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# A novel analog fuzzy controller for intelligent sensors

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**Abstract**

A new analog fuzzy logic controller implemented in CMOS technology is described. The chosen membership function generator keeps the needed area for the inference engine very small while giving a big flexibility in the configuration of the membership function. The proposed solution for defuzzification gives an additional area reduction over earlier implementations. High speed, low power fuzzy controller hardware make the chip appropriate for intelligent sensor application. Simulation results as well as test measurements are presented and discussed to illustrate the properties and robustness of the proposed circuit.

*Keywords:* High-speed; Analog; Fuzzy controller; Sensors

## 1. Introduction

Since the first control application of Mamdani in 1974, many fuzzy implementations have been proposed. The control areas in which the theory of fuzzy sets has been successfully applied have become very broad: quality control [14], elevator control [2], automatic train operation system [16, 17], car damping system [7], nuclear reactor control [3], etc. Usually in those applications it is difficult or even in some cases impossible to build accurate mathematical models for the processes under control. If the control application requires only a low-speed implementation or can afford large memory devices [1], a software solution or a look-up table stored in memory devices is sufficient to give in time the required answer. But for complex and real-time control applications where area or processing time are very important a special purpose fuzzy controller is very often the only solution. Until now several solutions have been proposed, both digital [13] and analog [15].

Digital circuitry, while offering obvious advantages for most applications in terms of ease of design and computational accuracy important for crisp operation, needs a bigger area for arithmetic operation than an

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analog circuit. The heart of every fuzzy controller is an inference block. It is built up of rules which describe the complex process to be controlled. The number of rules can be from a few to several hundreds. For each input and output signal of a rule a membership function is needed. These input signals are computed to built rules. The whole inference process contains a big number of repeating rule blocks which have to be computed for each incoming signal. If in addition the signal is coming from an analog sensor and the actuator is driven by an analog signal the needed area for the analog digital and vice versa converting is increasing the needed area for the fuzzy logic controller.

The shortcomings of analog techniques are well known but the advantages of having a continuous asynchronous computation, small circuits for the rule blocks and the possibility to build nonlinear membership function (not through linear approximation) have led us to adopt an analog approach for the fuzzy controller for intelligent sensors.

The rest of the paper is organized as follows. The theoretical background for the implemented functions is introduced in Section 2. Section 3 describes the circuit configurations of the proposed controller. In Section 4 some simulation and test measurement results are presented. Finally, in Sections 5 and 6 an application is presented and some concluding remarks are given.

## 2. The fuzzy inference algorithm

The fuzzy theory utilized for VLSI implementation is based on the theory of fuzzy sets first proposed by Zadeh [18] in 1965. In this chapter we give a brief definition of the theoretical background we used in our hardware implementation. For a detailed explanation of the definitions used see [4, 20].

Zadeh suggested a computing model for a fuzzy logic interface [19]. There are two aspects of such a model: inference rules and implication functions. Two important well known fuzzy implicated inference rules in approximate reasoning are the so called generalized modus ponens (GMP) and generalized modus tollens (GMT):

- GMP:
  premise: $x$ is $A'$
  implication: if $x$ is $A$ then $y$ is $B$
  ___
  consequence: $y$ is $B'$
- GMT:
  premise: $y$ is $B'$
  implication: if $x$ is $A$ then $y$ is $B$
  ___
  consequence: $x$ is $A'$

where $A$, $A'$, $B$ and $B'$ are fuzzy predicates, and $x, y$ are linguistic variables. The GMP, which is related to the forward data-driven interface, is the approach used in fuzzy logic control. The GMT, which is related to the backward goal-driven interface, is commonly used in expert systems.

Based on the GMP approach each fuzzy rule is transformed into a fuzzy relation $R$ that represents the correlation between the premise and the consequence. Assume $A$ and $B$ are two fuzzy sets defined over $U$ and $V$, respectively. The fuzzy relation $R$ for the fuzzy rule $A \to B$ can be expressed as follows:

$$\mu_R(x, y) = f_{\text{imp}}(\mu_A(x), \mu_B(y)); \quad x \in U, \ y \in V, \tag{1}$$

where $f_{\text{imp}}$ is called the implication function. Following Zadeh's introduction, a number of researchers have proposed various implication functions. The most widely used one is the minimum operation rule suggested by Mamdani [4] (Fig. 1). For simplicity, assume that we have two fuzzy control rules as follows:

$R_1$: if $x$ is $A_1$ and $y$ is $B_1$ then $z$ is $C_1$,

$R_2$: if $x$ is $A_2$ and $y$ is $B_2$ then $z$ is $C_2$,

where $x$, $y$ and $z$ are linguistic variables representing two process state variables and one control variable; $A_i$, $B_i$, and $C_i$ ($i = 1,2$) are expected values of the linguistic variables $x$, $y$ and $z$ in the universe of discourse $U$, $V$ and $W$. The inputs are usually measured by sensors and then broadcasted to all the rules simultaneously to be compared to stored premises (IF blocks). Conceptually, the better the match of all the inputs to a stored rule, the more influence it will have in the final weighted output. The weights $\alpha_1$ and $\alpha_2$ of the first and second rules are calculated as follows:

