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Intelligent high resolution sensor for detecting of liquid mediums

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The paper presents the construction and working principles of intelligent sensor used for detecting water, alcohol, oil and oil modified samples. The sensor consists of an intensity fibre head mounted on lift and computer measurement device with a detection block. The head works on the Fresnel reflection intensity basis and is the ending of large core polymer optical fibre. The optical signal from the head is converted in optoelectronic interface and fed into detection block. The detection is based on the pre-processed data which was passed to the neural network. The sensor inelegance is effect of simultaneous indirect examination of different physical phenomena. They occur during the head submerging, submersion, emerging and emergence in the detected medium.

1. Sensor construction

The sensor consists of three functional blocks: a measuring block, a mini-lift of the head block and optic block, as schematically represented in Fig. 1.

The measuring block is built on the basis of PC computer, input-output cards and optoelectronic interface [1], [2]. The task of the block consists in data

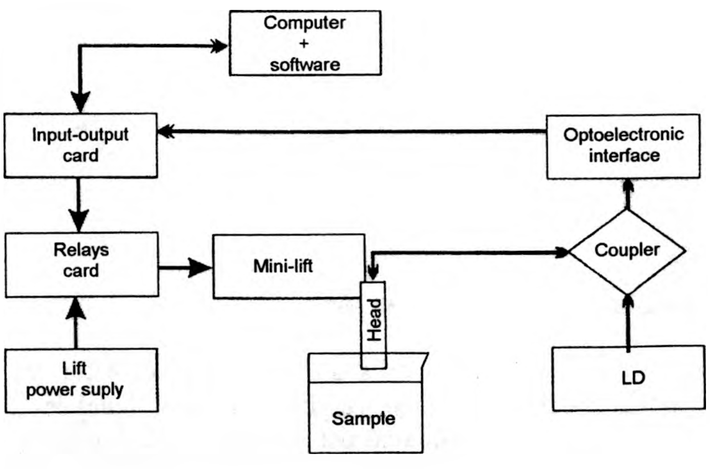

Fig. 1. Block diagram of automatic sensor.

acquisition and processing. It also controls the movement of a few centimetres of the measuring head that is mounted on a mini-lift. The mini-lift has been used to ensure the repeatability of the measuring cycle. The optic block consists of fibre optic head which is connected by a coupler to the semiconductor laser and optoelectronic interface. The head of the sensor is the ending of the large core polymer optical fibre PFM-22E-750 made by Toray that is resistant to the degrading activity of the oil. The coupler was made on the same fibre, since its core of 750 μm in diameter enables stable connection with the source of light [3]. The head construction with telecommunication multimode fibre were also examined. The test showed that polymer large core fibre is more suitable for this application than telecommunication multimode one because of mechanical (flexibility), and optical (large numerical aperture) properties. A semiconductor laser was used as the light source. It has stabilised 3 mW power, a wavelength of 670 nm, and 1 kHz amplitude modulation. The optical output signal from the optic block is received by optoelectronic interface presented in [4].

2. Measuring procedure

The cycle of measuring procedure includes: submerging, submersion, emerging and emergence of the head from the tested liquid. The transient response of the light reflected from the tested medium, observed during the measuring cycle, includes data on the type of liquid. A typical characteristic of full the measuring cycles is shown in Fig. 2.

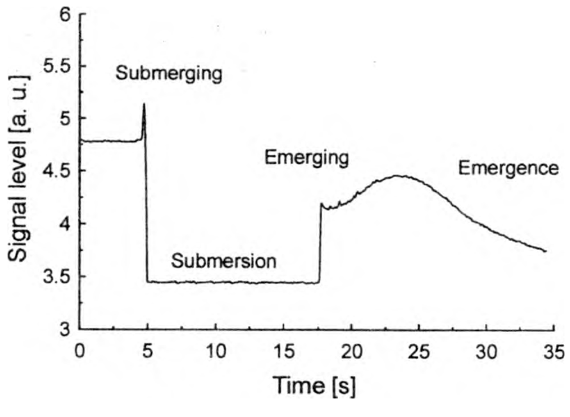

Fig. 2. Full measuring cycle in the time domain for eatable oil sample.

