mode computation. In this class of circuits, accumulated weighted inputs are represented as conductances, and a conductance-mode neuron is used to apply nonlinearity and produce an output. In the hardware implementation of neural networks it is important to consider flexibility and power consumption in order to satisfy a wide range of applications. The present invention has been to focus on circuits which consume very little power per connection allowing for a high number of connections per neuron.

It is an object of the present invention to provide a compact, low-power neural network with a high input range that operates at high speed. It is adaptable to different (even low-voltage) supply conditions and it requires no additional interfacing to be compatible with digital environments. It may also be used in portable devices.

One advantage of the present invention is that it implements synapses by a simple circuit based on a pair of floating-gate transistors, providing both analog multiplication and weight storage with low power consumption, high density and high precision. Both the weight storage and analog multiplication are implemented concurrently in a pair of floating gate transistors.

The advantages of this class of circuits are twofold: firstly, conductance-mode computation is fast - circuits based on these principles can compute at about 5-10 MHz; secondly, because conductance-mode computation requires the minimum charge necessary to compare two conductances, its energy consumption is self-scaling depending on the difficulty of the decision to be made. The computing precision of these circuits is high. Test results on a small test structure indicate an intrinsic precision of 8-9 bits.

A preferred, non-limiting embodiment of the present invention will be described by way of example with reference to the accompanying drawings.

### BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 shows a symbolic representation of a neuron according to the McCulloch-Pitts model.

FIG. 2 is a schematic showing use of a flash EEPROM device as it will function as a programmable, switched conductance.

FIG. 3 is a schematic of a differential, summed synaptic conductance neuron.

FIG. 4A is a block diagram of the principle blocks of the present invention.

FIG. 4B is a block diagram of the present invention.

FIG. 4C shows an overall circuit diagram of a neural network circuit according to the present invention.



FIGS. 5 to 7 show plots of a number of quantities of the circuit in FIG. 4C.

FIG. 8 shows a schematic of a test structure.

FIG. 9 shows a block diagram of a new test structure.

FIG. 10 shows an intrinsic precision curve of test structure.

FIG. 11 shows a precision curve with 1 k devices of common mode.

FIG. 12 shows a precision curve with 0.5 k devices of common mode.

FIG. 13 shows bit precision curve versus LSB voltage for 1 k devices of common mode.

FIG. 14 is a diagram of neuron functionality at 10 MHz.

FIG. 15 is a power consumption measurement driven by a 1.7 MHz clock with a 5 volt power supply. Integrated supply current through a 9 k Ohm resistor is shown.

#### DETAIL DESCRIPTION OF THE INVENTION

The present invention uses a single pair of Flash-EEPROM devices for both analog storage and analog computation. Basically, the computational concept is to make use of a floating-gate device as a programmable switched conductance. By storing one analog value as the threshold of a floating gate device and applying a second digital value on a gate terminal of the floating-gate device, the conductance of the device can be either zero (off) or a pre-programmed analog value. In this way, a single programmable device is able to implement a multiplication of a single binary value ( $V_g$  of programunable transistor) by an analog value ( $V_{High} - V_{Th}$ ). The single programmable device is a conductance synapse whose weight is computed by the neuron when the input is taken high.

In one implementation, a differential input scheme comprising two conductance summing lines allows weights to be stored in the form of a pair of conductances. The weights are either "positive" or "negative." For each two transistor synapse, one device is programmed to be always off, independent of input, and the other device is programmed to be on only when the input is high. Synapse polarity (positive or negative) is determined by which summing line to which the on device is connected. A conductance comparison neuron can then compare the sum of the total "positive" conductance to the sum of total "negative" conductance and make a decision on the polarity of the total weighted inputs (conductance). A binary output is provided whose value is base on the results of the comparison

FIG. 3 shows a schematic of an electrical representation of such a conductance neuron device's functionality. Each collection of the total "positive" conductance devices 2 or the total "negative" conductance devices 3 constitutes the synapses of a neuron. The conductance or weights of these synapses are determined by a threshold voltage ( $V_t$ ) programmed on the neuron. The precision to which this threshold voltage can be controlled gives the effective bit-equivalent precision of the synapse weight.

The analog programmed value is controlled by the programmed threshold voltage. In this embodiment, the actual value is equal to the digital on voltage,  $V_H$ , minus the  $V_T$ .  $V_T$  is programmed to a value as selected by the user, a control circuit, or a program. These values can be provided by any number of accepted techniques, including via a hardware data transfer, software program, or internal adaptation. The internal adaptation may occur by use of neural algorithms implemented or feedback loops on the same chip so that self programming and modification can be controlled on a single chip without need for a host processor.

It is possible to program the threshold of a floating-gate device to a precision in the range of 8 mV to 64 mV. Of course, future improvements in programming and storage technology may permit long term storage of even more precision. This corresponds to 8 bits to 5 bits (256 to 32 levels) over a 2V input dynamic range. While current technology will permit flash EEPROMs to be used for long term storage, up to one year for 5 mV to 8 mV threshold variations, and for 64 mV variations up to 10 years, other conductance storage devices may be used. Usage of two devices adds an additional sign bit to increase the total to 9 to 6 bits per weight.

The present invention uses a conductance comparator as a neuron to apply the "activation function" of the neuron that converts the total analog conductance input to a binary voltage output suitable for long range communication and digital analysis. Directly comparing two conductances allows the present invention to compute using very little energy, reducing the overall power consumption.

