New Trends on Odor Sensing and Classification

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Outline of the Lecture

- Human olfactory mechanism
- Odor sensing system
- Odor classification
- Odor evaluation
- Future research for odor processing
- Conclusions

Five Senses

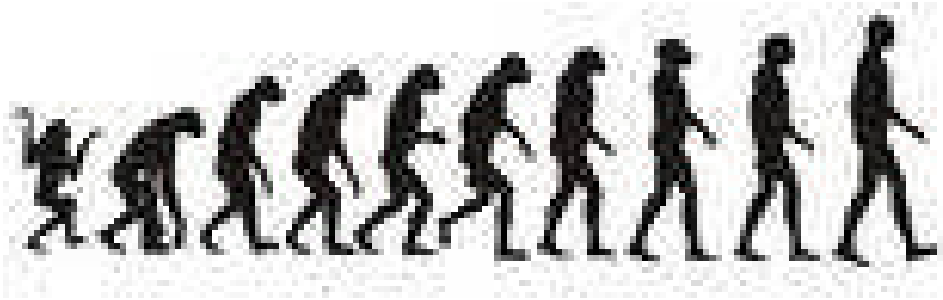
- Living organisms (in the beginning)

Genetically

sense of smell,

sense of taste

- Animals/Human being

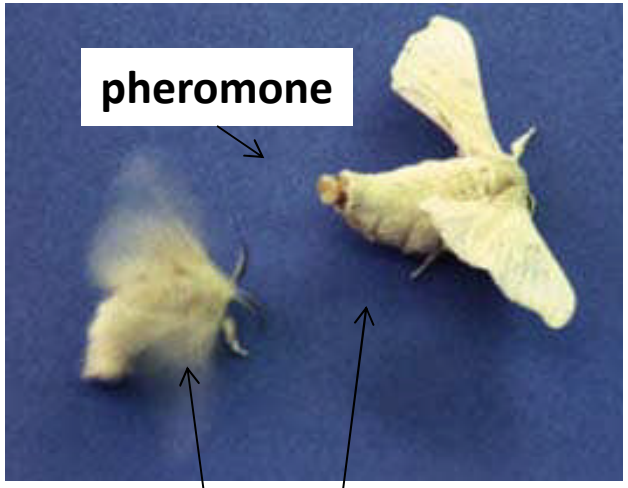


sense of touch

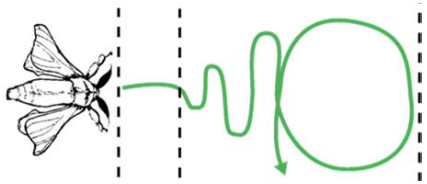
sense of hearing

sense of sight (90%)

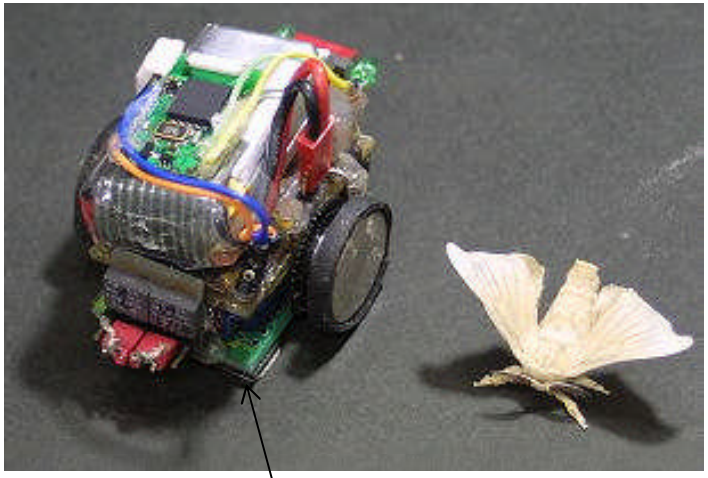
Silkworm Moth Odor Searching



male, female



Motion pattern



Odor Source searching robot

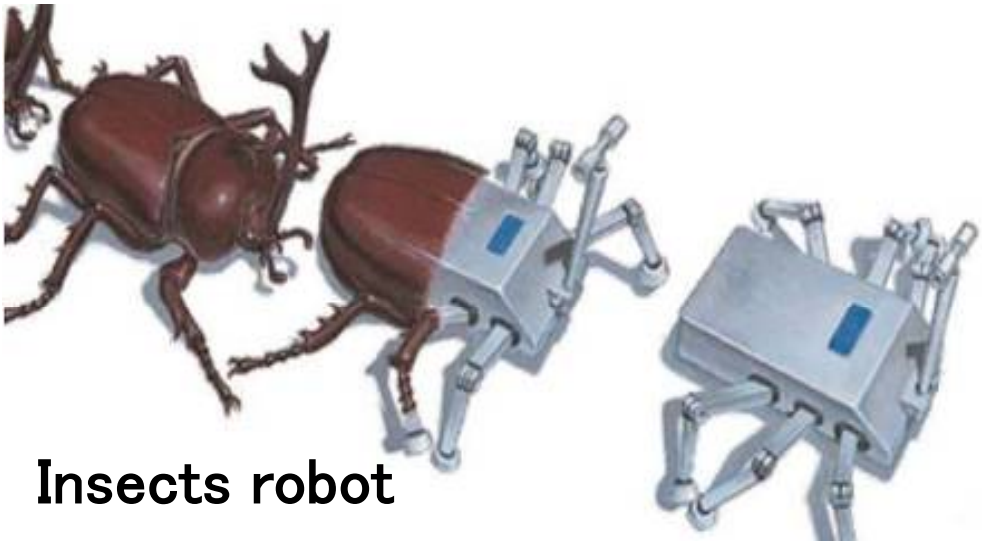
feeleran antennae

Pheromone transmission

By Prof. Kanzaki (Univ. of Tokyo)