$$\alpha_1 = \min(\mu_{A_1}(x_0), \mu_{B_1}(y_0)), \tag{2}$$

$$\alpha_2 = \min(\mu_{A_2}(x_0), \mu_{B_2}(y_0)), \tag{3}$$

where $\mu_{A_i}(x_0)$ and $\mu_{B_i}(y_0)$ are called fuzzy membership functions and represent the degrees of the partial match between the inputs and the data stored in the rule base. In Mamdani's minimum operation which is adopted in this paper, the $i$th rule leads to the conclusion (THEN blocks):

$$\mu_{C_i'}(z) = \min(\alpha_i, \mu_{C_i}(z)), \tag{4}$$

which implies that the membership function $\mu_C$ of the inferred consequence $C$ is given by

$$\begin{aligned} \mu_C(z) &= \max(\mu_{C_1'}, \mu_{C_2'}) \\ &= \max(\min(\alpha_1, \mu_{C_1}(z)), \min(\alpha_2, \mu_{C_2}(z))). \end{aligned} \tag{5}$$

Moreover, if we apply De Morgan's law to the fuzzy max and min operation as follows [9]:

$$\min\{\mu_A(x), \mu_B(x)\} = \overline{\max\{\mu_{\bar{A}}(x), \mu_{\bar{B}}(x)\}}. \tag{6}$$

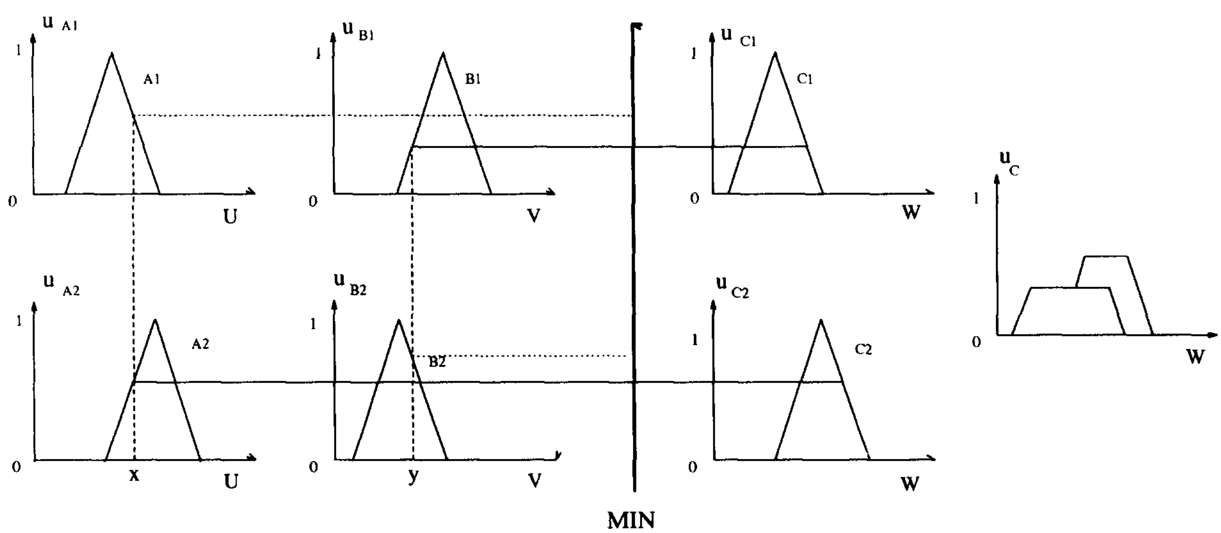


Fig. 1. Graphical representation of Mamdani's method.

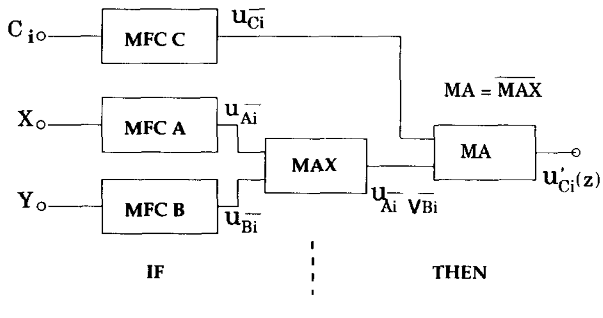


Fig. 2. A rule block.

Eq. (4) can be written as:

$$\begin{aligned}\mu_{C_i'}(z) &= \min(\alpha_i, \mu_{C_i}(z)) \\ &= \min(\min(\mu_{A_i}(x), \mu_{B_i}(y)), \mu_{C_i}(z)) \\ &= \min(\overline{\max(\mu_{\overline{A_i}}(x), \mu_{\overline{B_i}}(y))}, \mu_{C_i}(z)) \\ &= \overline{\max(\max(\mu_{\overline{A_i}}(x), \mu_{\overline{B_i}}(y)), \mu_{\overline{C_i}}(z))}. \end{aligned} \tag{7}$$

Based on Eq. (7) a rule block can be implemented as shown in Fig. 2.

The last step in the fuzzy controlling process which is called defuzzification, is to deliver a crisp output. This is a mapping from a space of fuzzy sets into a space of crisp values. In the conclusion part of each rule a value is assigned to each output variable. These values can be represented by a fuzzy set or by a crisp value which represents the degree of certainty of that rule. The widely used strategy of the center of area method (COA) [8] which computes the center of gravity of the output fuzzy set can then be written for discrete values:

$$z_0 = \frac{\sum_{i=1}^{n} \mu_C(z_i) * z_i}{\sum_{i=1}^{n} \mu_C(z_i)}, \tag{8}$$

where $n$ is the number of quantization levels of the output.