During the submerging process the head works as a distance detector. In submersion the head position in medium is stable. In this case, the signal level reflected from the liquid-core border can be estimated using the relation describing the Fresnel reflection coefficient [5]. If the input signal power level is assumed to be 100%, the relative power of reflected signal can be estimated according to Fig. 3.

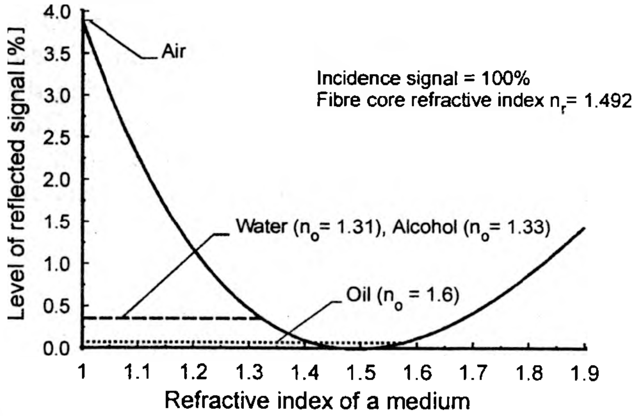

Fig. 3. Reflected signal from a submersed head.

As a result of the above calculation it is possible to distinguish between signals reflected from water, oil and alcohol on the basis of Fresnel phenomenon, during the head immersion. This task is difficult due to the low level of received signals and slight differences between them. The level of received signal is determined by the input signal power, its reflection on fibre tip and by the efficiency of the coupler launching optical signal to the head and from the head to the detector. The slight difference between signals for the medium under examination is due to their low refractive index distinctions. Therefore, the reasonable solution is to make use of information involved in successive phases of measuring cycle.

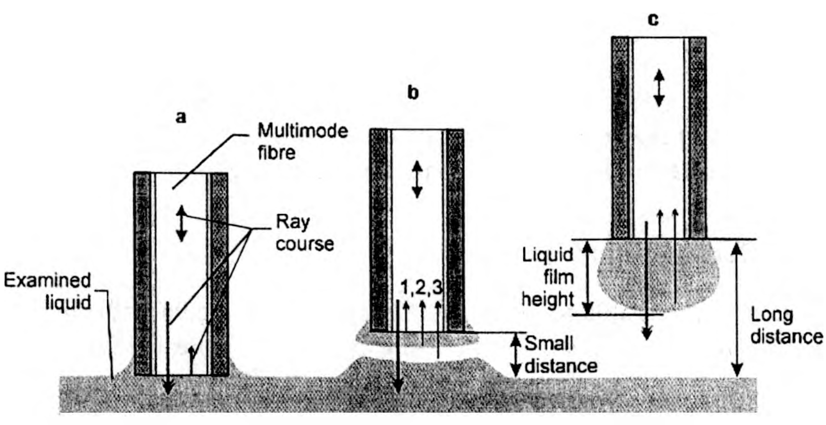

Fig. 4. Emerging of the sensor from the liquid under examination.

The next phase of the measuring cycle is the emerging of the head. At the moment of pulling out the ending of the head out of the liquid, the meniscus and then drops appear on it.

The maximum estimated level of the reflected signal for situations presented in Fig. 4 equals 10.19% of input signal for oil and 4.08% for water and alcohol. These values are true only when the head is perpendicular to liquid surface. During the emergence, drops or thin layers of liquid are formed on the ending of the optic fibre. In this case, the signal level was calculated using a numerical simulation method, according to the non-linear ray tracing principles [2]. Results of simulations are presented in Fig 5.