Roles of Nose for Technology

- Drug-sniffing dog



Insects robot

- Bad smell

3 months rule

pulp mills

Role of Nose for Culture

- Traditional Culture
  - perfume

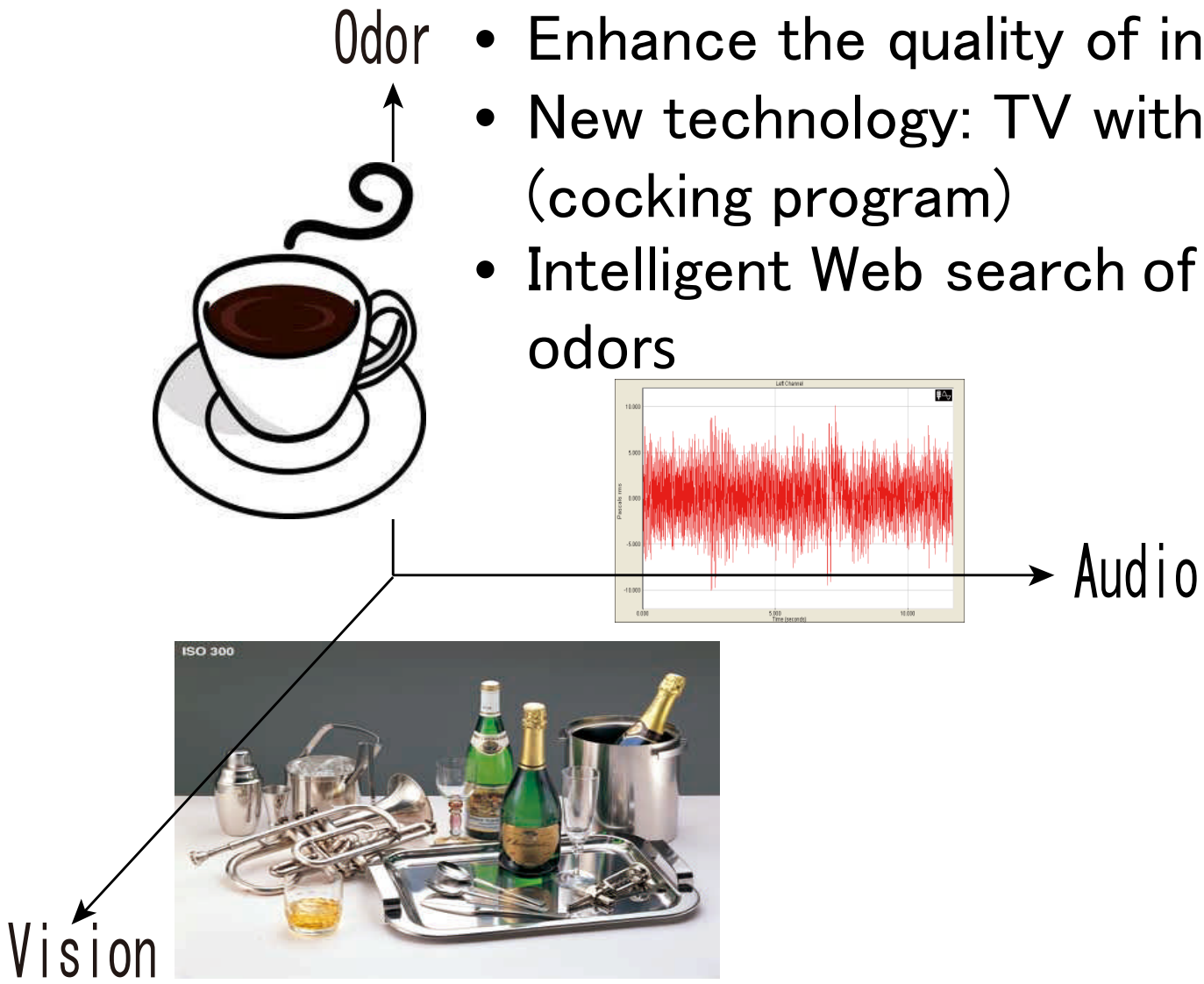
canine

  - fragrance

perfumer

joss stick

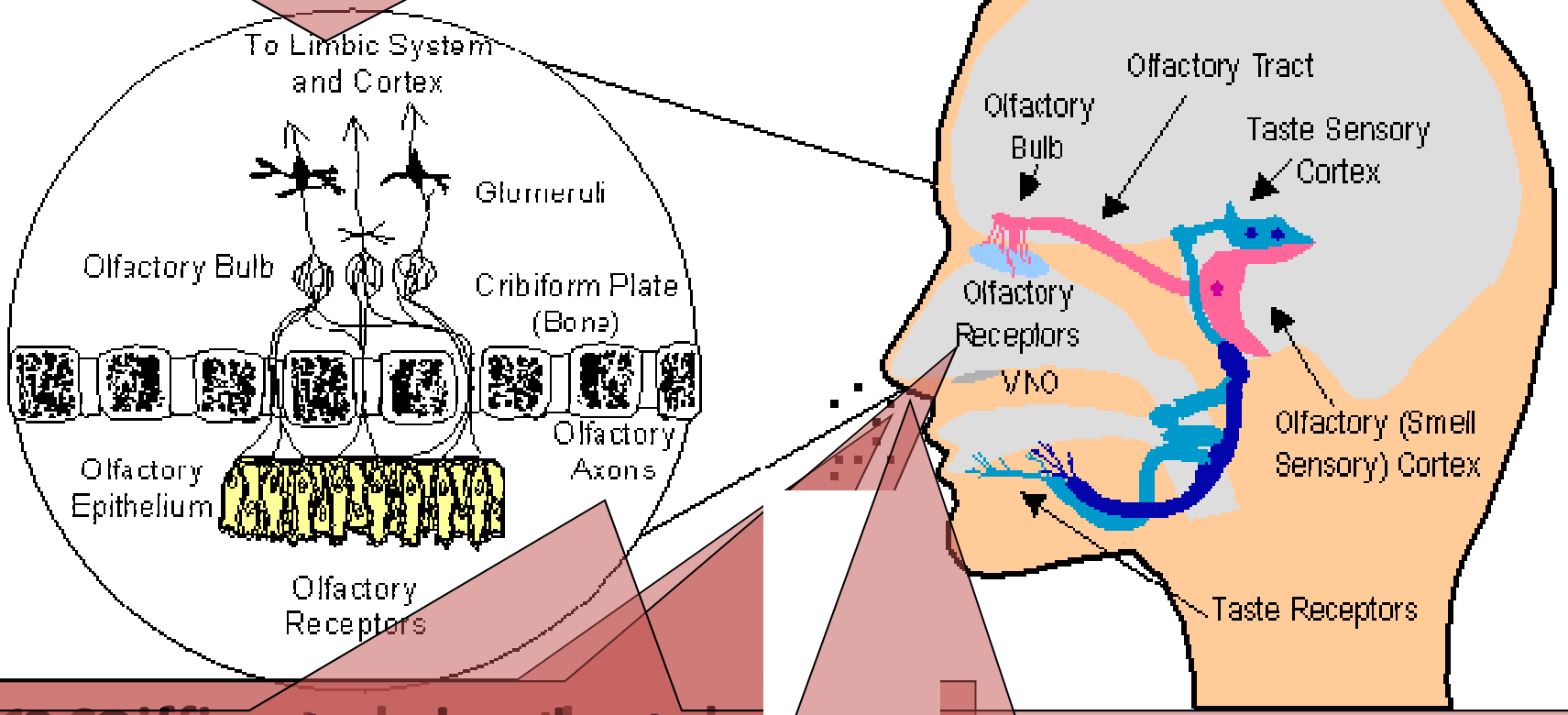
Aim of Odor Research



- Enhance the quality of information
- New technology: TV with odor (cocking program)
- Intelligent Web search of special odors

Human Olfactory Mechanism

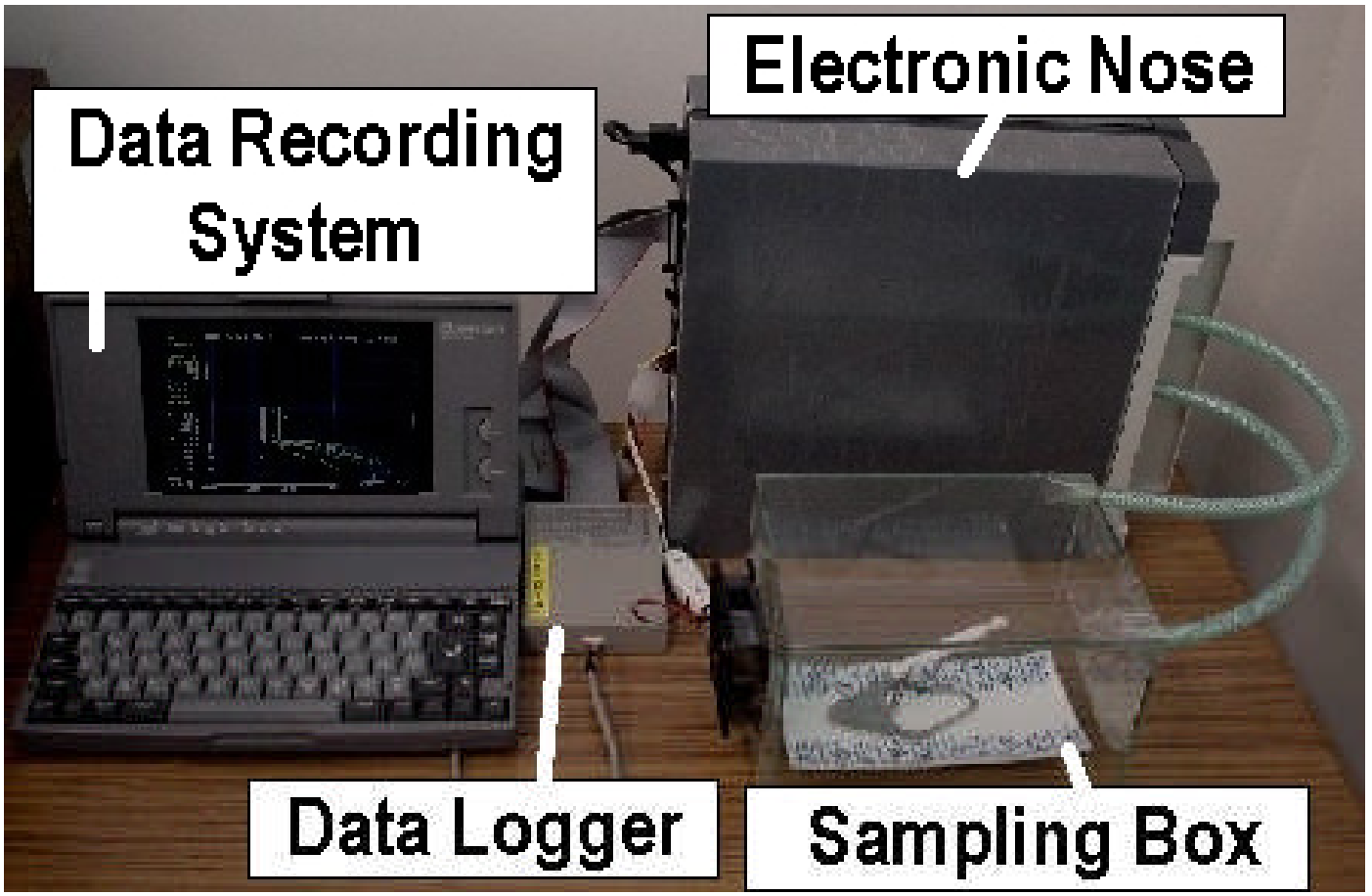
5.The olfactory information is transmitted to the cerebral cortex(the advance portion of brain))



3. Chemical reaction in receptors produces electrical stimulus and 6.Cleaning by breathing fresh air in order to test the new smell

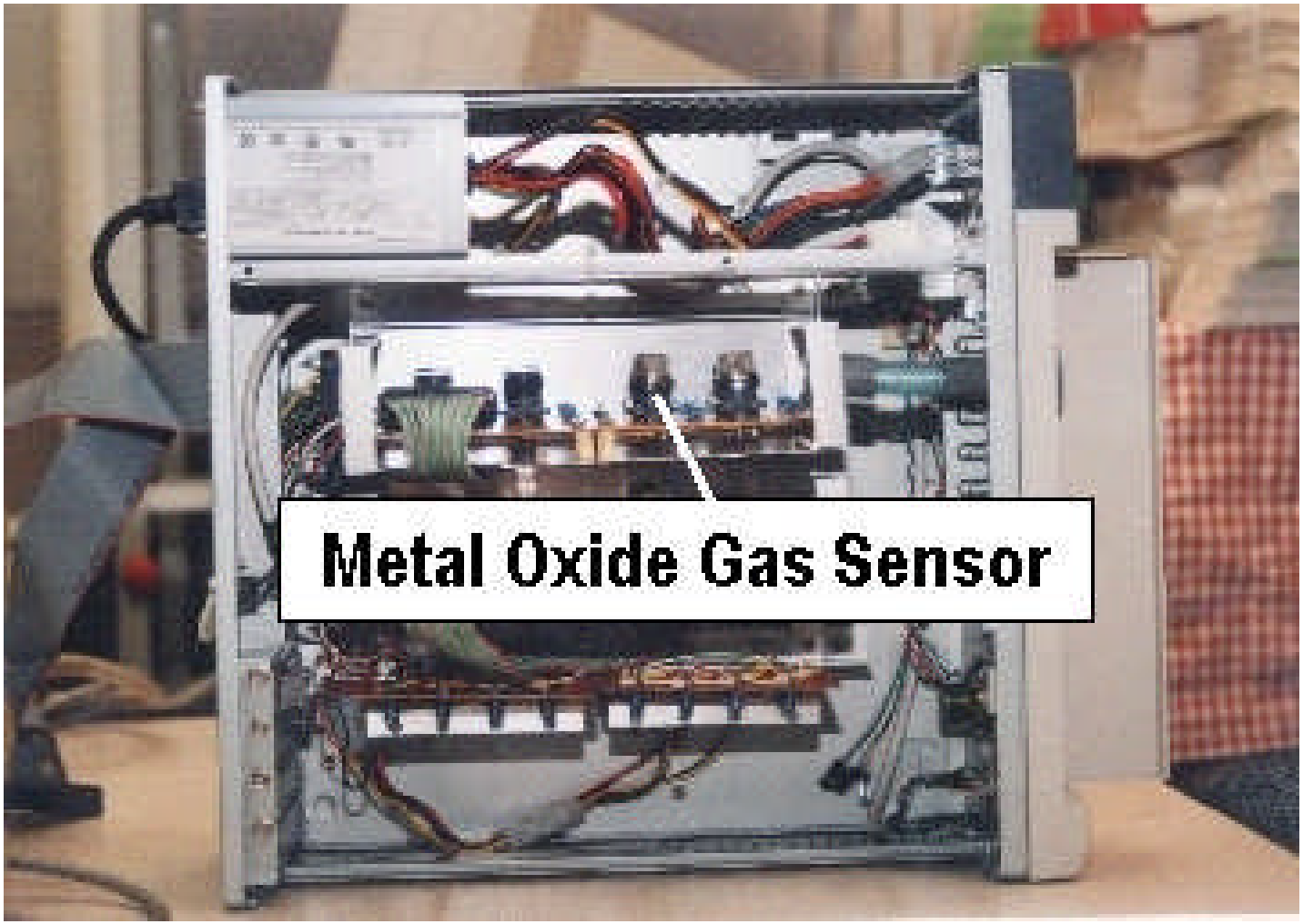
Source: *http://www.emsl.pnl.gov:2080/proj/neuron/papers/keller.spie99a.html*

Prototype of Electronic Nose System



- A simple EN without a mechanism to control measuring environment

Electronic Nose (Initial Phase)