FIG. 4A illustrates a circuit that performs the neuron computation. The circuit is a conductance measuring device that comprising two principal blocks: conductance synapses 91 and a neuron 5. FIG. 4B shows a current buffer 4 decoupling the synapses 91 from the neuron 5 where the neuron performs the comparison of conductance of the synapse 91. The circuit may also include a latch 6 to digitize an output of the circuit. In one embodiment of FIG. 4A and 4B, each conductance synapse is composed of a single conduction element whereas in n alternative embodiment, each conduction synapse is composed of two conduction elements.

FIG. 4C indicates a neural network 1 comprising a first exciting (positive-weighted) synapse block 2; a second inhibiting (negative-weighted) synapse block 3; a decoupling stage (buffer) 4; a comparing stage (neuron) 5; and a latch circuit 6.

Synapse block 2 has a number (n) of inputs 11 supplied with (n) input signals  $x_1, x_2, \dots, x_n$ ; a set of (n) positive value synapses 15; and an output 12 which is the sum of the current through all positive synapses through which flows current  $I_1$ . Synapse block 3 comprises an equal number of inputs 13 supplied with the same n input signals (each input signal is supplied in parallel to an input 11 of exciting synapse block 2, and to an input 13 of inhibiting synapse block 3); a set of (n) negative values synapses 17; and an output 14 through which flows current  $I_2$ .

In this embodiment, the synapses 91 are implemented with a positive-weighted synapse block 2 and a negative-weighted synapse block 3; however, other conduction schemes within the context of the present invention use only one type of weighted synapses. While certain advantages are obtained using positive and negative synapses in a comparison mode, this is not required in all implementations making use of the present invention.

Synapse block 2 comprises a number of synaptic elements 15 comprising memory cells 15—in this case flash-EEPROM cells—of the same number as inputs 11. More specifically, each synapse cell 15 has a grounded source terminal, a gate terminal connected to a respective input 11, and a drain terminal connected to the drain terminals of the other cells 15 and to output 12. Similarly, synapse block 3 comprises a number of synaptic elements comprising memory cells 17 (of the same number as cells 15); and each cell 17 has a grounded source terminal, a gate terminal connected to a respective input 13, and a drain terminal connected to the drain terminals of the other cells 17 and to output 14. As can be seen by viewing FIG. 4C, the sources of each conductance element 15 and 17 are tied to a common voltage potential, which in one embodiment is ground.



Flash-EEPROM memory cells are used for cells **15** and **17** is one embodiment of the present invention. The use of floating gate technology for efficient long term analog storage is well known in the art, especially in neural network imple-  
 5 mentations. See, for example, an article by A. Kramer et al., entitled "Flash-based Programmable Nonlinear Capacitor for Switch Capacitor Implementations for Neural Network," IEDM Technology Digest, pp. 17.6.1–17.6.4, December 1993. However, other possible conductance storage devices, such as EEPROM memory cells, dynamic floating gate  
 10 devices, non-programmable, non-floating gate devices (i.e., standard MOS transistors of selected size) or other types of storage elements suitable for generating conductance, are used in other embodiments.

Referring to FIG. 4C, decoupling stage or buffer **4** comprises a first diode-connected N-channel MOS transistor **20**, and a second and third N-channel MOS transistor **21**, **22**. More specifically, first transistor **20** has the drain terminal connected to a supply line **25** at supply voltage  $V_{DD}$  via a current source **26** for generating current  $I_b$ ; the gate terminal  
 15 (node A) connected to its own drain terminal and to the gate terminal of transistors **21**, **22**; and the source terminal grounded. Second transistor **21** has the source terminal connected to output **12** of synapse block **2**, and a drain terminal defining a first output **27** of buffer **4**. Third transistor **22** has the source terminal connected to output **14** of synapse block **3**, and a drain terminal defining a second output **28** of buffer  
 20 **4**.

A reset transistor (represented in FIG. 4C by a switch **29**) is located between the gate and source terminals of transistor **20**, and presents a control input **29a**. In the presence of a control signal at input **29a** (voltage  $V_R$ ), switch **29** grounds the gate terminals of transistors **20–22**, and hence the drain  
 25 terminals of memory cells **15**, **17**, to eliminate the current through the memory cells when network **1** is not used.

Neuron **5** comprising a conductance comparator which senses the difference between the synapse blocks **2** and **3** separated in positive and negative weights. This conductance mode neuron is a suitable building block for large-scale  
 30 array-based analog neural network implementation and has been designed using a mixture of analog and digital subcircuits (mixed-mode). The neuron circuit uses analog weighting and analog computation internally to reduce silicon area and power consumption while its data inputs and outputs are digital. One of the concepts underlying the present invention  
 35 is to make use of conductance summing for performing computation and for converting an analog-valued conductance signal into a binary-valued output signal suitable for communication. The use of digital I/O signals greatly simplifies integration at the system level. In one embodiment, the I/O is digital; but, alternatively analog I/O may be used.

