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Multi-parameter detection in fluid flows

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Abstract

A micromechanically fabricated thermal flow sensor is presented. The sensor incorporates multiple, 100 μm spaced, resistive sensing elements on a glass substrate in a silicon flow channel. This sensor works on the principle of a travelling heat pulse through the fluid. The response to this heat pulse at different positions upstream and downstream from a heater is used to determine not only flow velocities but also fluid properties. Theoretical analysis of the sensor response shows that the sensor is more able to discriminate between flow velocities and fluid properties when certain combinations of sensing element signals are used. It is shown that the sensor can also measure mass flow as long as the 'time of flight' of a heat pulse can be measured at equal distances from the heater upstream and downstream. Combination of the 'time of flight' at two different positions downstream can be used to determine the diffusivity of the fluid. The sensor can be made sensitive to flow velocity by taking the heat pulse response at two different locations downstream at an instant in time when the signal amplitudes are equal. The 'time of flight' measured at one position downstream is only accurate when the velocities are high enough since the diffusive effect can be neglected. The ability of an artificial neural network to learn to discriminate between the flow velocity and fluid properties is analyzed.

Keywords: Fluid flow; Thermal flow sensor

1. Introduction

Parameter detection in fluid flows is mostly carried out by selective sensors which are designed to detect only one physical or chemical parameter. Many fluid sensors have been made this way to detect mass-flow or velocity, gas concentration in mixtures or thermal properties, such as thermal conductivity and heat capacity. When a sensor is not optimized for one parameter, and is still sensitive to other parameters, it seems a logical step to investigate the detection of these other parameters with non-selective sensors. A single measurement with one sensor does not provide any selectivity.

Glatzmaier and Ramirez show that by using a steady state measurement followed by a transient measurement, one can determine two parameters [1]. Another method, which has been used in gas discrimination is to operate two identical sensors at different states [2]. The approach discussed in this paper uses micromachining techniques to locate multiple sensing elements in a small area around the sensor actuation element. A discussion on the location/placement of the detection elements is given by El Jai [3] in his paper on sensor and actuator placement for linear systems.

In our work multi-parameter detection is achieved with thermal flow sensors. The thermal flow sensing system is non-linear by nature. A theoretical model describing the transduction of thermal pulse signals is given, which is then expanded to multi-parameter detection. This model is then used to optimize the measurement signals for an artificial neural network (ANN).

2. Thermal flow sensing using pulse signals

In our laboratory we have knowledge about thermal flow sensors [4]. The detection scheme of these sensors was altered from static thermal signals to dynamic thermal signals, since this enables us to distinguish more parameters. The architecture of the sensor is given in Fig. 1. The heater (a resistor) provides a thermal pulse. This pulse is taken by the flow and diffuses in the fluid. At small distances upstream and downstream the thermal response is measured using resistive elements.

The transport of the heat generated in a line source through a fluid is governed by the combined diffusion, forced convection equation:

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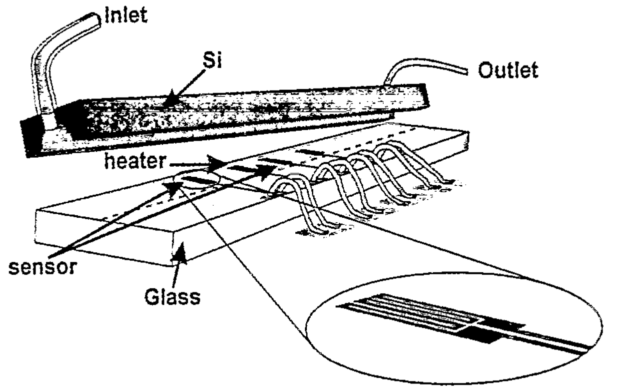

Fig. 1. Exploded view of the thermal flow sensor.