## 3. Fuzzy blocks implementation

Basically a fuzzy logic controller (FLC) can be divided into three blocks: fuzzification, decision making logic or inference and defuzzification. In this section each component of the fuzzy controller will be described in detail. The inference process is based on Eq. (7) and the output of the defuzzification circuit on Eq. (8). A block design of a fuzzy controller with 2 inputs each with seven linguistic terms $NL, \ldots, PL$ and one output is presented in Fig. 3.

### *3.1. The fuzzy membership function circuit*

The membership function circuit (MFC) is the kernel of a fuzzy logic system. It converts a crisp input value $X$ into a fuzzy value $V_{i\mathrm{OUT}}$, where $i = \{NL, \ldots, PL\}$ (fuzzification process). The newly developed circuit implements a bell-shaped membership function with two differential amplifiers and a two-gate neuron MOSFET (Fig. 4). The inputs to the MFC are $V_x$ for the crisp value $X$, and two reference voltages $V_{ri}$, $V_{r(i+1)}$,

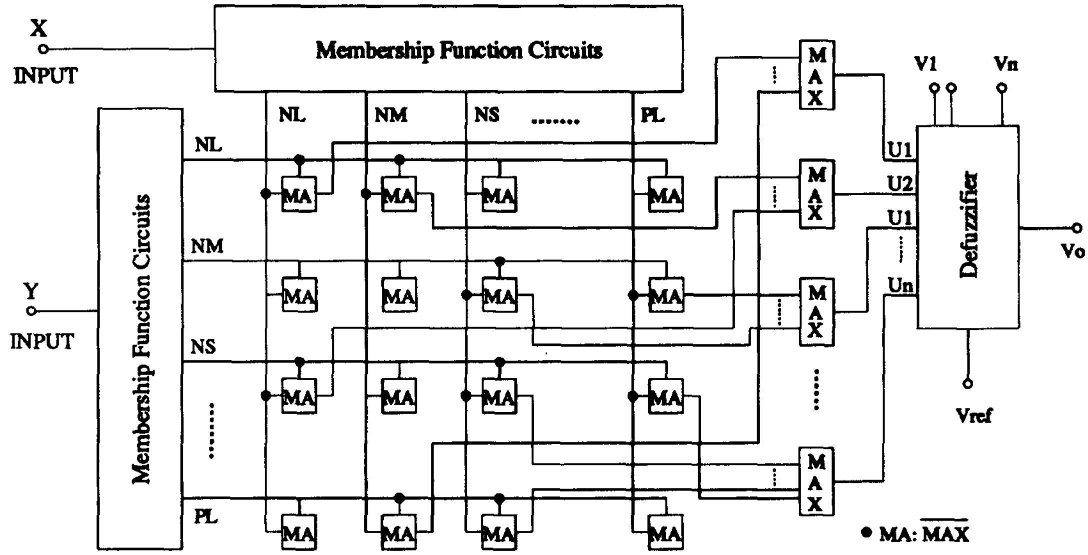


Fig. 3. A fuzzy logic controller.

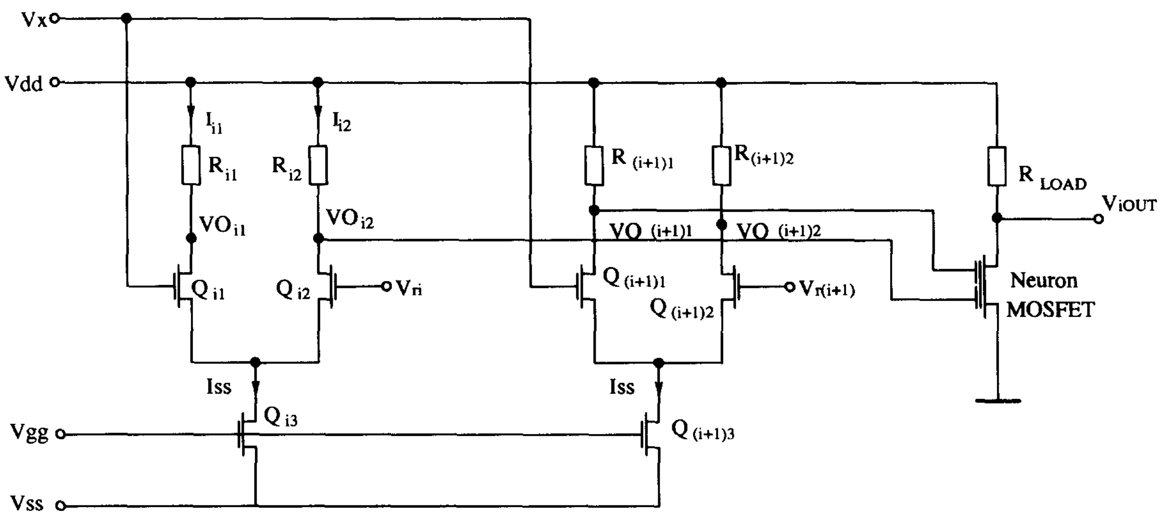


Fig. 4. The membership function circuit (MFC).

which define the linguistic term $V_r$, where $V_r = \{NL, \ldots, PL\}$. The output of the MFC, $V_{i\mathrm{OUT}}$, gives the answer of a bell-shaped membership function to the input $V_x$ and represents the degree of partial match between $V_x$ and the defined linguistic term $V_r$.