Neuron **5** comprises a symmetrical first and second section **31**, **32** connected respectively to outputs **27**, **28** of buffer **4** and cross-connected to each other. Section **31** comprises  
 40 three P-channel MOS transistors **33–35** with the source terminals all connected to supply line **25**, and the gate terminals connected to one another; transistor **33** is diode-connected, forms a current mirror with transistors **34**, **35**, and has the drain terminal connected to a node **36** in turn connected to output **27** of buffer **4**; transistor **34** has the drain terminal connected to a node **37** of section **32**; and the drain terminal of transistor **35** forms output **38** of the neuron, and is connected to latch circuit **6**.  
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Similarly, section **32** comprises three P-channel MOS  
 50 transistors **43–45** with the source terminals all connected to supply line **25**, and the gate terminals connected to one

another, transistor **43** is diode-connected, forms a current mirror with transistors **44**, **45**, and has the drain terminal connected to node **37** in turn connected to output **28** of buffer  
 5 **4**; transistor **44** has the drain terminal connected to node **36** of section **31**; and the drain terminal of transistor **45** forms output **39** of the neuron, and is connected to latch circuit **6**.

Reset transistors (represented in FIG. 4C by switches **40**, **41**) are located between supply line **25** and the gate terminals of transistors **33–35** and **43–45** respectively, and present control inputs **40a**, **41a**. In the presence of control signals at inputs **40a**, **41a** (voltages  $V_R$ ), switches **40** and **41** short the gate terminals of transistors **33–35** and **44–45** to the supply and so turn off the transistors when network **1** is not used.  
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Latch circuit **6** is a conventional type comprising three  
 15 N-channel MOS transistors **47–49**. More specifically, transistor **47** has the source and drain terminals connected to outputs **38**, **39** of neuron **5**, and the gate terminal forms a control input **50** supplied with an enabling signal EN; transistor **48** has the drain terminal connected to output **38** of neuron **5**, the gate terminal connected to output **39** of neuron **5**, and the source terminal grounded; and transistor **49** has the drain terminal connected to output **39** of neuron **5**, the gate terminal connected to output **38** of neuron **5**, and the source terminal grounded.  
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A single synapse can be viewed as being comprised of one synapse element **15** from block **2** and one synapse element **17** from **7**. These two synapse elements have a common input and form a single synapse together. As previously stated, in a preferred embodiment, one of these elements will  
 25 be programmed on to the desired conductance value when the input is high and the other will be programmed to always be off, regardless of the input value. The conductance of respective elements **15** will be summed to provide a positive conductance signal and the conductance of respective elements **17** will be summed to provide a negative conductance signal. These are compared to provide a binary output, the comparison being one technique to provide a fast computation. Of course, the conductance synapses of this invention could also be composed of a single conductive element for each synapse, whose value is computed upon an input signal being provided. This could be implemented, for example, by using only a single block **2** and compare the output to some reference value for a digital output; or alternatively, to provide the neuron output as an analog output. Alternatively, a  
 30 synapse comprised of two devices as generally described can be programmed so that both devices are on when the input is high. In this case, the conductance value of the synapse corresponds to the difference in conductance value between the two elements. This embodiment can be useful in providing a circuit which is more insensitive to the effects of temperature variations on effective threshold voltage. In a further alternative, rather than comparing the conductance value with respect to ground, elements **15** and **17** could have their respective sources tied to a respective selected voltage potential other than ground. In one embodiment, all the elements **15** of block **2** are tied to a first selected voltage potential and all elements of block **3** to a different selected voltage potential. This could provide increased differences in the output signals for improved conductance measurement comparison. Thus, while, the conductances are shown measured with respect to ground in FIG. 4C, they are measured with respect to any selected fixed voltage, including different voltages for different individual elements **15** and **17**, or entire groups of elements within blocks **2** and **3**.  
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In one embodiment, each synapse is a single conductance element implemented by floating-gate or other storage devices. In an alternative embodiment, each synapse is a pair  
 40  
 45  
 50  
 55  
 60  
 65



of conduction elements implemented by a differential pair of floating gate devices. This presents several design constraints to the current buffer. Firstly, to minimize disturb programming it is helpful to keep the drain voltage of the floating-gate device of the synapse as low as possible. In one embodiment, this is less than 100 mV, but higher voltages could be used in other technologies or designs. Secondly, as the present invention intended to use many synapses and each has parasitic drain capacitance on the order of 2 fF, the drain terminal of the synapse will respond slowly if it must undergo large voltage swings. To have a neuron with a large dynamic range output voltage and high speed, it is desirable to decouple the drain node of the synapses from the neuron.

The number of synapses per neuron can be any number in one embodiment there are from 1 to 2000 memory cells **15** and **17** in each of synapse blocks **2** and **3**.

One advantage of the present invention is that it can correctly and rapidly compare the synaptic conductances, even in the presence of a large common mode conductance. Common mode conductance corresponds to that part of the signal which is conductive for both the negative and positive conductance summing lines. The difference conductance signal corresponds to the residual conductance present on either the positive or negative summing line, whichever is greater. The common mode conductance can vary over a wide range, from as few as no synapses on as common to as high as nearly all synapses on (i.e., 1000 or 2000). Compute precision corresponds to the residual conductance signal needed to correctly control neuron output in the presence of maximum common mode conductance.

Memory cells **15**, **17** of synapse blocks **2**, **3** of network **1** are programmed according to the weight  $w_i$  they are to represent, and, more specifically, may be programmed at different threshold levels to present a given conductance for each input voltage value. In the simplest case, they may be programmed to define only two binary levels (cell on or off for a given input voltage value at inputs **11**, **13** respectively), and the input voltage (input signals  $x_1, \dots, x_n$ ) may assume only a predetermined number of discrete values (e.g., two, binary high or low; or four). Alternatively, the cells may be programmed to store a number of different threshold values, and the input voltage may vary continuously within a predetermined range to actually evaluate the conductivity of the cells in the presence of data input signals.