$$\frac{\partial T}{\partial t}+u\nabla T=\frac{k}{\rho c}\nabla^2 T+\frac{Q}{\rho c} \quad (1)$$

where Q denotes the heat introduced into the flow (J), T the temperature (K), k the thermal conductivity (W m^{-1} K^{-1}), ρ the density (kg m^{-3}), t the time (s), u the average flow velocity (m s^{-1}) and c the heat capacity (J kg^{-1} K^{-1}). The analytical solution of this differential equation for a pulse signal with input strength Q_0 (J m^{-1}) is given by Marchal [5]:

$$T(x, y, t)=\frac{Q_0}{4\pi kt}\exp\left\{-\left[\frac{(x-ut)^2+y^2}{4\alpha t}\right]\right\} \quad (2)$$

where α denotes the thermal diffusivity (m^2 s^{-1}). By measuring the top time τ at which the signal passes the detection element ($y=0$), in other words differentiating Eq. (2) with respect to time, one can obtain the basic equation for the so-called 'time of flight' of the heat pulse:

$$u=\frac{x}{t} \quad (3)$$

For Eq. (3) to be valid the term $4\alpha\tau$ must be much smaller than the heater–sensor distance x; this assumes that forced convection by the flow is dominating over the diffusive component. In other words Eq. (3) is true at high flow velocities. When the diffusive effect is taken into account the top time is given by

$$t_{\text{top}}=\tau=\frac{-2\alpha}{u^2}+\frac{[4\alpha^2+u^2x^2]^{1/2}}{u^2} \qquad u\neq 0 \quad (4)$$

$$\tau=\frac{x^2}{4\alpha} \qquad u=0$$

In micromechanical devices we can assume that the diffusive part of the equation is the dominating factor.

3. Multi-parameter detection

Let us consider two sensing elements at a distance x_1 and x_2 from the heater where the two top times τ_1 and τ_2 are measured. With Eq. (4) we find:

$$\alpha=\frac{(\tau_1^2x_2^2-\tau_2^2x_1^2)}{4(\tau_2\tau_1^2-\tau_1\tau_2^2)} \quad (5)$$

$$u=\left(\frac{\tau_1x_2^2-\tau_2x_1^2}{\tau_1\tau_2^2-\tau_2\tau_1^2}\right)^{1/2} \quad (6)$$

From these equations the velocity of the flow and diffusivity of the fluid can be determined. The flow velocity can be determined independently, by choosing different measuring points in time at x_1 and x_2. If the measurement is taken at the time when the temperature increase at the two sensing elements is equal, one can deduce from Eq. (2):

$$u=\frac{x_1+x_2}{2t} \quad (7)$$

Lambert [8] shows that for heat waves and steady state convective heat exchange the response of these sensors to mass flow is independent of pressure. In this case the output is determined by the Peclet number (Pe). Pe is proportional to u/α and is only a function of mass flow if α/ρ is independent of pressure. With heat pulses it is also possible to measure the mass flow by taking the natural logarithm of the output signal at a distance x and $-x$ from the heater at the top time τ:

$$\frac{u}{\alpha}=\frac{1}{x}\ln\left[\frac{T_{\max,+x}}{T_{\max,-x}}\right] \quad (8)$$

This equation is independent of time.

4. Parameter extraction

In the previous section it was shown that a combination of detection elements at different locations is capable of discriminating flow parameters. In other words a fluid flow can be characterized by an array sensor. In addition, the above equations are also valid for mixtures of fluids, where the parameters in Eq. (2) are those of the mixture. The parameter extraction from the measurements is achieved using an artificial neural network. Since a function approximation is needed a multi-layer perceptron network is chosen, whereas for gas discrimination a Kohonen network is often used [6]. The use of the multi-layer perceptron network is further discussed in the paper by Lammerink et al.[7].

The mathematics of the previous section can be used to allocate sensing elements or, as has been done in our work, to reduce input data for a neural network. Besides this we can draw some conclusions on the learning ability of the neural network to compute a relationship between measured values and fluid parameters. One of the conclusions is that the neural network may be inefficient in determining the relation between small flow velocities and the top time. This is because the differential sensitivity for velocities around zero, as derived from Eq. (4), is equal to zero:

$$\frac{\partial\tau(u=0)}{\partial u}=\frac{\partial}{\partial u}\left(\frac{x^2}{4\alpha}\right)_{u=0}=0 \qquad (9)$$

Therefore Eq. (6) cannot be used. However, we have shown that other sensor element locations and combinations can be used to determine the velocity. Eq. (7) is best suited to do this. This equation is similar to the linear time-of-flight Eq. (3), but is fundamentally different since it does not use the top time. Eq. (5) is suited to determine the diffusivity and this gives the thermal conductivity, together with Eq. (2). Thus the sensor design should be such that the top times are measured to determine fluid properties, and signal amplitudes are used to determine flow velocities. More sensing elements can be placed upstream to extend the range for measuring the velocity, using Eq. (7). For higher velocities Eq. (3) is valid.