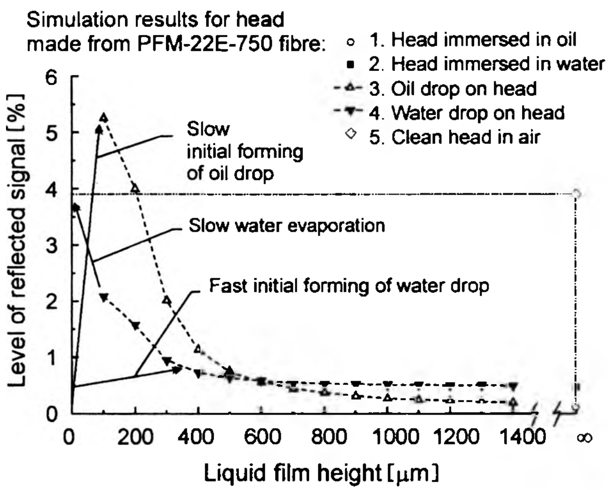

Fig. 5. Slow variation and constant reflected signals coming from the head.

The results show that the of signal level transient in the emergence state can significantly differ for oil, water and alcohol. Signal level for oil medium should first increase, then decrease as a result of drop forming. Signal levels for water and alcohol should increase as a result of liquid evaporation. In this case, the increasing of signal level should be faster for alcohol than for water medium.

3. Recognizing different liquid types

The theory shows that it is possible to recognize different liquid media with similar index of refraction. Signals from particular measuring cycles were collected for water, oil and alcohol.

The signals collected during measuring cycles for one medium are well repeatable. What follows from this fact is the characteristic features of the particular signal or the measuring cycle, collected into a model, can be used for the media recognition. For recognizing the data models a neural network can be employed. Its use for the recognition of oil, water and alcohol media seems especially reasonable due to the small differences between signals recorded for particular media, for the case of immersed head. The signal data model included the following: starting level,

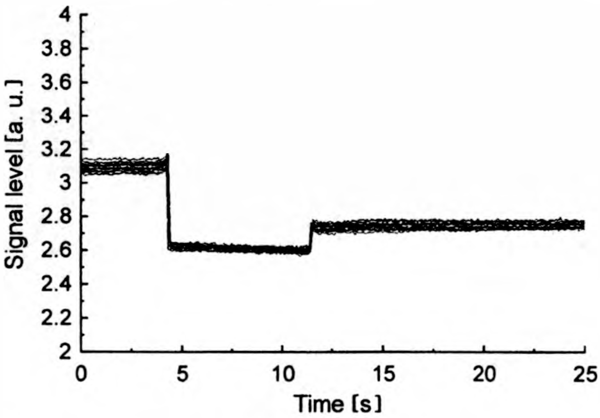

Fig. 6. Measuring cycles for water sample.

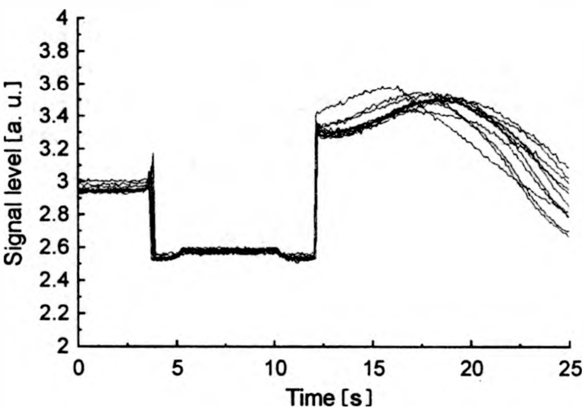

Fig. 7. Measuring cycles for eatable oil sample.