Consequently, when input signals  $x_1, \dots, x_n$  are supplied to inputs **11**, **13**, the current through each of memory cells **15**, **17** is related to the conductance of the cell, which is the programmed, stored weight. The current  $I_1, I_2$  through each node **12**, **14** equals the sum of the currents in all the cells of the respective synapse blocks **2**, **3**, and as such is related to the total conductance of the synapse.

Buffer **4** provides for decoupling, and more specifically for ensuring the neuron only sees the capacitance of transistors **21**, **22** (the capacitance between the drain and gate terminals plus the capacitance between the drain and source terminals of transistors **21**, **22**) and not the total capacitance of cells **15**, **17**, which, in view of the large number of cells that may be provided (even as many as a few thousand synaptic elements per neuron), may be extremely high. This provides for much faster evaluation by network **1**, as explained in more detail herein.

To reduce the power consumption in the computation it is better that all the devices implementing synapses work in the triode region. However, this is not always required. In the present invention, buffer **4** provides for maintaining a low voltage at outputs **12**, **14** of synapse blocks **2**, **3**, so that

memory cells **15**, **17** operate in the triode region, and network **1** can also operate at low supply voltages and low power.

Operation of buffer **4** will now be described mathematically with reference to exciting summing line **12** from positive synapse block **2**; the same also applies to inhibiting summing line **14** from inhibiting synapse block **3**.

As the voltage drop between the source and gate terminals of a MOS transistor equals the threshold voltage (minimum voltage at which the transistor is turned on) plus the overdrive voltage (voltage in excess of the threshold value), the following equation applies for transistor **20**:

$$V_A = V_{GS,20} = V_{OV,20} + V_{th,20} \quad (1)$$

where  $V_A$  is the voltage drop between node A and ground; and  $V_{GS,20}$ ,  $V_{OV,20}$  and  $V_{th,20}$  are respectively the gate-source voltage drop, overdrive voltage and threshold voltage of transistor **20**.

Moreover, if  $V_B$  is the voltage drop between output **12** and ground (the voltage between the drain and source terminals of cells **15**):

$$V_A - V_B = V_{GS,21} = V_{OV,21} + V_{th,21} \quad (2)$$

where  $V_{GS,21}$ ,  $V_{OV,21}$  and  $V_{th,21}$  are respectively the gate-source voltage drop, overdrive voltage and threshold voltage of transistor **21**.

Since transistors fabricated using the same technology present roughly the same threshold voltage, so that  $V_{th,20} \approx V_{th,21}$ , substituting (1) in (2) with a few straightforward calculations gives:

$$V_B = V_{OV,20} - V_{OV,21} \quad (3)$$

Transistor **21** may be appropriately sized to present a negligible overdrive voltage in relation to that of transistor **20**, so that (3) becomes:

$$V_B \approx V_{OV,20} \quad (4)$$

and the voltage between the drain and source terminals of cells **15** equals the overdrive voltage of transistor **20**.

For transistor **20**, which operates in the normal region, the following equation applies:

$$I_b = K(V_{GS,20} - V_{th,20})^2 = K(V_{OV,20})^2 \quad (5)$$

where  $I_b$  is the current through transistor **20** and equal to the current generated by source **26**; and K is a proportion constant.

Substituting (4) in (5) with a few straightforward calculations gives:

$$V_B = \sqrt{I_b / K} \quad (6)$$

Consequently, by appropriately sizing current source **26**, the drain-source voltage drop of cells **15** (and **17**) may be predetermined, and more specifically, may be made less than the gate-source voltage drop of cells **15**.

Neuron **5** is a conductance sensing circuit that performs a comparison between two different conductances coming from the synapse devices. Neuron **5** provides for comparing



the respective currents  $I_1$ , and  $I_2$  of the exciting and inhibiting synapses, and, together with latch 6, for generating at output O (node 39) a digital signal, the value of which indicates which of the two currents is the higher. More specifically, it operates as a feedback current sensor, wherein a transient state is observed when the circuit is turned on, and at the end of which practically all the current flows into section 31 or 32 connected to the synapse with the higher output current, and the other section is practically turned off altogether. A digital output signal level is thus reached very quickly.

For an easy decision, namely, a large difference between the conductance values of blocks 2 and 3, the final digital output is reached very quickly with very low current consumption. Thus, even though many synapse elements may be turned on, the actual decision itself is based on a difference and thus is very quick and low in power if that difference is great. If the decision is difficult, namely, the value of currents  $I_1$  and  $I_2$  are nearly equal, slightly more time may be required to make the decision with slightly more current usage. Accordingly, the present invention provides the advantage that easy decisions are made quickly with low power consumption and the more difficult decisions are permitted the extra time needed to ensure a correct output.

To explain the working of neuron 5, currents  $I_1$  and  $I_2$  will be assumed to present a common term  $I_c$ , and to differ by a differential term  $\Delta I$ . For example, exciting synapse block 2 will be assumed to generate a current  $I_1=I_c+\Delta I$ , and inhibiting synapse block 3 to generate a current  $I_2=I_c$ .