The neuron MOSFET, is a new functional MOS transistor proposed by Shibata [10] for the implementation of the Sigma function for neural networks. The neuron MOSFET is a MOS transistor with a floating gate whose potential is controlled by the multiple input gates via capacitive coupling. The potential of the floating gate $\phi_F$ is given by

$$\phi_F = \frac{C_1 V_1 + C_2 V_2 + \cdots + C_n V_n}{C_{TOT}}, \tag{9}$$

where $C_{TOT} = \sum_{i=0}^{n} C_i$, $V_1, V_2, \ldots, V_n$ are the input signal voltages, $C_1, C_2, \ldots, C_n$ are the capacitive coupling coefficients between the floating gate and each of the input gates, $C_0$ is the capacitive coupling coefficient between the floating gate and the substrate. Here we assume that the substrate potential is $V_0 = 0$.

The floating gate potential $\phi_F$ is a linear sum of all input signals, weighted by their capacitive coupling coefficients. The value of the floating gate potential $\phi_F$ can be directly read out employing a source-follower circuit. If we use such a MOS transistor just with two equal input gates we get its output the response of a fuzzy bell-shaped membership function.

The detailed function of the MFC can be described as follows. We assume that the current source Iss is ideal and that there is an ideal symmetry between $Q_{i1}$, $Q_{i2}$ and $R_{i1}, R_{i2}$ ($R_{i1} = R_{i2} = R$). $\beta$ is the mutual conductance of the MOS transistor and $\Delta V_i = \sqrt{\mathrm{Iss}/\beta}$ is the half-width of transmission region of the differential amplifier. There are three operating regions which depend on the input voltage $V_x$ and the reference voltages $V_{ri}$ and $V_{r(i+1)}$, respectively.

- When $V_x < V_{ri} - \Delta V_i$,

$$I_{i1} = 0, \tag{10}$$

$$I_{i2} = \mathrm{Iss}, \tag{11}$$

so

$$VO_{i1} = VDD, \tag{12}$$

$$VO_{i2} = VDD - \mathrm{Iss}\,R. \tag{13}$$

- When $V_{ri} - \Delta V_i \leqslant V_x \leqslant V_{ri} + \Delta V_i$,

$$I_{i1} = \frac{1}{2}(\mathrm{Iss} - \beta(V_x - V_{ri})\sqrt{\frac{2\mathrm{Iss}}{\beta} - (V_x - V_{ri})^2}), \tag{14}$$

$$I_{i2} = \frac{1}{2}(\mathrm{Iss} + \beta(V_x - V_{ri})\sqrt{\frac{2\mathrm{Iss}}{\beta} - (V_x - V_{ri})^2}), \tag{15}$$

and

$$VO_{i1} = VDD - I_{i1}R, \tag{16}$$

$$VO_{i2} = VDD - I_{i2}R, \tag{17}$$

for $V_x = V_{ri}$, we have $I_{i1} = I_{i2} = \frac{1}{2}\mathrm{Iss}$ and $VO_{i1} = VO_{i2} = VDD - \frac{1}{2}\mathrm{Iss}\,R$.

- When $V_x > V_{ri} + \Delta V_i$,

$$I_{i1} = \mathrm{Iss}, \tag{18}$$

$$I_{i2} = 0, \tag{19}$$

and

$$VO_{i1} = VDD - \mathrm{Iss}\,R, \tag{20}$$

$$VO_{i2} = VDD. \tag{21}$$

As shown in Fig. 4 we choose the second output of the $i$th differential amplifier $VO_{i2}$ and the first output of the $(i+1)$th differential amplifier $VO_{(i+1)1}$ as the inputs to the neuron amplifier. Based on Eq. (9) the potential of the floating gate $\phi_F$ of the neuron MOSFET can be expressed as

$$\phi_{F_i} = W(VO_{i2} + VO_{(i+1)1}). \tag{22}$$

We assume that the substrate potential is $VO_0 = 0$, the two inputs $VO_{i2}$ and $VO_{(i+1)1}$ have the same capacitor coupling coefficient, $C_1 = C_2 = C$, and $W = C/(2C + C_0)$. The output of the circuit is the complement membership function $\overline{\mu_A(x)}$ (Fig. 5). The advantage of using this type of circuit to build a membership function circuit is:

- small area; just 7 MOS transistors and 5 load resistances are needed to implement the circuit;
- through the two reference voltages $V_{ri}$, $V_{r(i+1)}$ the shape of each generated membership function can be changed very easily; with the same simple circuit triangle, trapezoidal and Gauss like membership function can be built;
- the signal input and output are in voltage mode; therefore several MFC can be connected to the same input signal or can drive several MAX circuit without additional circuitry.

The needed area for the implementation of a fuzzy engine is therefore very small.