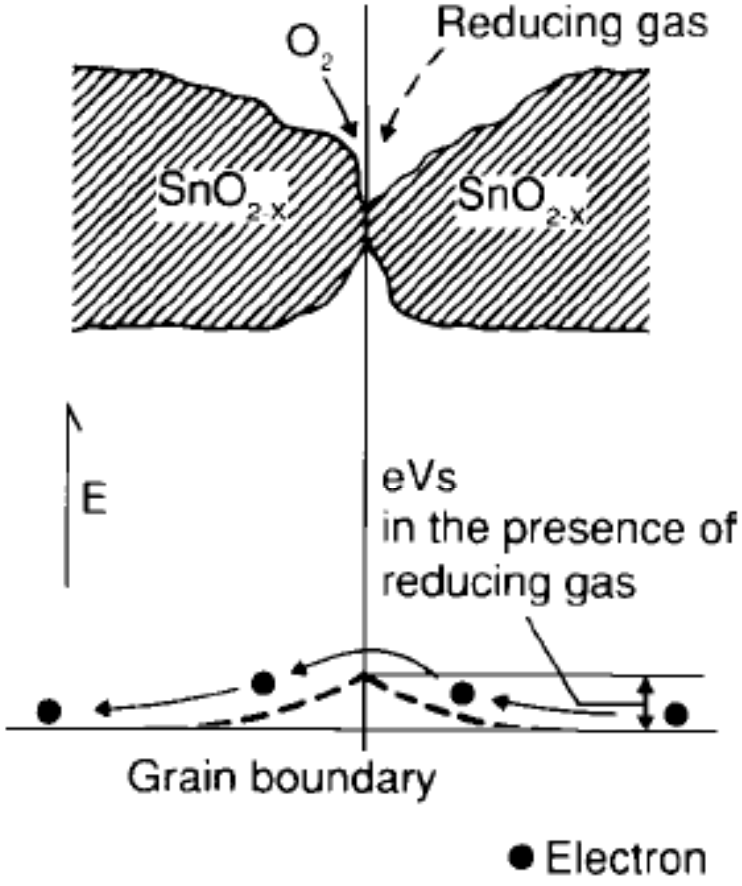
Commercial Metal Oxide Gas Sensors

Metal Oxide Gas Sensors

Sensor Model	Main Detecting Gas
SP-53	Ammonia, Ethanol
SP-MW0	Alcohol, Hydrogen
SP-32	Alcohol
SP-42A	Freon
SP-31	Hydrocarbon
SP-19	Hydrogen
SP-11	Methane, Hydrocarbon
SP-MW1	Cooking vapor

Metal oxide gas sensors from FIS. Inc, Japan

MOGS Principle



1/2C nO_{2x})

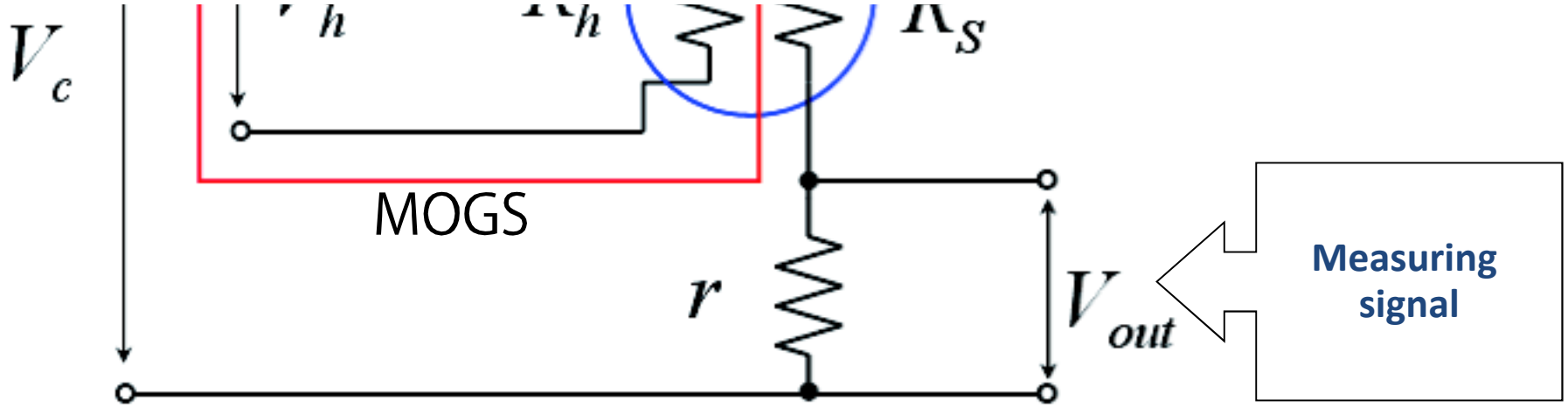
CO+ -(SnO_{2x})*

and

Fig. 3 - Model of inter-grain potential barrier
(in the presence of gases)

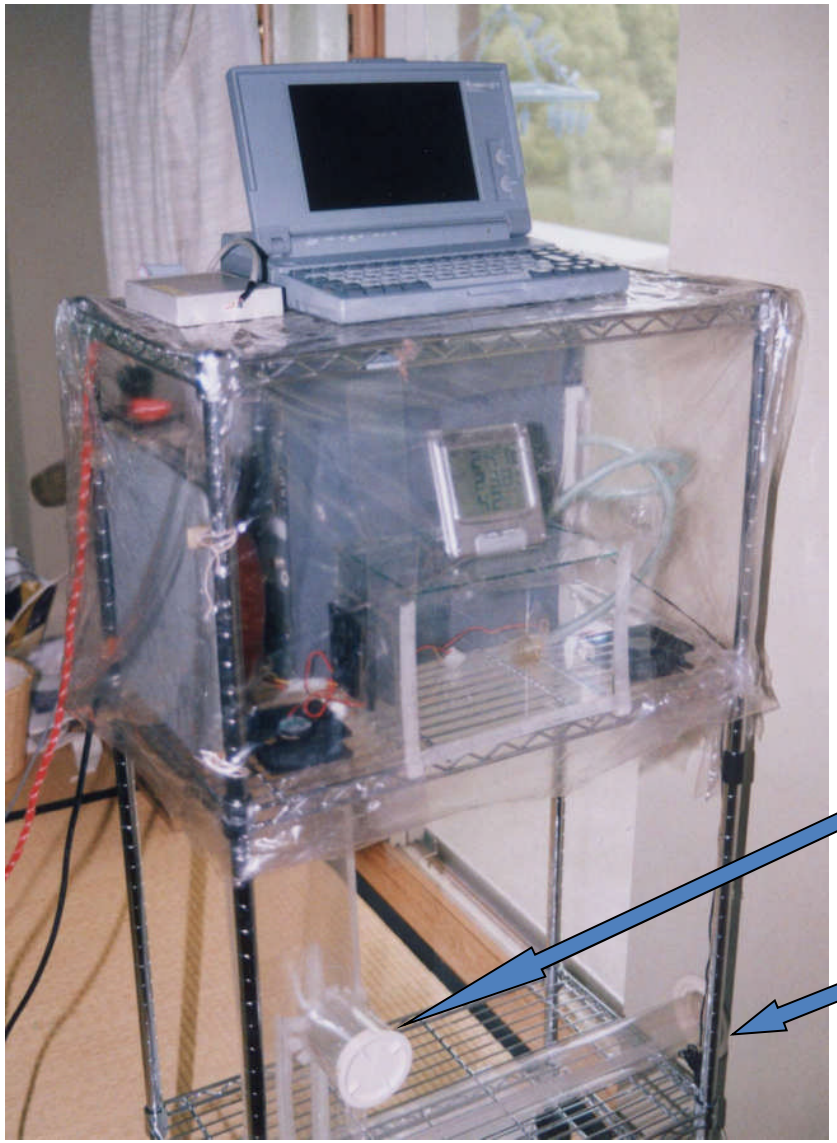
Source: ***Figaro Engineering Inc.*** (Reduction/Oxidation)

Metal Oxide Sensors Circuit



Source: ***FIS Inc.***

E Nose (revised one)



- 20-30 °C
- 30-40%RH
- Distance from tested smell to the EN 1.5m

List of Tested Materials

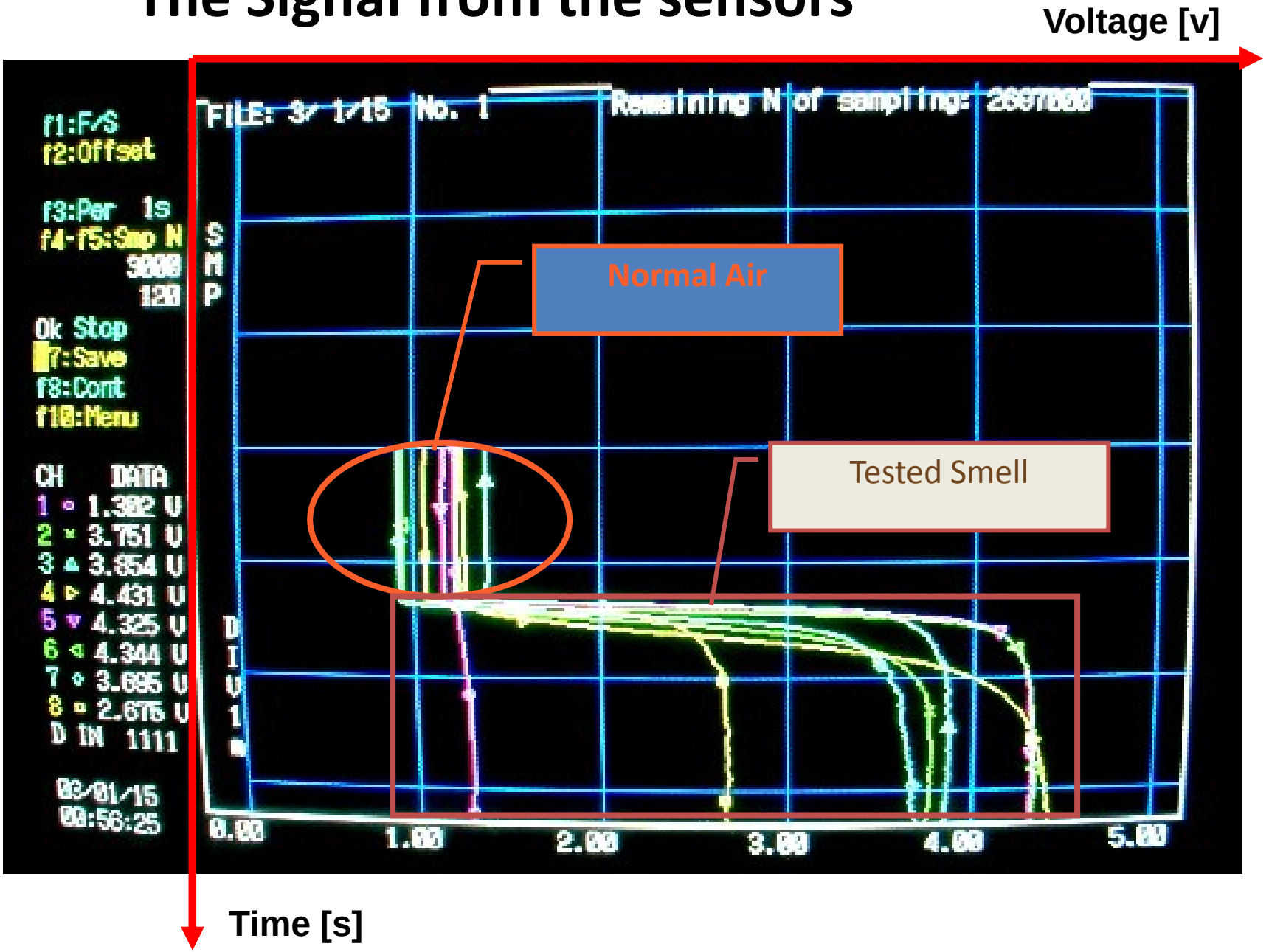
Tested Smell	Symbol
1. Boiling water steam	Steam
2. Burning joss stick	Joss
3. Burning mosquito coil	Mos
4. Aroma Oil	Aroma
5. Aroma Candle	Candle
6. Flame from (LPG)	Flame
7. Leakage of LPG	LPG
8. Japanese soup	Oden
9. Boiling vegetable oil	Oil
10. Toasted bread	Toast
11. Burning paper	Paper
12. Burning wood	Wood