When reset signal  $V_R$  switches to eliminate the shorted condition of buffer 4 and neuron 5, cells 15, 17 begin drawing current, and currents  $I_1$ , and  $I_2$  begin flowing through sections 31, 32 to turn them on. At this transient stage, however, the current mirrors of the two sections are not turned on at the same speed: the mirror connected to the lower-capacitance line (i.e., lower conductance—higher current) is turned on faster, so that, in the case in question, transistors 33 and 34 of section 31 are turned on faster than transistors 43 and 44, and begin drawing and supplying current more rapidly to node 37. More specifically, transistor 33 (and hence transistor 34) draw current  $I_1=I_c+\Delta I$ . As only current  $I_2=I_c$  is required, however, from node 37, the excess portion supplied by transistor 34 tends to go to transistor 43, which, not supporting such a condition, begins to go off, and, at the same time, the voltage at node 37 rises to supply voltage  $V_{DD}$ .

On the other hand, when turned on, transistor 44 supplies current to node 36, thus reducing the current through transistor 33 and causing a brief variation in the current supplied by transistor 34 to node 37. On account of the cross-connection of sections 31 and 32, a sort of feedback is produced between them, which causes the 30 section connected to the higher-current synapse block (in this case, section 31) to supply practically all the current required by synapse blocks 2, 3, while the other section is practically turned off. In the case in question, therefore, at the end of the transient state, practically all of current  $I_c+\Delta I$  flows into section 31, and only a negligible current flows into section 32. By using a cross mirror and positive feedback on the neuron, the present invention is able to subtract a common mode current and discriminate lines of synapses with a minimum conductance. This allows the circuit to achieve high precision over a wide range of input current. The speed of the circuit changes with the overall current, therefore, to optimize the speed performance and to digitize the output the present invention use a standard latch 6.

The FIG. 7 plots show the currents in transistors 33, 34, 43, 44, as determined in a simulation test conducted by the

Applicant, upon switching of reset signals  $V_R$  at the inputs of switches 29, 40, 41, and enabling of latch 6 (EN signal). As can be seen, at the end of the transient state, current  $I_{33}$  equals  $I_c+\Delta I$ , current  $I_{34}$  equals  $I_c$ , and currents  $I_{43}$ ,  $I_{44}$  are zero. The FIG. 6 graph shows output voltages O and at node 38 (voltage  $V_{38}$ ).

The off state of the section connected to the lower-current synapse (section 32) disconnects the respective output node (39) from the supply; whereas the high-conductance condition of the section connected to the higher-current synapse (section 31) latches the respective output node (38) to supply voltage  $V_{DD}$ . Consequently, in the example shown, upon signal EN switching to low and turning off shorting transistor 47, transistor 49, whose gate terminal is connected to the turned-on section 31, is turned on and grounds output O; and the other transistor 48 remains off. Conversely, if inhibiting synapse block 3 presents a lower conductance (higher current) than exciting synapse block 2, section 32 and transistor 48 are turned on, and section 31 and transistor 49 are turned off, so that output O is high and latched to supply voltage  $V_{DD}$  via transistor 45.

The advantages of the neural network according to the present invention are as follows. By implementing the synapses using memory cells whose conductance varies according to the programming level, the synapses may be so biased as to present a low output voltage (nodes 12, 14), thus permitting network 1 to be used in low-voltage conditions and hence also in portable devices and systems. Moreover, low-current operation of the synapses (100 pJ in the case of a thousand inputs) provides for low-power operation of the network as a whole, which may therefore also be used in applications in which voltage and power resources are limited.

Reducing the voltage at the drain terminals of cells 15, 17 also provides for preventing or minimizing soft-writing of the cells, thus ensuring a high degree of reliability of the network.

By virtue of the low current levels and buffer 4 decoupling the synapses and the neuron, the network provides for particularly high-speed evaluation.

Forming the neuron as a feedback conductance comparator, as described, provides for safely comparing even only slightly differing conductances in the synapses, and in particularly conductances differing by even a few orders of magnitude less than the conductances themselves (e.g., with a ratio of 1:1000), by virtue of the differential value of the two conductances being used to off-balance neuron 5 and hence latch circuit 6.

The network according to the invention also presents a high input range, can discriminate up to 10 bits, requires a small integration area ( $200 \times 32 \mu\text{m}$ ) by using a  $0.7 \mu\text{m}$  CMOS technology, presents a simple, easily integratable structure, and requires no interfacing with digital environments.

The present invention has further advantages as follows. The disclosed conductance mode computation causes a minimum current pulse in the summing node in order to make neuron decisions. In addition, by virtue of minimum current pulse as well as of fast computing time, a low power operation is obtained. The solution by the present invention has high precision, in particular the disclosed solution has a 9-bit inherent precision and a 7–8 bit measured precision.

FIG. 8 shows a test structure of an implementation of the neuron. The test structure contains two pairs of transistors connected to the neuron. One pair of the transistors are very big ( $B=800 \mu\text{m}/2 \mu\text{m}$ ) and represent the common mode signal for the positive and negative synapses; the other pair of



transistors are small ( $S=0.8 \mu\text{m}/2 \mu\text{m}$ ) like minimum flash devices and represents variable input signals. After offset compensation between the two large “common mode” transistors, a common mode voltage is applied to both pairs of transistors and a minimum input signal needed to control the output via the pair of small transistors is measured.

A measurement was made to characterize the percentage of times the output was correctly controlled by the input over 1000 cycles using a “001100. . .” input pattern. With a maximum common mode voltage ( $V_{\text{common}}$ ) fixed to 0.9 V (100–200 mV above  $V_t$ ) the statistical output as a function of delta input voltage ( $V_{\text{input}}$ ) between the two “small” transistors is measured. FIG. 10 shows a loss of precision starting at  $V_{\text{input}}=120$  mV. The correspondence between this measurement and precision depends critically on the precise threshold voltage of the devices; for a process with  $V_t$  varying between 0.7 V and 0.8 V which in the worst case means 8 bits and in the best case 9 bits of precision. This analysis is based on drawn transistor dimensions making exact precision characterization following fabrication difficulty.