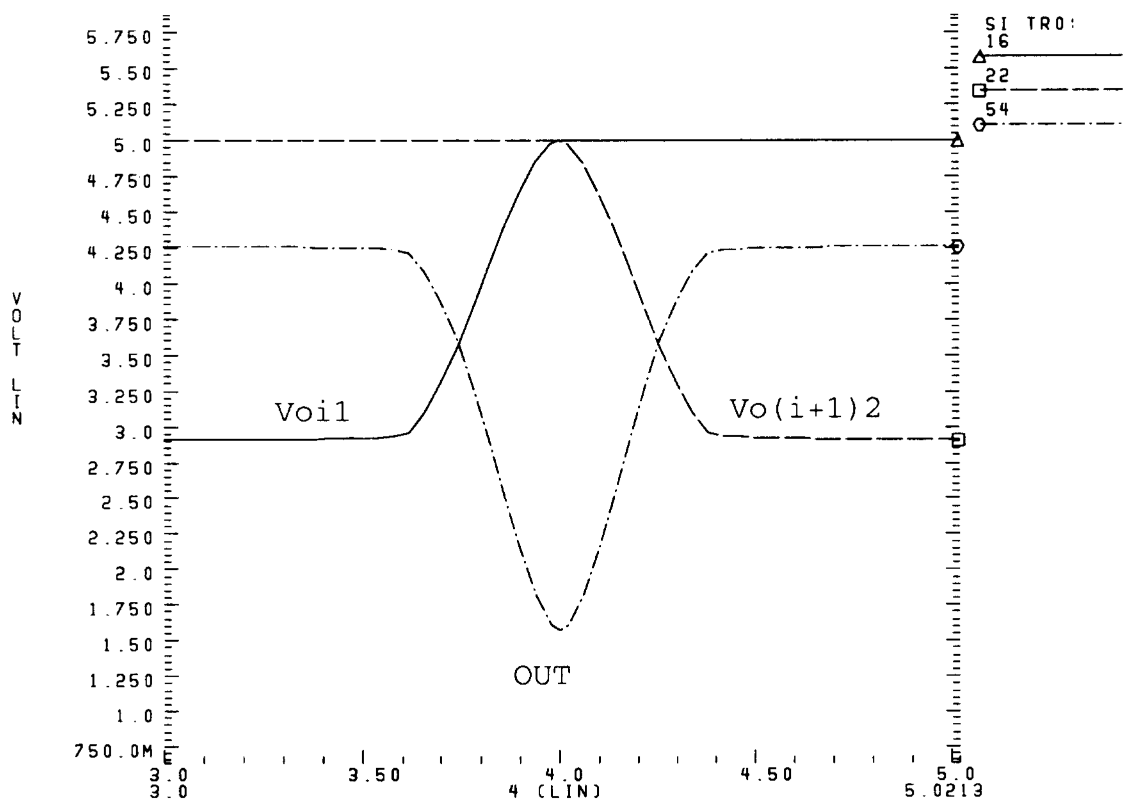


Fig. 5. The output of the membership function circuit.

### 3.2. The MAX operation circuit

The MAX circuit was realized with a NMOS circuit. The schematic for a MAX circuit with two inputs is presented in Fig. 6. $Q_1$ and $Q_2$ are the input transistors and act as drivers and $Q_3$ is a current source. The output voltage can be expressed as follows:

$$V_o = \max(V_1, V_2) - V_{off}, \tag{23}$$

where $V_1$, $V_2$ and $V_o$ are the input and output voltages respectively, and $V_{off}$ is the offset voltage of the circuit.

### 3.3. Defuzzification circuit

The last block in a fuzzy controller is the defuzzification circuit, which computes the sum of the output values of each rule weighted by its degree of certainty. In order to avoid the implementation of a division

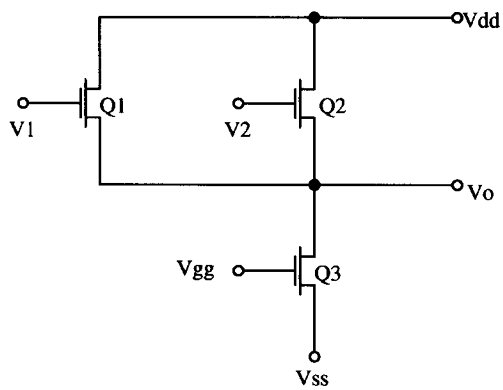


Fig. 6. A 2-input MAX operation circuit.

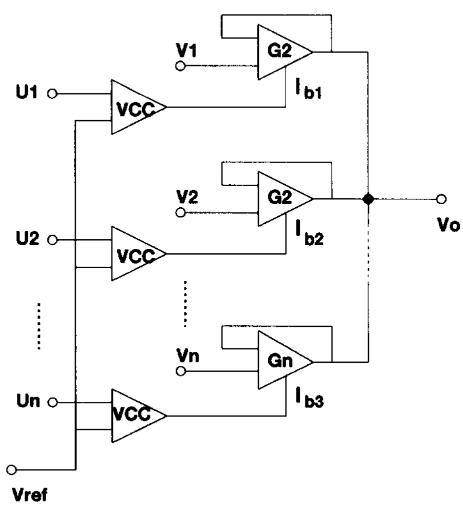


Fig. 7. The defuzzification circuit.

circuit, which is very area consuming, a high-speed follower-aggregation circuit [5] was used for the defuzzification block. According to Kirchhoff's current law the output of the follower-aggregation circuit (Fig. 7) is

$$V_o = \frac{\sum_{i=1}^{n} G_i V_i}{\sum_{i=1}^{n} G_i}. \tag{24}$$

This means $V_o$ is the average of the inputs $V_i$, where the contributions of each input to the output voltage is weighted by its transconductance $G_i$.