Fire alarm

Experimental Conditions

- 12 smells from various sources of fire
- 40 repetition data for each smell
- Testing period is 1 minute for the standard air and 2 minutes for tested smell
- The tested smells are burnt outside the test chamber
- Temperature in test chamber 20-30^{o}C
- Humidity in the test chamber 30-40 %RH

The Signal from the sensors



Voltage changed by Tested Smoke

$$V_{smell\ ,t\ ,i} = v_{smell\ ,t\ ,i} - \overline{v}_{air\ ,i}$$

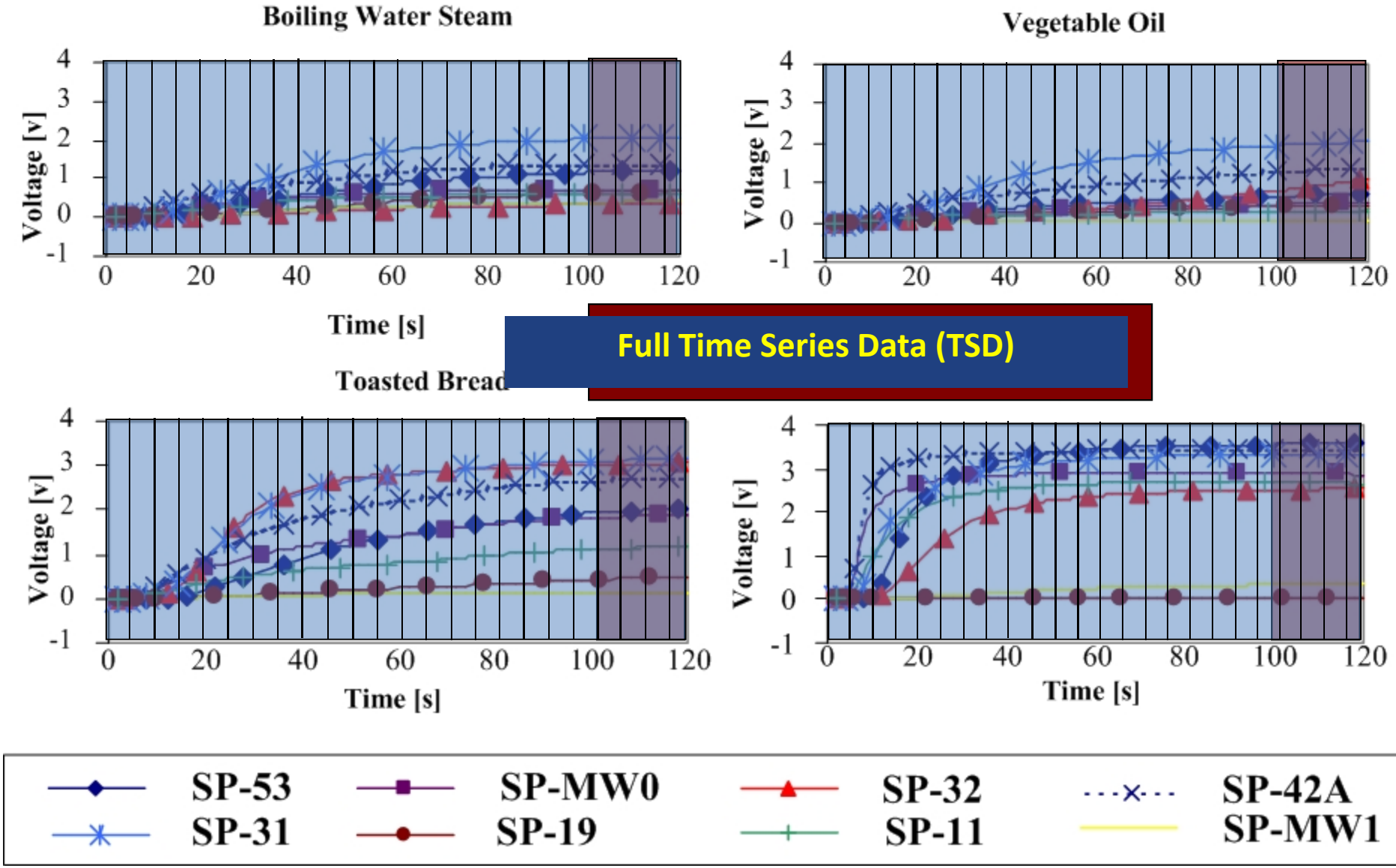
t = *is the measuring time*

$v_{smell\ ,t\ ,i}$ = *Voltage signal from sensor i (1,..,8) at t*

$\overline{v}_{air\ ,i}$ = *Average voltage of normal air from I*

$V_{smell\ ,t\ ,i}$ = *Voltage changed by the tested smell from I*

Sample Signals of the tested smells



Correlation of Experimental Data

Linear correlation value calculated by

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

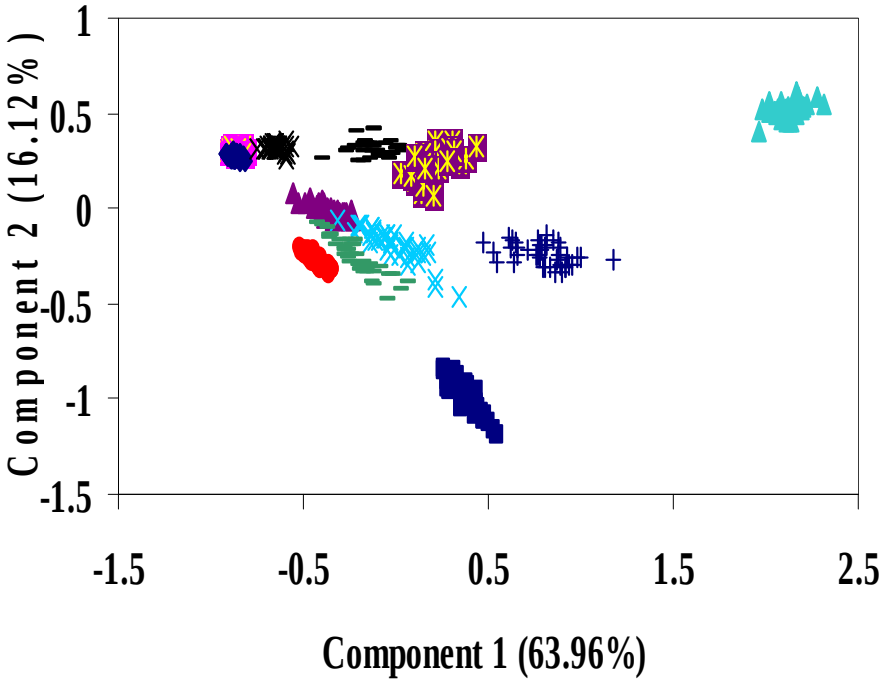
If r =>1. x and y are similar / If r => 0. x and y are different

Where x and y are the comparison data

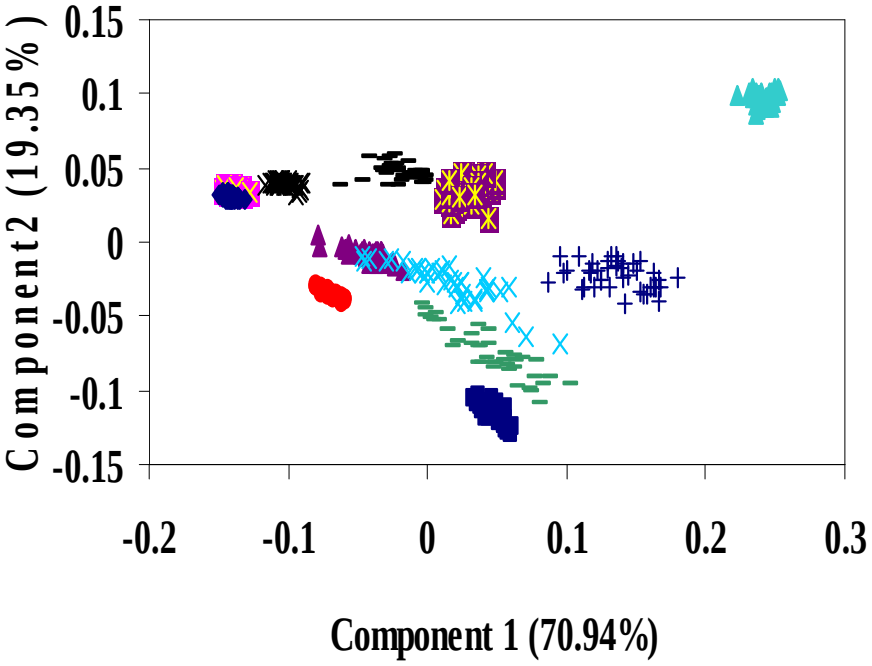
We call this value as **similarity index (SI)**