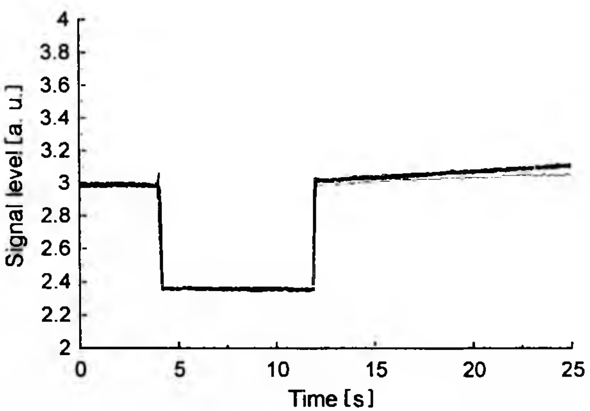

Fig. 8. Measuring cycles for alcohol sample.

maximum level during the submersion process, level in the submersion, levels during the emergence process determined by the time of the measurement for: 12.5, 15.0, 17.5, 20.0, 22.5, 25.0 s, as moving average of 3 measurement points in ± 0.1 s time. Because three media were assumed for detection, a network with three outputs was designed. The output signal was assumed within the range 0 – 1, according to Tab. 1. All other liquids were classified outside those values.

Table 1. Assumed network output signals.

Signal/Input No.	1	2	3
Oil	1	0	0
Water	0	1	0
Alcohol	0	0	1

For the learning process a multilayer perception [6] network with the following parameters was selected: 4 layers, input layer with 9 elements and 9 inputs, with a linear transfer function, first hidden layer, 7 elements with sigmoid transfer function, second hidden layer, 5 elements with sigmoid transfer function, output layer, 3 element with sigmoid transfer function. The training process of the network was worked out for data presented in Figs. 6, 7 and 8, that is, 30 data models with 6 test data models. The training errors for 1000 iterations of the "back propagation" algorithm are presented in Tab. 2.

Table 2. Network statistics.

Data type	Output No.	Standard deviation	Maximal error
Learning model	1	0.00647	0.01328
	2	0.00875	0.02378
	3	0.00973	0.02714
Testing model	1	0.02094	0.05800
	2	0.01148	0.01770
	3	0.03041	0.07939

The network statistics show that the training process of the desired features occurred. The trained network was tested for oil, water and alcohol discrimination. The output signals of it for newly collected and converted data are presented in Tab. 3.

The results presented in Tab. 3 show that there is no difficulty in recognizing the liquids in the system proposed. To this end, it is enough to set the threshold recognition level for network outputs according to their maximal error presented in Tab. 2 [7]. Liquids that give the signal outside those limits should be treated as not defined in the sensor system.

Table 3. Responses of recalled network.

Liquid	Sample No.	Network answer on output No.		
		1	2	3
Oil	13	0.98557	0.07486	−0.05061
	14	1.00101	0.05216	−0.0477
Water	13	0.00543	1.0047	−0.01153
	14	0.00067	1.01315	−0.01494
Alcohol	13	−0.00812	−0.01068	1.01637
	14	−0.00731	−0.0118	1.01652

4. Recognition of liquid modification

A liquid with modified properties could be recognised in the similar way as liquid type. The data of eatable oil with modifications were gathered. The frying process was chosen as modification. Oil was fried individually and with chips. The data collected show that for oil modification recognition the depth of head submersion is very important because it influences the drop forming process. The head should be submersed at a depth of 10 mm (see Figs. 9 and 10).

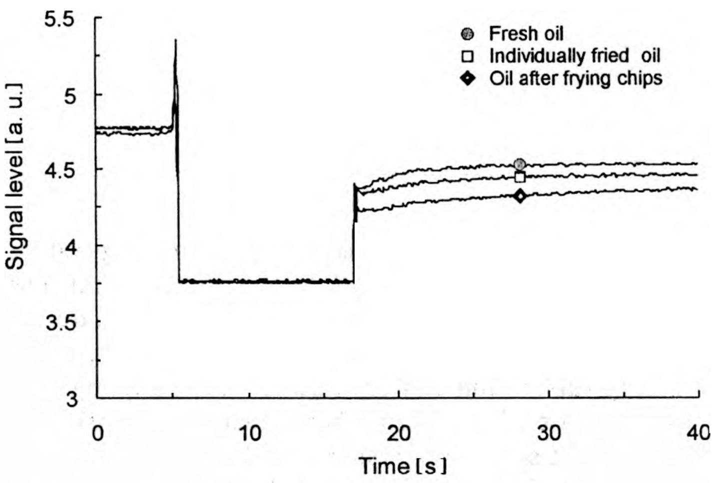

Fig. 9. Measuring cycles for the head immersed 1 mm in oil.