Another test structure is realized to estimate the computing precision of the neuron comparator in FIG. 9. The test structure contains 1 k flash devices ( $0.81 \mu\text{m}/2 \mu\text{m}$ ) for common mode input whose inputs are controllable by a shift register and 32 flash devices for differential input whose inputs are controlled by a latch. The test structure circuit also contains programming and erasing drivers for the flash devices. The entire 1 k flash devices represents the common mode signal for the positive and the negative synapses; 16 compensation flash devices are able to compensate the programming error and the remaining 16 input flash devices are used to apply the input signal to measure the overall precision. After all the flash devices have been programmed to  $V_t=2.5$  V, the shift register is filled with “1” s. A gate voltage is fixed for all the flash devices to  $V_t+V_{\text{LSB}}$ . Applying a  $V_t+V_{\text{LSB}}$  voltage to the flash gate devices means fixing a common mode signal for the positive and the negative synapses (as has been done by the big transistors of the previous test structure). After compensation, a sequence of “00110011. . .” is applied to 1 to 16 of the inputs testing for the correct output over 1 million cycles.

FIG. 11 shows the percentage of correct output as a function of the number of inputs applied (1 to 16). It is clear that as the number of inputs increases the percentage of correct outputs increases, approaching 100% for 6 inputs with a  $V_{\text{LSB}}=32$  mV. This corresponds to a precision of 7+ bits. FIG. 13 shows the precision as a function of the LSB voltage. As can be seen, increasing the LSB voltage to 128 mV, 1 bit of precision is lost. The effective precision of the circuit depends on the common mode signal. FIG. 12 shows the same test using only 0.5 k flash devices (reduced common mode) In this case, the differential input needed for 100% correct output is 2 synapses 15 or 17 being on and the effective precision is close to 8 bits.

FIG. 14 shows a measurement of the neuron functionality clocked at 10 MHz. FIG. 15 shows power consumption of the neuron over one computation. The consumption is equal to 166 pJ at 5 V of power supply at a frequency of 1.7 MHz. This corresponds to 166 pJ per input multiply-accumulate operation (1 k inputs).

Clearly, changes may be made to the neural network as described and illustrated herein without, however, departing from the scope of the present invention. A number of alternative embodiments have been described herein for implementing a conductance synapse is a neuron. The invention is to be interpreted broadly, covering all embodiments and modifications thereof which fall within the scope of the appended claims.

What is claimed is:

1. A neural network comprising:

a plurality of synaptic weighting elements organized in a first set and a second set, each having a respective programmable conductance, each of the synaptic weighting elements having a respective synaptic input connection for receiving an input signal and an output connection;

a neuron stage coupled to the synaptic weighting elements;

a conductance comparing circuit within the neuron stage, the conductance comparing circuit comparing the conductance of the first set of synaptic weighting elements to the conductance of the second set of synaptic weighting elements and outputting an indication of which set has the higher conductance without determining the conductance values; and

a latch stage coupled to the neuron stage to digitize the outputted indication.

2. The network according to claim 1 wherein the synaptic weighting elements include a nonvolatile memory cell having a floating gate and a control gate in a programmable conductance.

3. The network according to claim 1, further including:

an exciting conductive input terminal coupled to the conductance comparing circuit;

an inhibiting conductance input terminal coupled to the conductance comparing circuit;

a connection between the first set of the synaptic elements and the exciting conductive input terminal; and

a connection between the second set of synaptic elements and the inhibiting conductive input terminal, the conductance comparing circuit outputting an indication of the results of the comparison between the exciting synaptic elements and the inhibiting synaptic elements.

4. A neural network comprising:

a plurality of exciting synaptic elements having a programmable conductance;

a plurality of inhibiting synaptic elements having a programmable conductance;

a neuron stage having a first and second conductance input connected to the exciting and inhibiting synaptic elements, respectively, the neuron stage including a comparing circuit [for] providing a comparison of the conductance of the inhibiting synaptic elements and the exciting synaptic elements and generating an output signal indicative of which conductance is greater without determining the value of the conductance of the inhibiting synaptic elements and the exciting synaptic elements; and

a latch stage coupled to the neuron stage to digitize the output signal.

5. A neural network comprising:

a plurality of exciting and inhibiting synaptic weighting elements having a respective programmable conductance;

a neuron stage coupled to the plurality of exciting and inhibiting synaptic weighting elements, each of the synaptic weighting elements having an associated exciting or inhibiting conductance and an input connection terminal for receiving a respective input signal and an output coupled to the neuron stage, the neuron stage further including a conductance sensing circuit that generates an output signal indicative of which of the total exciting and inhibiting conductances of the plural-



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ity of synaptic weighting elements is greater without determining the actual value, collectively and individually, of the exciting and inhibiting conductances; and

a latch stage coupled to the neuron stage to digitize the output signal.