If we consider the voltage inputs $V_1, \ldots, V_n$ as the conclusion rules (see Fig. 2) and $G_1, \ldots, G_n$ the discrete values of the degree of certainty $\mu_1, \ldots, \mu_n$ of the output rules to the input then the output $V_o$ is the defuzzified answer of the fuzzy controller.

To keep the maximum and minimum voltage of the output independent of the input levels an additional reference voltage $V_{ref}$ is needed to calibrate the output.

## 4. Simulation and test results

The circuits were simulated with HSPICE. To verify the flexibility of the designed circuit we simulated and tested shape and position changes of the membership function circuit (MFC), the behavior of the MAX circuit for different input voltages, the connection in parallel of IF blocks and a complete fuzzy inference machine.

We present here only part of the test measurements. The shape changes of the membership function can be realized either by changing the sizes of the input devices of the differential amplifier ($Q_{i1}$ and $Q_{i2}$ in Fig. 4) or by changing the external reference voltage $V_{ri}$ and $V_{r(i+1)}$. The sizes of the input MOSFET's influence the slope, whereas the reference voltages influence the position and width of the membership function.

To get different linguistic terms like SMALL, BIG, etc. the output of the membership function can be translated to the wished value in the universe $U$ of discourse by changing the two reference voltages $V_{ri}$ and $V_{r(i+1)}$. Fig. 8 illustrates the output of the MFC for different reference voltages. The six chosen reference voltages were: $V_{ri} = (1.6 + 0.4 * i)\,V$, where $i = 0, 1, \ldots, 5$.

The width of the MFC is dependent on the difference $\Delta V_r$ between the two reference voltages $V_{ri}$ and $V_{r(i-1)}$. Fig. 9 illustrates different shape forms for the same linguistic term. The two membership function ladder-shape and Gauss-distribution correspond to $\Delta V_r = 0.8\,\mathrm{V}$ and $\Delta V_r = 0.4\,\mathrm{V}$, respectively.

One of the important test steps of the fuzzy controller is the test of the inference engine (IF–THEN Block) built with the above-described circuits. For the presented test we chose overlapping membership function with a width between the crosspoints of 0.4 V. Therefore the chosen crosspoints (CP) are equidistant. The linguistic terms SMALL ($S$), MEDIUM ($M$) and BIG ($B$) have their peak values $V_r$ at 2.2, 2.6 and 3.0 V, respectively.

The fuzzy rules have the following structure:

$R1$: if $X$ is $S$ and $Y$ is $S$ then $Z$ is $B$,

$R2$: if $X$ is $M$ and $Y$ is $M$ then $Z$ is $M$,

$R3$: if $X$ is $B$ and $Y$ is $B$ then $Z$ is $S$.

Fig. 10 shows the outputs of the rule circuit for two different input values. In the first example $X$ and $Y$ are 2.6 V, rule two is active and the membership function, values are $\mu_Z(B) = 0$, $\mu_Z(M) = 1.0$ and $\mu_Z(S) = 0$. In the second example $X$ and $Y$ are 2.8 V, rule two and three are active and the corresponding membership functions have the values $\mu_Z(B) = 0$, $\mu_Z(M) = 0.5$ and $\mu_Z(S) = 0.5$.

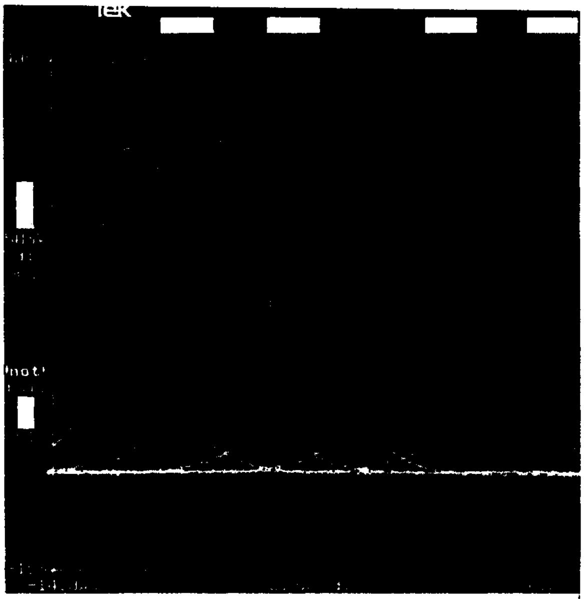

Fig. 8. Outputs of the membership function circuit.

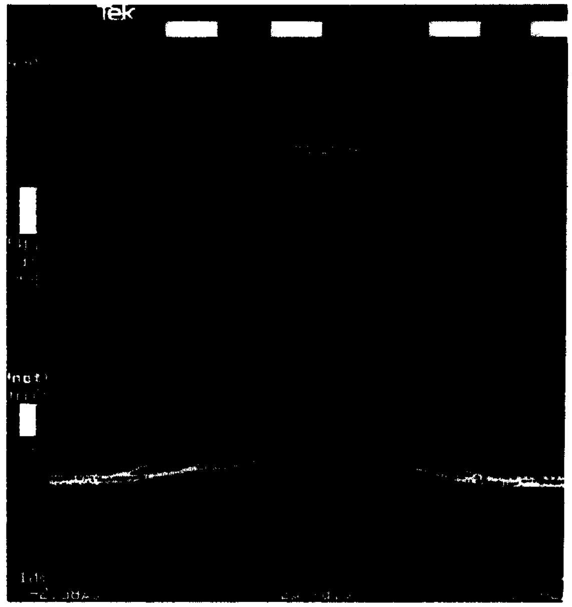

Fig. 9. Different shapes of the membership functions.