PCA of TSD and SSD

Principal Component Analysis of *Full Time Series Data*



Principal Component Analysis of *Saturation Stage Data*

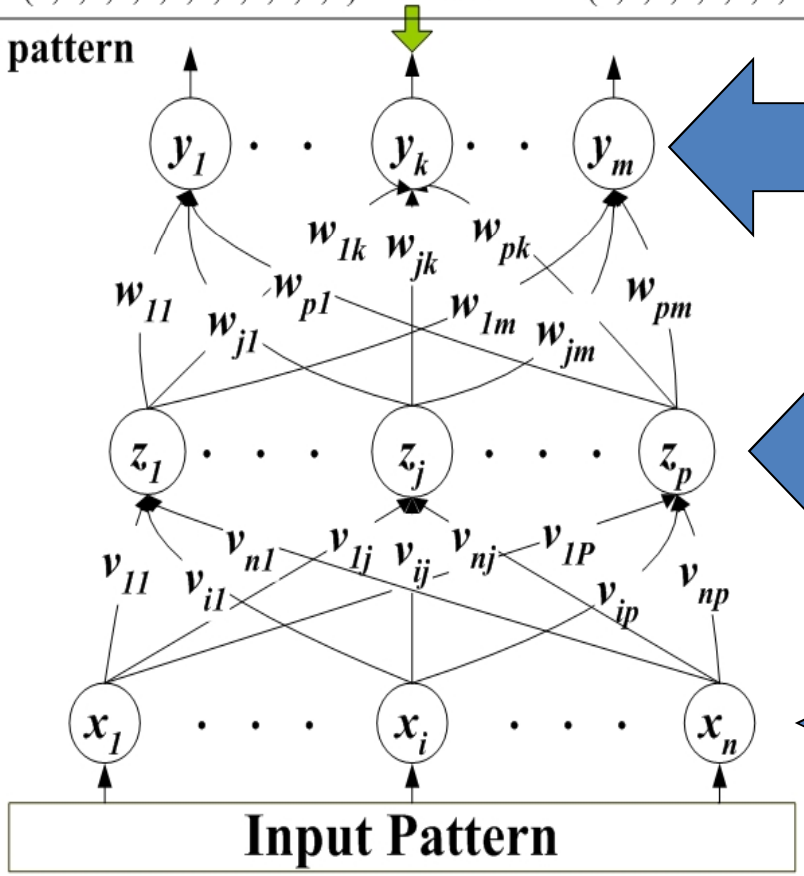


Steam
Candle
Oil
Joss
Flame
Toast
Mos
LPG
Paper
Aroma
Oden
Wood

Back Propagation Structure

STEAM	= (1,0,0,0,0,0,0,0,0,0,0,0)	LPG	= (0,0,0,0,0,0,1,0,0,0,0,0)
JOSS	= (0,1,0,0,0,0,0,0,0,0,0,0)	ODEN	= (0,0,0,0,0,0,0,1,0,0,0,0)
MOS	= (0,0,1,0,0,0,0,0,0,0,0,0)	OIL	= (0,0,0,0,0,0,0,0,1,0,0,0)
AROMA	= (0,0,0,1,0,0,0,0,0,0,0,0)	TOAST	= (0,0,0,0,0,0,0,0,0,1,0,0)
CANDLE	= (0,0,0,0,1,0,0,0,0,0,0,0)	PAPER	= (0,0,0,0,0,0,0,0,0,0,1,0)
FLAME	= (0,0,0,0,0,1,0,0,0,0,0,0)	WOOD	= (0,0,0,0,0,0,0,0,0,0,0,1)

reference pattern



12

40

Training rate = 0.1

Momentum rate 0.001

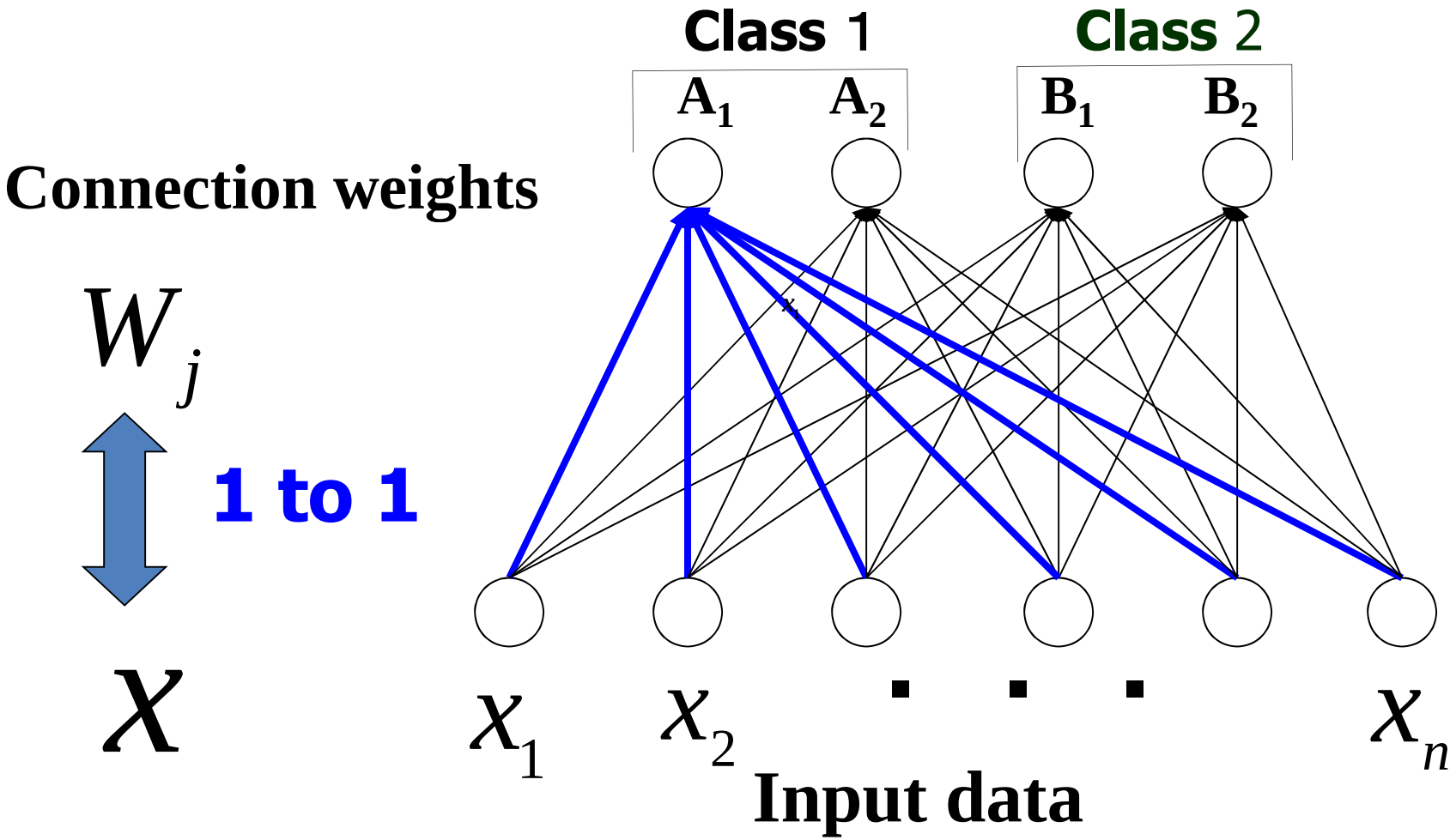
MSE = 0.0003

TSD =480 / SSD = 8

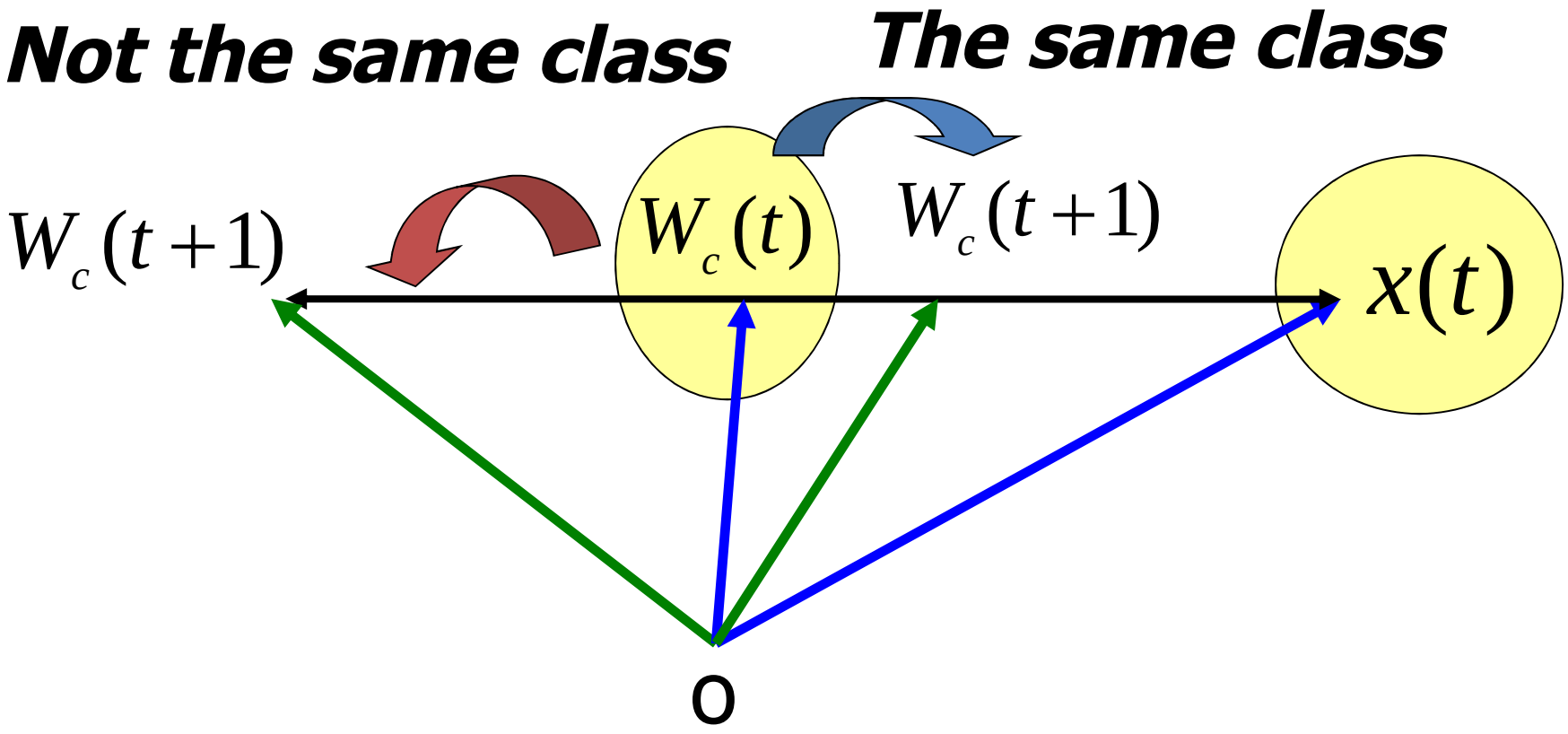
Classification Results TSD/SSD

Sources	TSD				SSD			
	BP		k-means		BP		k-means	
	TRUE	%	TRUE	%	TRUE	%	TRUE	%
Steam	39/39	100	40/40	100	38/39	97	39/40	98
Joss	39/39	100	40/40	100	39/39	100	40/40	100
Mos	39/39	100	40/40	100	39/39	100	40/40	100
Aroma	39/39	100	40/40	100	39/39	100	40/40	100
Candle	39/39	100	40/40	100	39/39	100	40/40	100
Flame	39/39	100	40/40	100	39/39	100	40/40	100
LPG	39/39	100	40/40	100	39/39	100	40/40	100
Oden	39/39	100	40/40	100	39/39	100	40/40	100
Oil	39/39	100	40/40	100	38/39	97	37/40	93
Toast	39/39	100	40/40	100	38/39	97	40/40	100
Paper	38/39	95	35/40	88	31/39	80	28/40	70
Wood	39/39	100	37/40	93	32/39	82	28/40	70
Average	94	94	94	94	94	94	94	94