The theory in this paper was tested using an artificial neural network. The ANN is better at discriminating between velocity and diffusivity using top times for diffusivity and the equal temperature for velocity than it is at using top times only. The velocity was varied between 0.1 and 100 mm s^{-1} and the diffusivity was varied by using different concentrations of helium in a helium–nitrogen mixture. Fig. 2 shows the errors which the network makes using the different techniques.

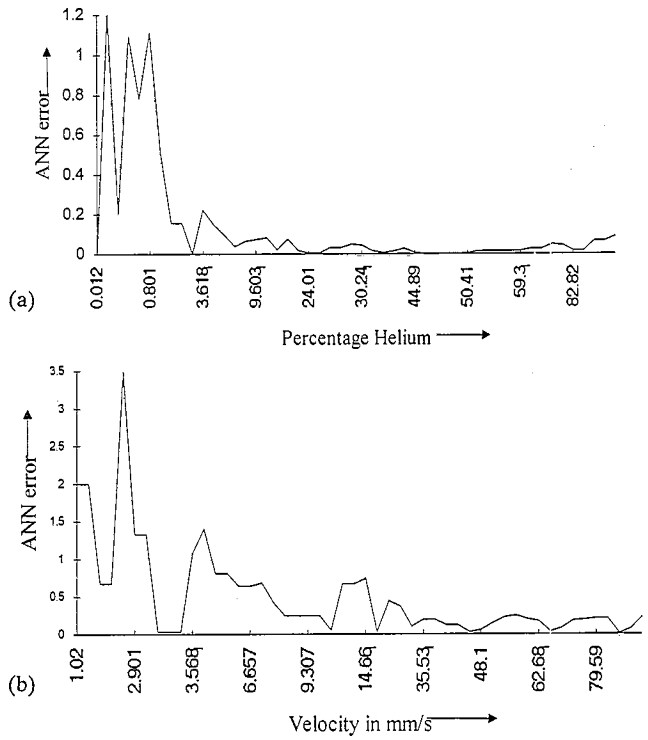

Fig. 2. ANN error as a function of (a) helium concentration and, (b) flow velocities between 0.1 and 100 mm s^{-1}.

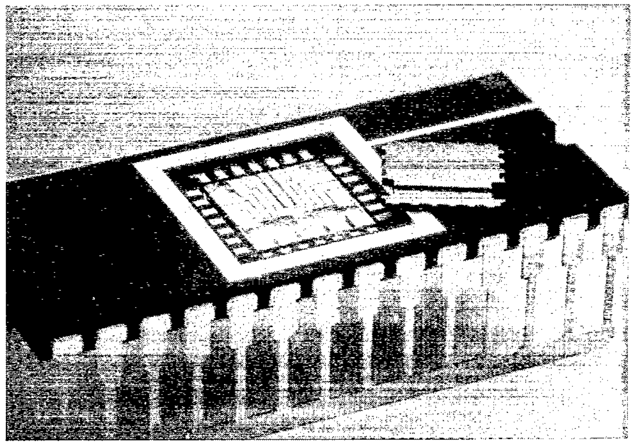

Fig. 3. Picture of a packaged flow sensor. The flow channel has been removed to show the sensor.

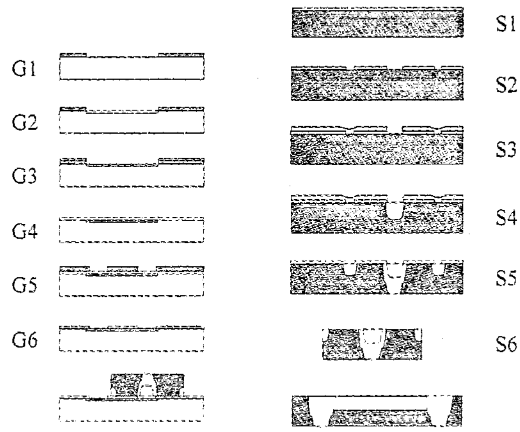

Fig. 4. Process steps for sensor fabrication (left) and flow channel fabrication (right).

Fig. 2(a) shows that the network makes large errors when determining the diffusivity at low helium concentrations; Fig. 2(b) shows that the network also makes larger errors when determining the velocity around zero flow.