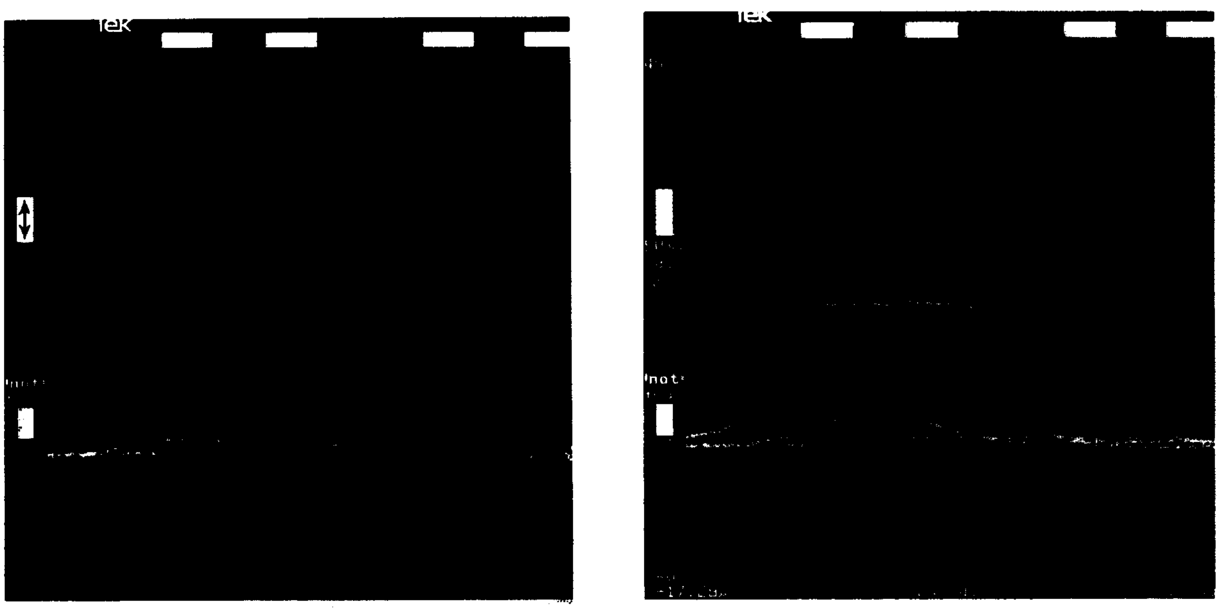

Fig. 10. The output of a 3 rule-block (a) $V_X = V_Y = 2.6\,\mathrm{V}$ and (b) $V_X = V_Y = 2.8\,\mathrm{V}$.

The tested prototype circuits fitted the simulation results very well. For the tested chips the inference process was completed within 0.5 μs. This is equivalent to 2 000 000 FIPS (fuzzy inferences per second).

To give an estimation of the needed area for an inference engine, the design area for a 9-term membership function circuit is 1500 μm by 210 μm. The circuits were implemented with a 2.4 μm double-poly process.

## 5. Application

The problem of adaptive damping systems was selected as a research paradigm in the test of qualitative reasoning systems because of the conflicting problems which have to be solved. Safety and ride comfort can have opposite demandings. The comfort requirements are dependent on the quality of the road, while the safety requirements on the driver's reaction. In general safety rules require a rough damping, while the comfort feeling requests a soft one [6]. To solve this conflict the requirements have to be analyzed giving adequate priority to each demand.

The analysis and evaluation of the driver's ride comfort feeling, preference, intentions, and operating capabilities [11] is difficult since they cannot be measured. A fuzzy description – using linguistic variables – is well suited for this purpose. Therefore the input of the comfort decision block should be related to fuzzy