LVQ Method


Class 1
Class 2
A1
A2
B1
B2
Connection weights
Wj
1 to 1
X
x1
x2
xn
Input data

Principle of LVQ Algorithm



LVQ Algorithm(1)

Step 1. **Find the unit *c* at the output layer which has the minimum distance from the input data $x(t)$ such that**

$$\|x(t)-W_c\| = \min_i \|x(t)-W_i\|$$

Step 2. **If the input $x(t)$ belongs to category *c*,**

$$W_c(t+1) = W_c(t) + \alpha(t)(x(t)-W_c(t)),$$

if the input $x(t)$ belongs to the other category,

$$W_c(t+1) = W_c(t) - \alpha(t)(x(t)-W_c(t)),$$

$$W_i(t+1) = W_i(t) \text{ for } i \neq c$$

LVQ Algorithm(2)

where $\alpha(t)$ is a positive function and denotes learning rate. In the the usual LVQ is given by

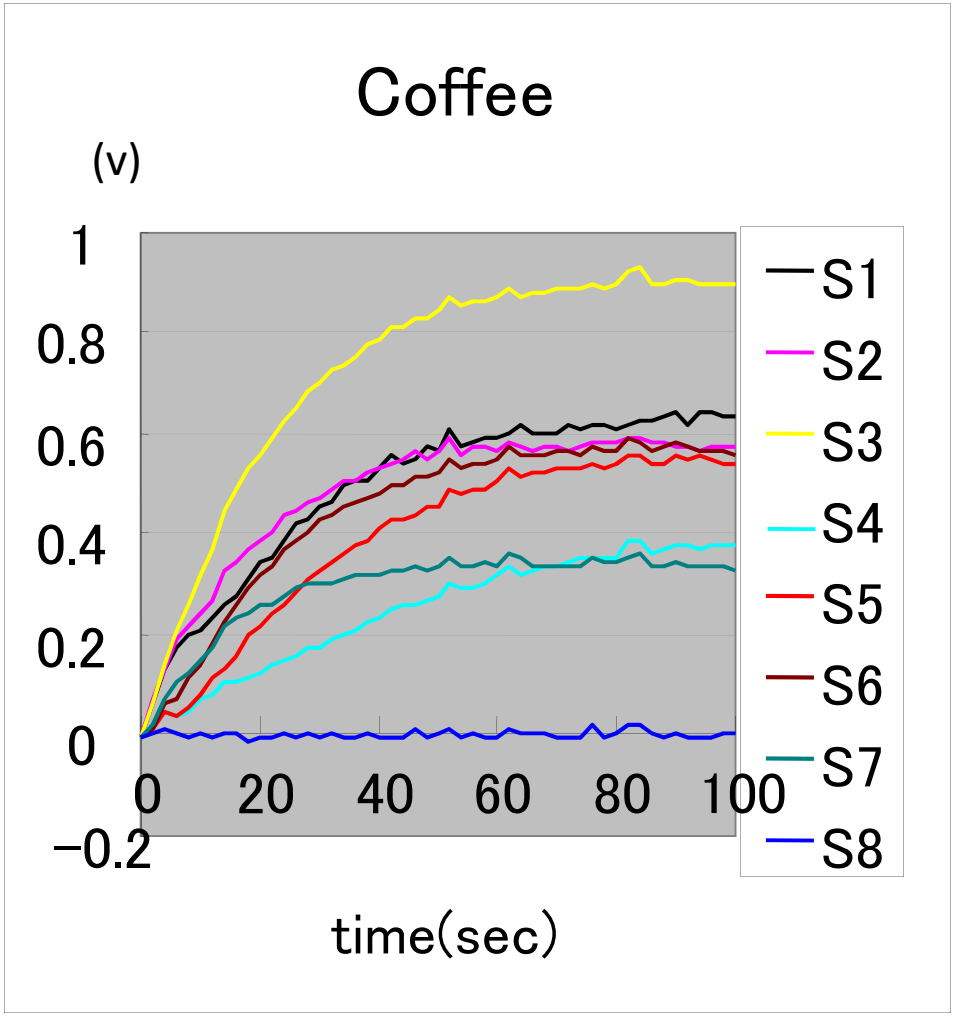
$$\alpha(t) = \alpha_0(1 - \frac{t}{T}).$$

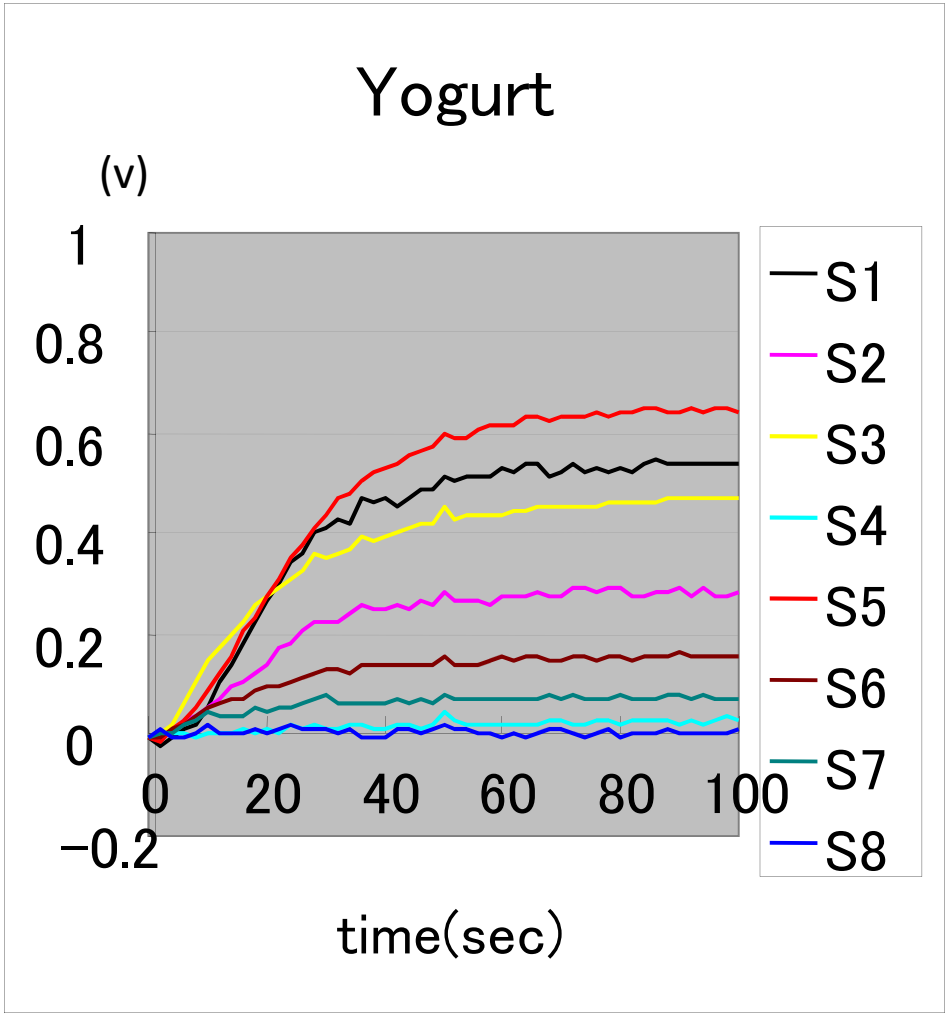
Here, α_0 is a positive and T is a total number of learning iterations