5. Sensor fabrication

A picture of the packaged sensor is shown in Fig. 3. The fabrication process is shown in Fig. 4. The die size is 7 mm by 7 mm. The flow channel is 300 μm wide and the actual sensor consisting of 9 meander shaped resistor elements is 300 μm long and 100 μm wide, 100 μm spaced.

The sensing elements are fabricated on a Hoya [9] glass wafer. First, the glass wafer is coated with resist and patterned (G1). The glass wafer is etched in HF to lower the metal (Pt) pattern (G2) which is then sputtered on (G3), after which the Pt pattern is formed by lift-off technique in acetone. Next a glass layer of 1 μm is sputtered (G4) so that an anodic bond to the silicon wafer may be made later. A resist layer is spun on and patterned (G5) to etch away the glass in HF thus opening the sensing elements and bondpads (G6). The flow channels are fabricated in the silicon wafer by reactive ion etching, in a double mask process. The first mask, sputtered AlO_x (S1), contains the channel and feedthrough pattern (S2). On top of this mask an Al mask is evaporated (S3) which contains only the feedthroughs. The silicon is now etched using an SF_6–O_2 plasma to a depth equalling the wafer thickness minus the channel depth (S4). The next step is to remove the Al mask and etch through the silicon wafer, in the same manner as the first etch step (S5). Then the AlO_x is removed and the wafer is cleaned (S6). The silicon and glass wafer are then anodically bonded together, after which the sensor is packaged.

6. Conclusions

A multi-sensing element multi-parameter sensor is demonstrated. The use of different sensing element signals allows the flow velocity and fluid properties to be distinguished. Just the response of one heater signal is needed to make the distinction. The theoretical results of sensor location are verified by the learning ability of the artificial neural network to different inputs for different outputs. The sensor itself is fabricated in a simple process, separate from the flow channel fabrication process.

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References

[1] G.C. Glatzmaier and W.F. Ramirez, Simultaneous measurement of the thermal conductivity and thermal diffusivity of unconsolidated materials by the transient hot wire method, *Rev. Sci. Instrum., 56* (1985) 1394–1398.

[2] F.A.M. Davide and A. D'Amico, Pattern recognition from sensor arrays: theoretical considerations, *Sensors and Actuators A, 32* (1992) 507–518.

[3] A. El Jai, Distributed system analysis via sensors and actuators, *Sensors and Actuators A, 29* (1991) 1–11.

[4] T.S.J. Lammerink, N.R. Tas, M. Elwenspoek and J.H.J. Fluitman, Micro-liquid flow sensor, *Sensors and Actuators A, 37–38* (1993) 45–50.

[5] D.C. Marshall, Measurement of sap flow in conifers by heat transport, *Plant Physiol., 33* (1958) 385–396.

[6] D.R. Bull, G.J. Harris and A.B. Ben Rashed, A connectionist approach to fuel cell sensor array processing for gas discrimination, *Sensors and Actuators B, 15–16* (1993) 151–161.

[7] T.S.J. Lammerink, F. Dijkstra, Z. Houkes and J. van Kuijk, Intelligent gas-mixture flow sensor, *Sensors and Actuators A, 46–47* (1995) 380–384.

[8] D.K. Lambert, Mass flow sensing with heat waves: the effect of gas pressure, *Int. J. Heat Mass Transfer, 36* (1993) 2623–2634.

[9] Hoya Europe B.V., Electronics Division Special Hoya glass with an expansion coefficient of silicon.

Biographies

Joost van Kuijk graduated from Delft University in 1992 from the Department of Mechanical Engineering in the field of precision engineering. He then followed a two year designer education at the MESA Research Institute within the Micromechanics group. His subject of research was the distributed flow sensor presented here. Joost is currently working on his Ph.D. degree in the same Micromechanics group. His current research area is the development of a micropump based on LIGA and silicon technology together with the Institute für Micromechanic Mainz (IMM).

Theo Lammerink graduated from Twente University in 1982 from the Department of Electrical Engineering. He received his Ph.D. degree for his thesis on optical operation of micromechanical resonator sensors in 1990. Since then he has been working as a university teacher at the MESA Research Institute within the Micromechanics group specializing in the field of fluid handling systems.

Hans-Elias de Bree graduated from Twente University in 1994 from the Department of Electrical Engineering. His thesis was on the electronic measurement circuit for the sensor described in this paper. He is currently working as an assistant in the Micromechanics group, waiting to start his Ph.D. research on an acoustic sensor.