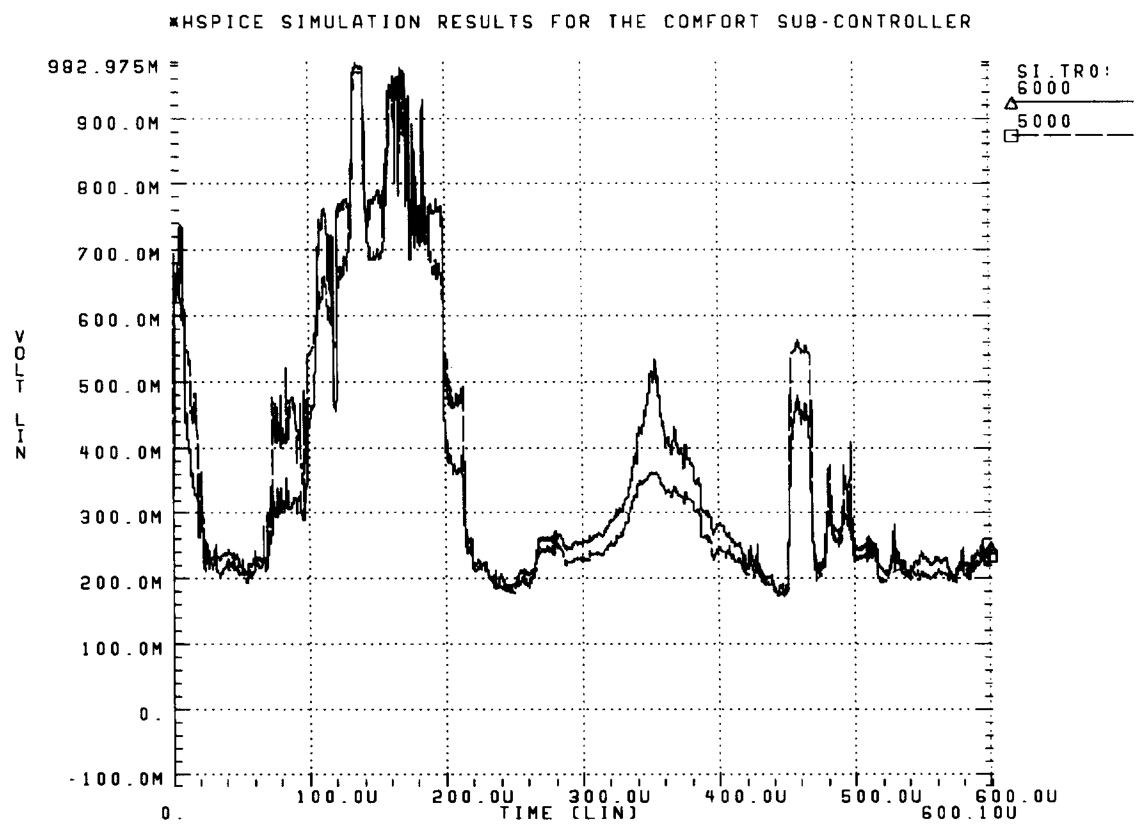


Fig. 11. Comparison of simulation results for the "comfort" controller. Dashed line: calculated simulation results; solid line: HSPICE hardware response. Time is given in 1/10 s.

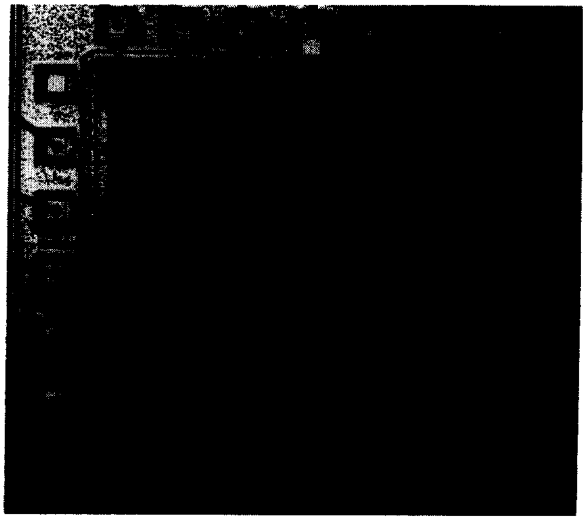

Fig. 12. Layout of the analog fuzzy controller.

linguistic values, like rough, bumpy, or smooth road. Ride comfort is dependent on the vertical acceleration of the car body and wheel. These values can be measured by sensors mounted on the car chassis.

The safety aspects depend mainly on the car speed and the action of the driver, e.g. when the driver turns the steering wheel, safety requirements call for a rough damping. Safety requirements can be correlated to the turning angle of the steering wheel, the car speed, and the use of brakes.

Based on the approach proposed by [7] the driver's comfort feeling can be improved by adjusting the damping system based on the measure of unevenness $H$ and waviness $W$. These two values are dependent on the car body and wheel acceleration. $H$ gives a qualitative measure of the street and depends on frequencies between 0–20 Hz. $W$ detects the low frequent spectrum of the street which is responsible for passengers feeling "car sick".

To test our analog fuzzy chip we developed based on the presented circuits an adaptive damping controller. As input the chip had $H(t)$ and $W(t)$ and as an output a voltage driving the damping system. In Fig. 11 we present the outputs from the hardware simulation of the controller overlapped over the software simulation of the controller which worked in a close loop. The controller was implemented with 13 rules and the output reflects the answer of the controller to a 60 s long street where several signal types were mixed:

- between 7–20 s – low-frequency waves near the resonance of the car body;
- between 27–40 s – waves around 10 Hz near the resonance of the engine and axle;
- at second 45 a small step was introduced.

Comparing both simulation results hardware and software it is easy to see, that the hardware implementation fits the software model developed. The hardware simulation results show even a faster adaption to changes than the software models did. The overall improvement of the comfort was about 22%.

The chip layout for this application is presented in Fig. 12 and has an area of $3750 \times 4270\,\mu m^2$ and a complexity of about 1400 transistors.

## 6. Summary

In this paper, we have proposed a novel architecture for analog fuzzy logic controller using voltage mode for input and output signals. The presented test results confirm the simulation. The small area needed for the

MFC implementation and the avoidance of a division circuit for the defuzzification makes it possible to implement a fuzzy controller on a small area. Another advantage of the controller is its analog in- and output which makes it very interesting for intelligent sensor application. Such an application was presented and the obtained results show an improvement over the standard solution. Future work will concentrate on the development of intelligent sensors where sensors and fuzzy controller are on the same die.

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