New Sensors（2nd Stage）

SnO_{2-x}

Measurement Data

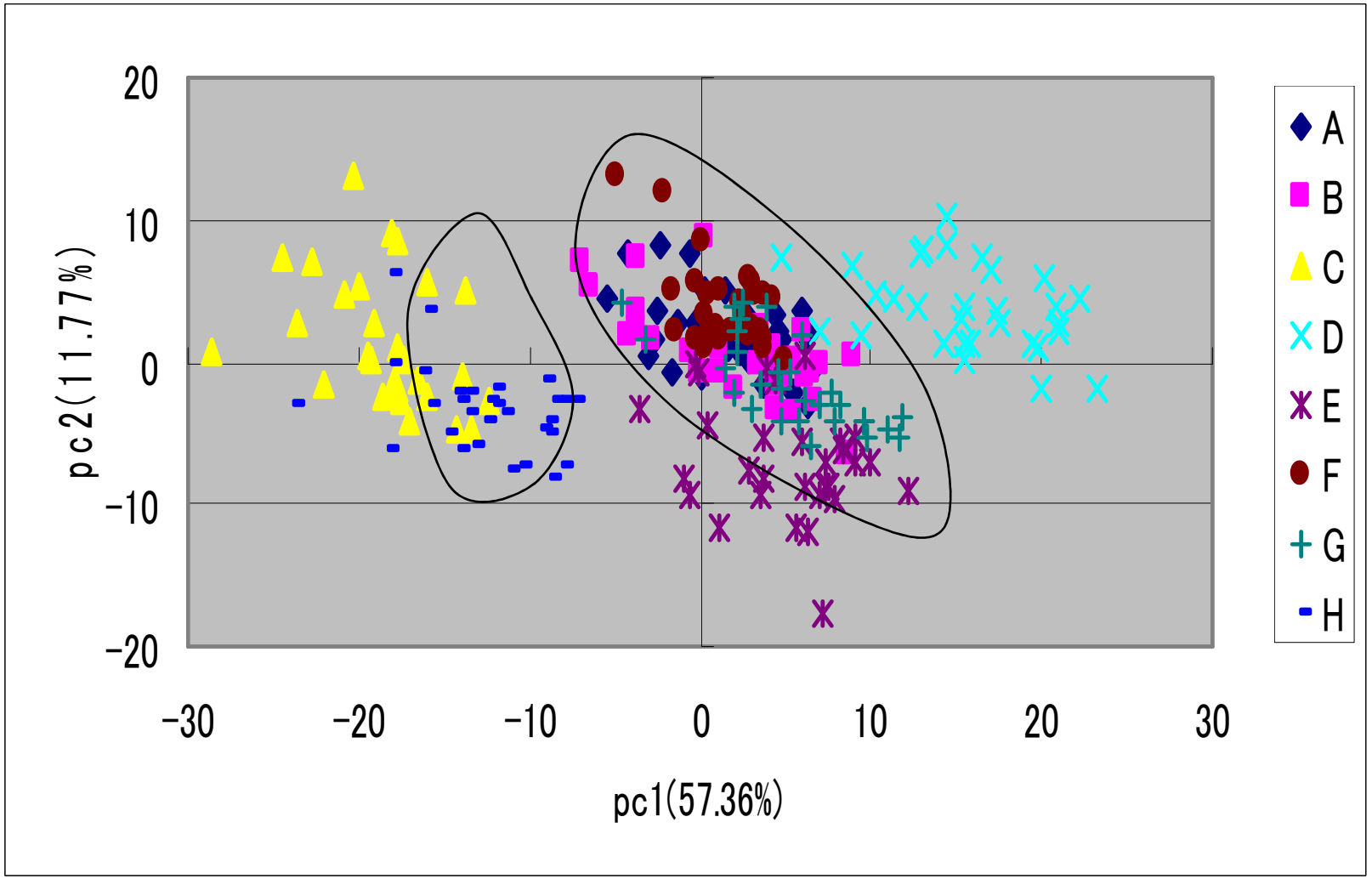




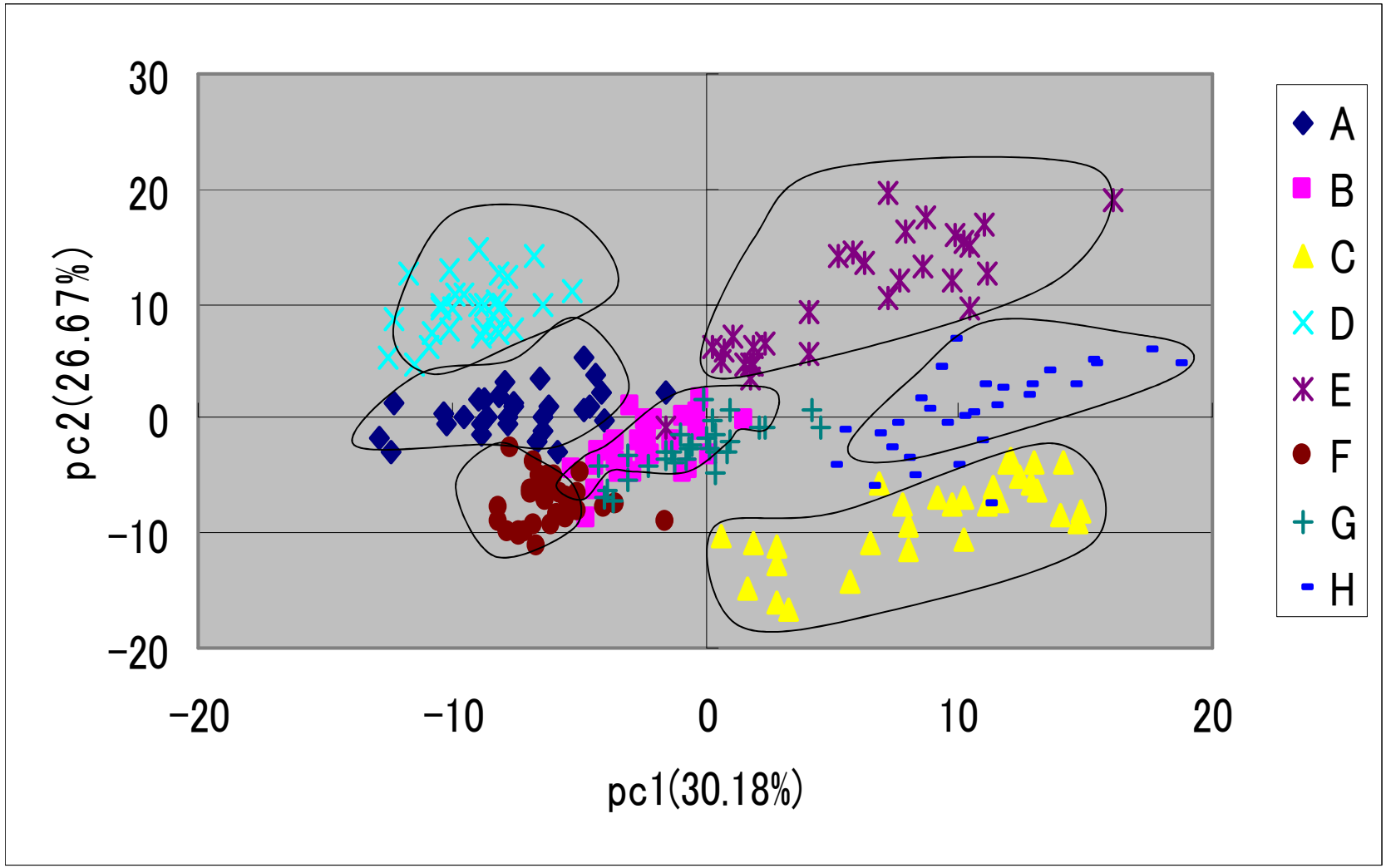
Coffee Kinds for Classifications

A	AGF	Blendy
B	AGF	MAXIM
C	Rising	COFFEE BREAK
D	Nestle	NESCAFE Excella
E	Nestle	NESCAFE GOLDBLEND
F	Nestle	NESCAFE GOLDBLEND kilimanjaro
G	Nestle	NESCAFE GOLDBLEND mocha
H	Nestle	NESCAFE matinal

PCA for Measurement Data



PCA for Normalized Data



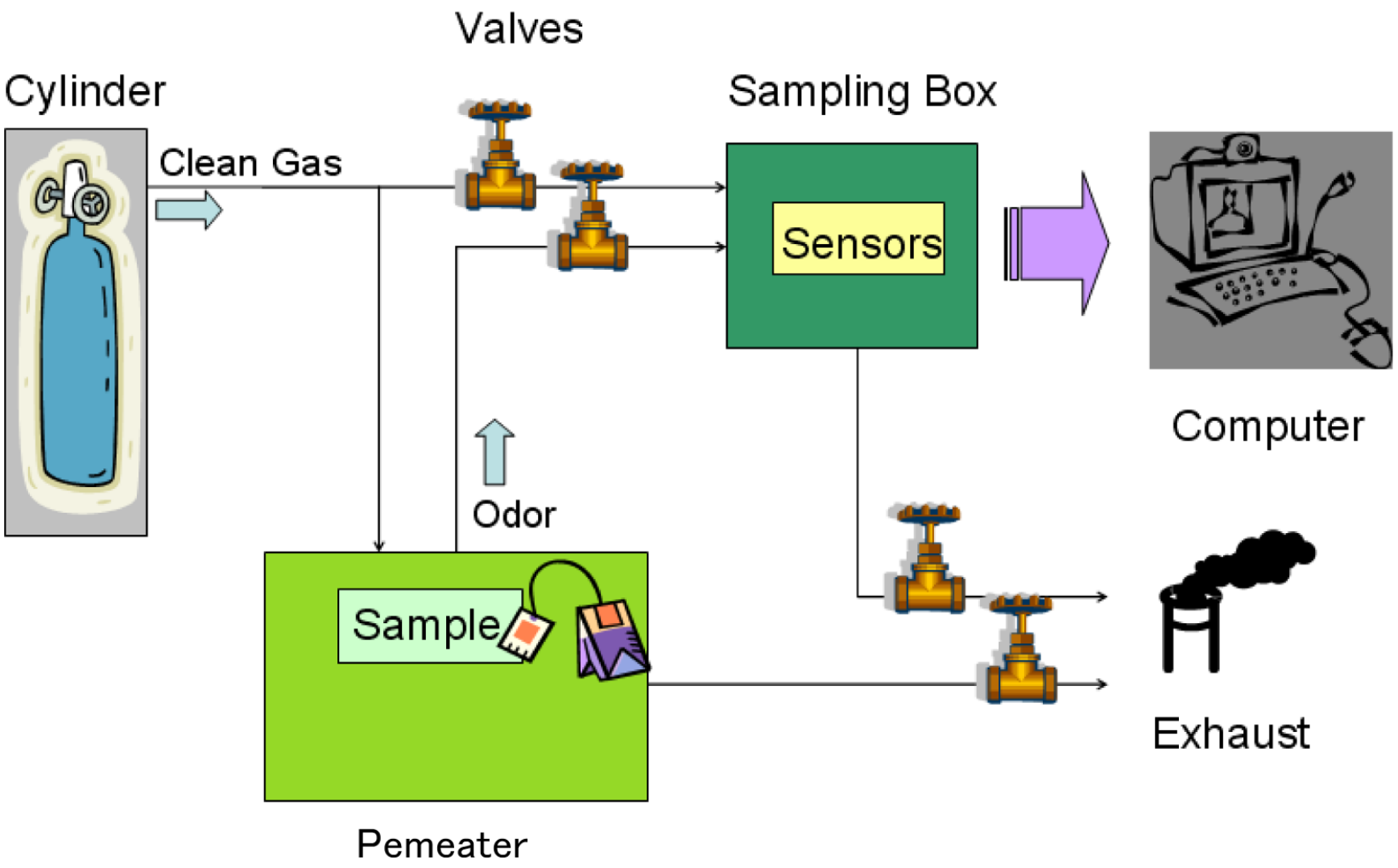
Classification Results for LVQ

No of Nodes	3	4	5	6	7	Mean
LVQ1	88.8%	89.8%	88.4%	89.5%	87.9%	89.2%
OLVQ1	84.1%	85.1%	86.9%	86.6%	86.0%	85.7%
LVQ2	82.0%	84.0%	84.8%	85.6%	85.8%	84.4%
LVQ3	86.1%	87.1%	89.1%	88.6%	87.6%	87.7%