6. A neural network comprising:

a plurality of exciting synaptic weighting elements, each having a respective programmable conductance, each of the exciting synaptic weighting elements having output terminals which are connected in common to each other to provide an output which is the sum of the conductances of all the exciting synaptic weighting elements;

a plurality of inhibiting synaptic weighting elements, each having a respective programmable conductance, each of the inhibiting synaptic weighting elements having output terminals which are connected in common to each other to provide an output terminal having an output which is the sum of the conductances of all the inhibiting synaptic weighting elements;

a neuron stage having an exciting input connected to the output of the plurality of exciting synaptic weighting elements and having an inhibiting input connected to the output of the plurality of the inhibiting synaptic weighting elements; and

a conductance comparing stage [for] comparing the conductance between the sum of the exciting synaptic weighting elements and the inhibiting synaptic weighting elements without determining the value of the conductances and outputting a signal indicative of which of the sums of the respective pluralities of synaptic weighting elements has the greatest conductance.

7. A network comprising:

a plurality of synaptic weighting elements organized in a first set and a second set, each set having a respective programmable conductance, each of the synaptic weighting elements having a respective synaptic input connection for receiving an input signal and an output connection;

a conductance comparing circuit coupled to the synaptic weighting elements, the conductance comparing circuit comparing the conductance of the first set of synaptic weighting elements to the conductance of the second set of synaptic weighting elements and outputting an indication of which set has the higher conductance without determining the conductance values; and

a latch stage coupled to the conductance comparing circuit to digitize the outputted indication.

8. The network according to claim 7 wherein the synaptic weighting elements include a nonvolatile memory cell having a floating gate and a control gate in a programmable conductance.

9. The network according to claim 7, further comprising: an exciting conductive input terminal coupled to the conductance comparing circuit;

an inhibiting conductance input terminal coupled to the conductance comparing circuit;

a connection between the first set of the synaptic elements and the exciting conductive input terminal; and

a connection between the second set of synaptic elements and the inhibiting conductive input terminal, the conductance comparing circuit outputting an indication of the results of the comparison between the exciting synaptic elements and the inhibiting synaptic elements.

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10. A network comprising:

a plurality of exciting synaptic elements having a programmable conductance;

a plurality of inhibiting synaptic elements having a programmable conductance;

a neuron stage having a first and second conductance input connected to the exciting and inhibiting synaptic elements, respectively, the neuron stage including a comparing circuit providing a comparison of the conductance of the inhibiting synaptic elements and the exciting synaptic elements and generating an output signal indicative of which conductance is greater without determining the value of the conductance of the inhibiting synaptic elements and the exciting synaptic elements; and

a latch stage coupled to the neuron stage to digitize the output signal.

11. A network comprising:

a plurality of exciting and inhibiting synaptic weighting elements having a respective programmable conductance;

a neuron stage coupled to the plurality of exciting and inhibiting synaptic weighting elements, each of the synaptic weighting elements having an associated exciting or inhibiting conductance and an input connection terminal for receiving a respective input signal and an output coupled to the neuron stage, the neuron stage further including a conductance sensing circuit that generates an output signal indicative of which of the total exciting and inhibiting conductances of the plurality of synaptic weighting elements is greater without determining the actual value, collectively and individually, of the exciting and inhibiting conductances; and

a latch stage coupled to the neuron stage to digitize the output signal.

12. A network comprising:

a plurality of exciting synaptic weighting elements, each having a respective programmable conductance, each of the exciting synaptic weighting elements having output terminals which are connected in common to each other to provide an output which is the sum of the conductances of all the exciting synaptic weighting elements;

a plurality of inhibiting synaptic weighting elements, each having a respective programmable conductance, each of the inhibiting synaptic weighting elements having output terminals which are connected in common to each other to provide an output terminal having an output which is the sum of the conductances of all the inhibiting synaptic weighting elements;

a neuron stage having an exciting input connected to the output of the plurality of exciting synaptic weighting elements and having an inhibiting input connected to the output of the plurality of the inhibiting synaptic weighting elements; and

a conductance comparing stage comparing the conductance between the sum of the exciting synaptic weighting elements and the inhibiting synaptic weighting elements without determining the value of the conductances and outputting a signal indicative of which of the sums of the respective pluralities of synaptic weighting elements has the greatest conductance.

13. An analog circuit, comprising:

a plurality of synaptic weighting elements organized in a first set and a second set, each set having a respective



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*programmable conductance, each of the synaptic weighting elements having a respective synaptic input connection for receiving an input signal and an output connection;*

*a conductance comparing circuit coupled to the plurality of synaptic weighting elements, the conductance comparing circuit comparing the conductance of the first set of synaptic weighting elements to the conductance of the second set of synaptic weighting elements and outputting an indication of which set has the higher conductance without determining the conductance values; and*

*a latch stage coupled to the conductance comparing circuit to digitize the outputted indication.*

14. *The analog circuit according to claim 13 wherein the synaptic weighting elements include a nonvolatile memory cell having a floating gate and a control gate in a programmable conductance.*

15. *The analog circuit according to claim 13, further comprising:*

*an exciting conductive input terminal coupled to the conductance comparing circuit;*

*an inhibiting conductance input terminal coupled to the conductance comparing circuit;*

*a connection between the first set of the synaptic elements and the exciting conductive input terminal; and*

*a connection between the second set of synaptic elements and the inhibiting conductive input terminal, the conductance comparing circuit outputting an indication of the results of the comparison between the exciting synaptic elements and the inhibiting synaptic elements.*

16. *An analog circuit, comprising:*

*a plurality of exciting synaptic elements having a programmable conductance;*

*a plurality of inhibiting synaptic elements having a programmable conductance;*

*a neuron stage having a first and second conductance input connected to the exciting and inhibiting synaptic elements, respectively, the neuron stage including a comparing circuit providing a comparison of the conductance of the inhibiting synaptic elements and the exciting synaptic elements and generating an output signal indicative of which conductance is greater without determining the value of the conductance of the inhibiting synaptic elements and the exciting synaptic elements; and*