The data from Figures 9 and 10 show that individually fried and fresh oil have more similar characteristic than oil fried with chips, therefore their recognition will be more difficult. For this reason the experiment was performed with individually

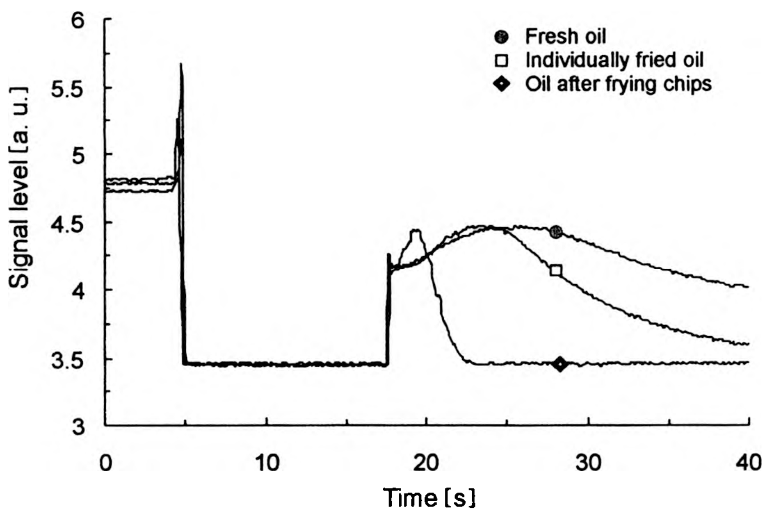

Fig. 10. Measuring cycles for head immersed 10 mm in oil.

Table 4. Responses of neural network trained in liquid modification recognition.

Oil	Network answer	
	Assumed	Achieved
Fresh No. 1	1	0.81
Fresh No. 2	1	0.95
Fried No. 1	0	−0.02
Fried No. 2	0	−0.02

fried and fresh oil. The temperature of the medium was held at room temperature and after each measuring cycle the head was cleaned with benzene and alcohol. The data model included the following signal levels: starting, submersion, levels during the emergence process for: 18, 20, 25, 30, 35, 40 seconds of measuring cycle. The maximum signal level during submersion was omitted and the sampling time lengthened in comparison with the case of recognizing liquid type. A network with one output was designed. The output signal was assumed within the range $0-1$, with 1 standing for fresh oil and 0 the fried one. The network was trained with 20 data samples without test ones. The learning RMS error equals 2%. The modification recognition results are presented in Tab. 4.

These results demonstrate that presented system correctly identifies liquid modification as well.

5. Conclusions

In the presented paper, the trained neural network distinguishes between different types of liquids and liquids with modifications. The neural network, due to the use of additional information about the liquid-optic-fibre interaction, obtained during the head emmergence processes, detects more precisely and repeatable the tested medium than a classic sensor that uses only the differences of the signal during head submerging. The data collected shows that for oil modification recognition the depth of head submersion is most important because it influences the drop forming process. The neural network input interrogator* [8], shows that 30 up to 60% of information about liquid results from the head emergence state. The sample memorisation which took place in this sensor network can be an advantage when recognition completely different types of liquid is considered. In such a case there is no place for neural network generalisation propriety. This way a small number of good quality samples can be used for network learning process.

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*Neural network input interrogator is often useful to determine what inputs are important to a network's output response. For this purpose the following procedure is implemented. On separated network inputs the training pattern is served. On the base of trained and obtained results the sensitivity of output signal on the input node is calculated and the results are normalised. The procedure is realised for all training patterns, then the outcome is averaged.