*a latch stage coupled to the neuron stage to digitize the output signal.*

17. *An analog circuit, comprising:*

*a plurality of exciting and inhibiting synaptic weighting elements having a respective programmable conductance;*

*a conducting sensing circuit coupled to the plurality of exciting and inhibiting synaptic weighting elements, each of the synaptic weighting elements having an associated exciting or inhibiting conductance and an input connection terminal for receiving a respective input signal and an output coupled to the conducting sensing circuit, the conductance sensing circuit that generates an output signal indicative of which of the total exciting and inhibiting conductances of the plurality of synaptic weighting elements is greater without determining the actual value, collectively and individually, of the exciting and inhibiting conductances; and*

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*a latch stage coupled to the conducting sensing circuit to digitize the output signal.*

18. *An analog circuit, comprising:*

*a plurality of exciting synaptic weighting elements, each having a respective programmable conductance, each of the exciting synaptic weighting elements having output terminals which are connected in common to each other to provide an output which is the sum of the conductances of all the exciting synaptic weighting elements;*

*a plurality of inhibiting synaptic weighting elements, each having a respective programmable conductance, each of the inhibiting synaptic weighting elements having output terminals which are connected in common to each other to provide an output terminal having an output which is the sum of the conductances of all the inhibiting synaptic weighting elements;*

*a neuron stage having an exciting input connected to the output of the plurality of exciting synaptic weighting elements and having an inhibiting input connected to the output of the plurality of the inhibiting synaptic weighting elements; and*

*a conductance comparing stage comparing the conductance between the sum of the exciting synaptic weighting elements and the inhibiting synaptic weighting elements without determining the value of the conductances and outputting a signal indicative of which of the sums of the respective pluralities of synaptic weighting elements has the greatest conductance.*

19. *A system, comprising:*

*a plurality of synaptic weighting elements organized in a first set and a second set, each set having a respective programmable conductance, each of the synaptic weighting elements having a respective synaptic input connection for receiving an input signal and an output connection;*

*a neuron stage coupled to the synaptic weighting elements;*

*a conductance comparing circuit within the neuron stage, the conductance comparing circuit comparing the conductance of the first set of synaptic weighting elements to the conductance of the second set of synaptic weighting elements and outputting an indication of which set has the higher conductance without determining the conductance values; and*

*a latch stage coupled to the neuron stage to digitize the outputted indication.*

20. *The system according to claim 19 wherein the synaptic weighting elements include a nonvolatile memory cell having a floating gate and a control gate in a programmable conductance.*

21. *The system according to claim 19, further comprising:*

*an exciting conductive input terminal coupled to the conductance comparing circuit;*

*an inhibiting conductance input terminal coupled to the conductance comparing circuit;*

*a connection between the first set of the synaptic elements and the exciting conductive input terminal; and*

*a connection between the second set of synaptic elements and the inhibiting conductive input terminal, the conductance comparing circuit outputting an indication of the results of the comparison between the exciting synaptic elements and the inhibiting synaptic elements.*

22. *A system comprising:*

*a plurality of exciting synaptic elements having a programmable conductance;*



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a plurality of inhibiting synaptic elements having a programmable conductance;  
 a neuron stage having a first and second conductance input connected to the exciting and inhibiting synaptic elements, respectively, the neuron stage including a comparing circuit providing a comparison of the conductance of the inhibiting synaptic elements and the exciting synaptic elements and generating an output signal indicative of which conductance is greater without determining the value of the conductance of the inhibiting synaptic elements and the exciting synaptic elements; and  
 a latch stage coupled to the neuron stage to digitize the output signal.

23. A system comprising:

a plurality of exciting and inhibiting synaptic weighting elements having a respective programmable conductance;  
 a conducting sensing circuit coupled to the plurality of exciting and inhibiting synaptic weighting elements, each of the synaptic weighting elements having an associated exciting or inhibiting conductance and an input connection terminal for receiving a respective input signal and an output coupled to the conducting sensing circuit, the conductance sensing circuit that generates an output signal indicative of which of the total exciting and inhibiting conductances of the plurality of synaptic weighting elements is greater without determining the actual value, collectively and individually, of the exciting and inhibiting conductances; and  
 a latch stage coupled to the conducting sensing circuit to digitize the output signal.

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24. A system comprising:

a plurality of exciting synaptic weighting elements, each having a respective programmable conductance, each of the exciting synaptic weighting elements having output terminals which are connected in common to each other to provide an output which is the sum of the conductances of all the exciting synaptic weighting elements;  
 a plurality of inhibiting synaptic weighting elements, each having a respective programmable conductance, each of the inhibiting synaptic weighting elements having output terminals which are connected in common to each other to provide an output terminal having an output which is the sum of the conductances of all the inhibiting synaptic weighting elements;  
 a neuron stage having an exciting input connected to the output of the plurality of exciting synaptic weighting elements and having an inhibiting input connected to the output of the plurality of the inhibiting synaptic weighting elements; and  
 a conductance comparing stage comparing the conductance between the sum of the exciting synaptic weighting elements and the inhibiting synaptic weighting elements without determining the value of the conductances and outputting a signal indicative of which of the sums of the respective pluralities of synaptic weighting elements has the greatest conductance.

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