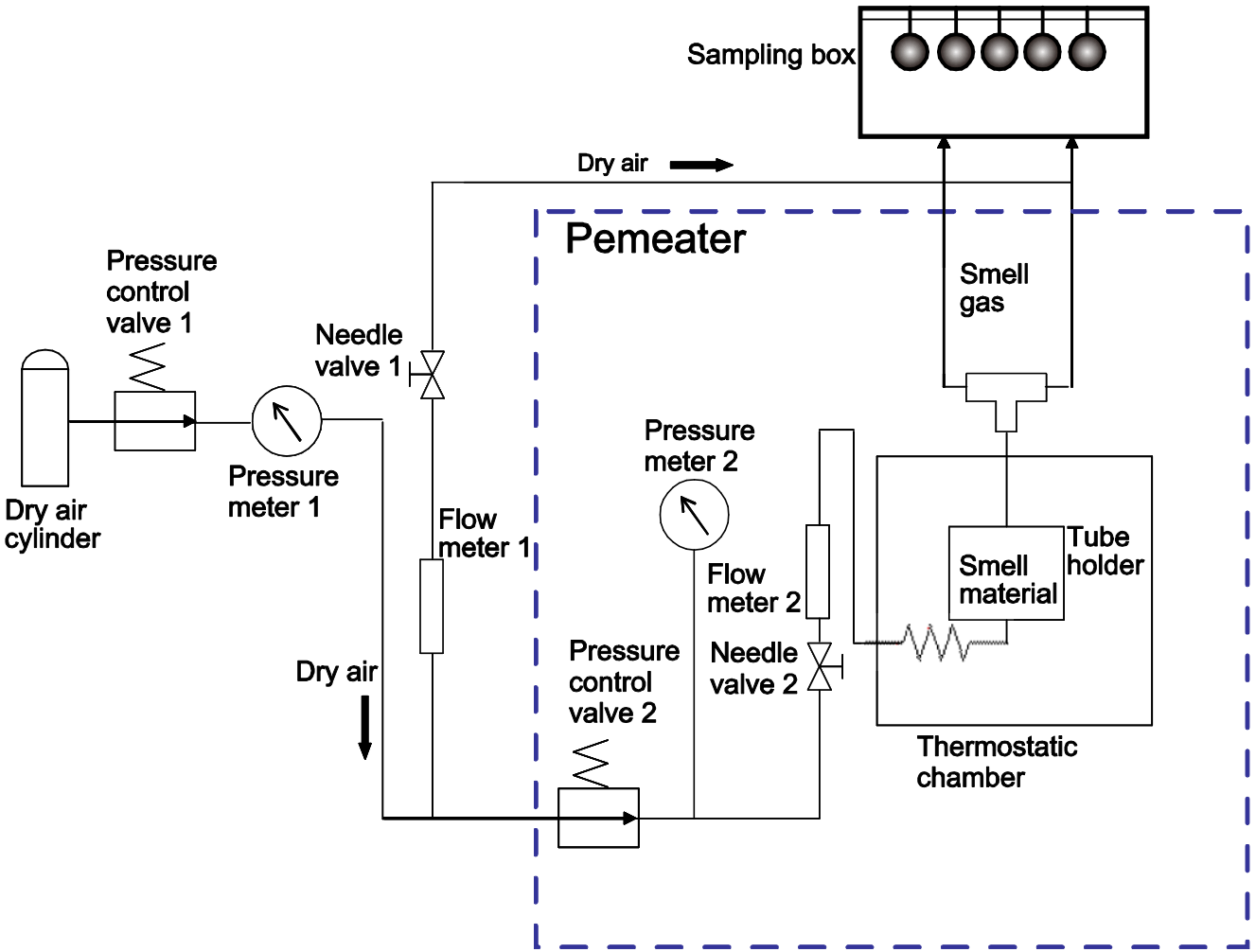
Classification Results by LVQ1

	A	B	C	D	E	F	G	H	Correct Rates
A	476	15	0	0	1	8	0	0	95.2%
B	2	330	0	0	0	29	139	0	66%
C	0	0	486	0	0	7	0	7	97.2%
D	0	0	0	500	0	0	0	0	100%
E	13	24	0	0	461	0	1	1	92.2%
F	3	30	0	0	0	461	6	0	92.2%
G	0	55	0	0	0	46	399	0	79.8%
H	0	2	31	0	6	0	5	456	91.2%

New Electronic Nose System

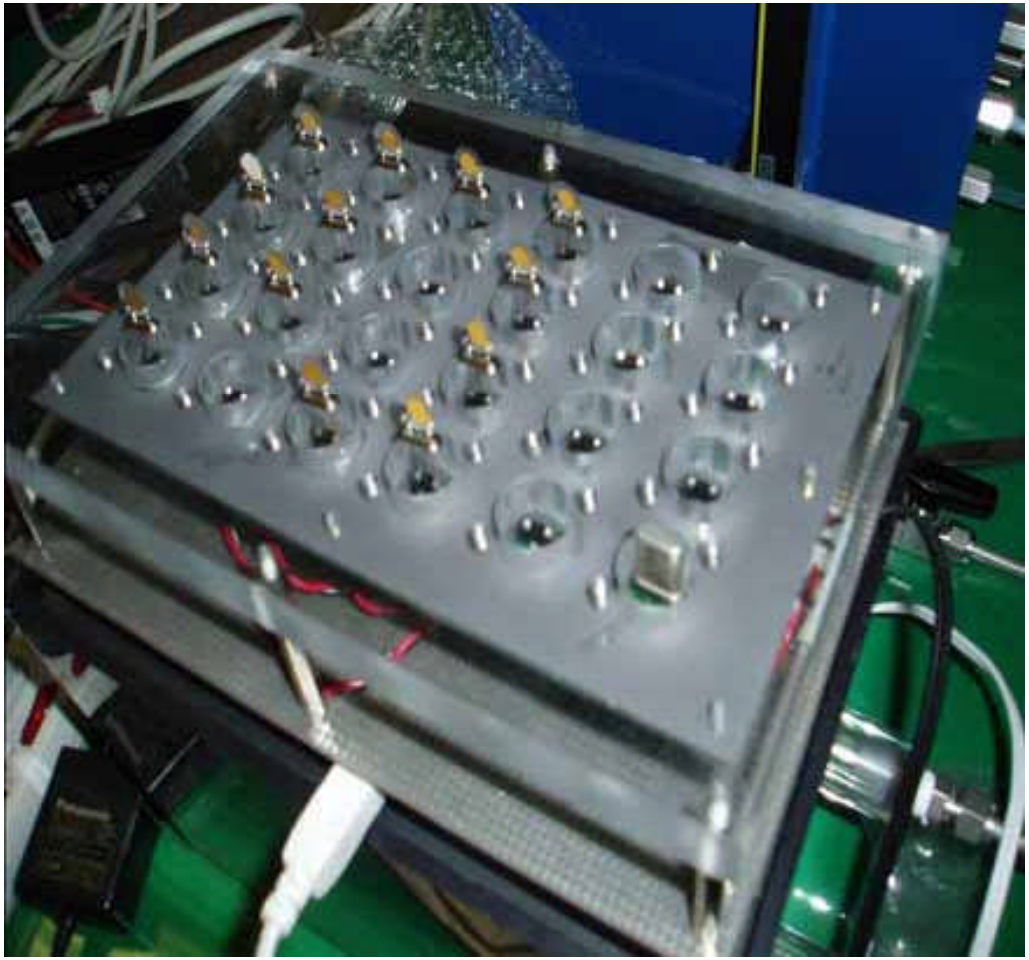


New EN System Structure

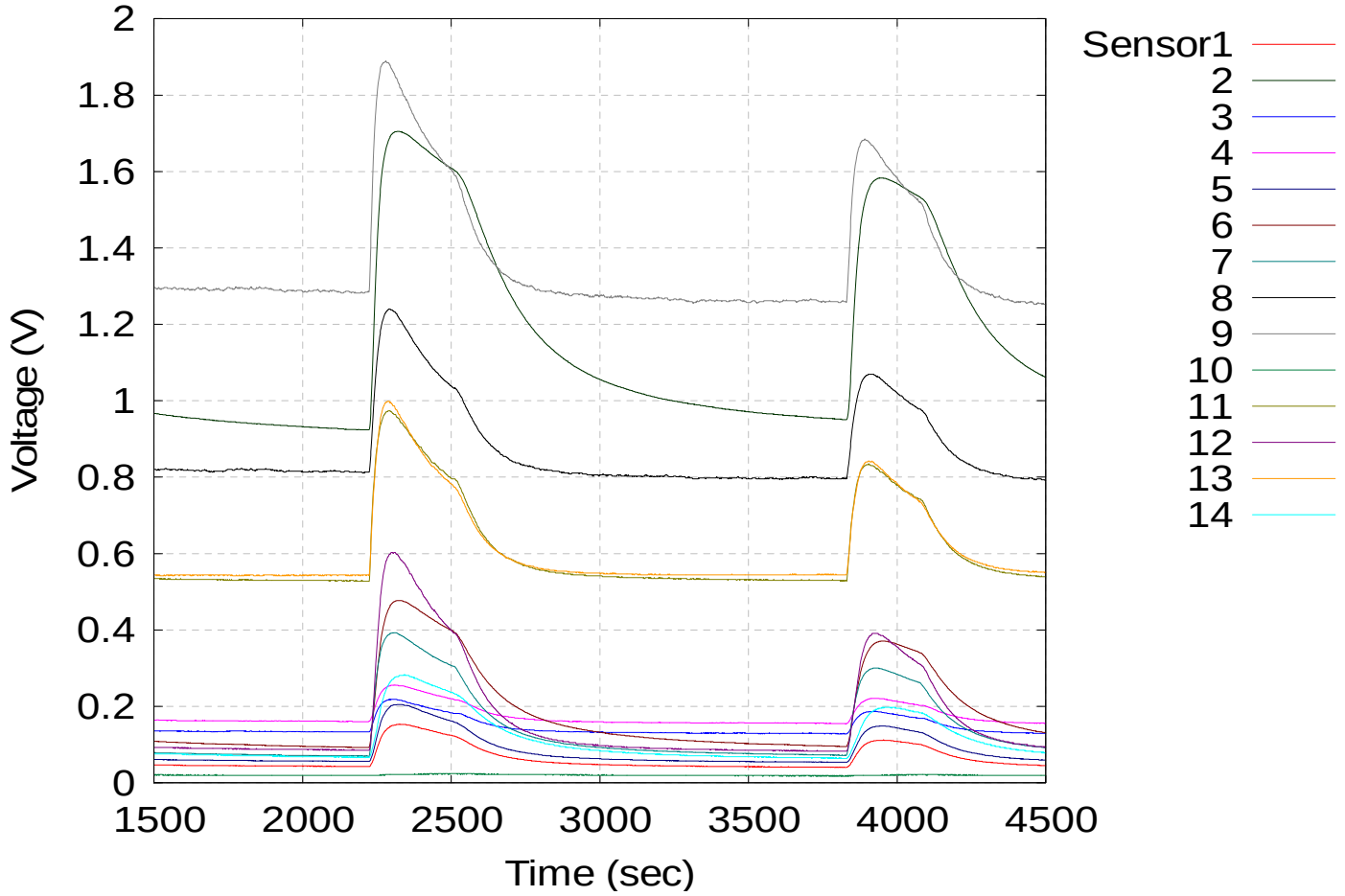


Experimental System

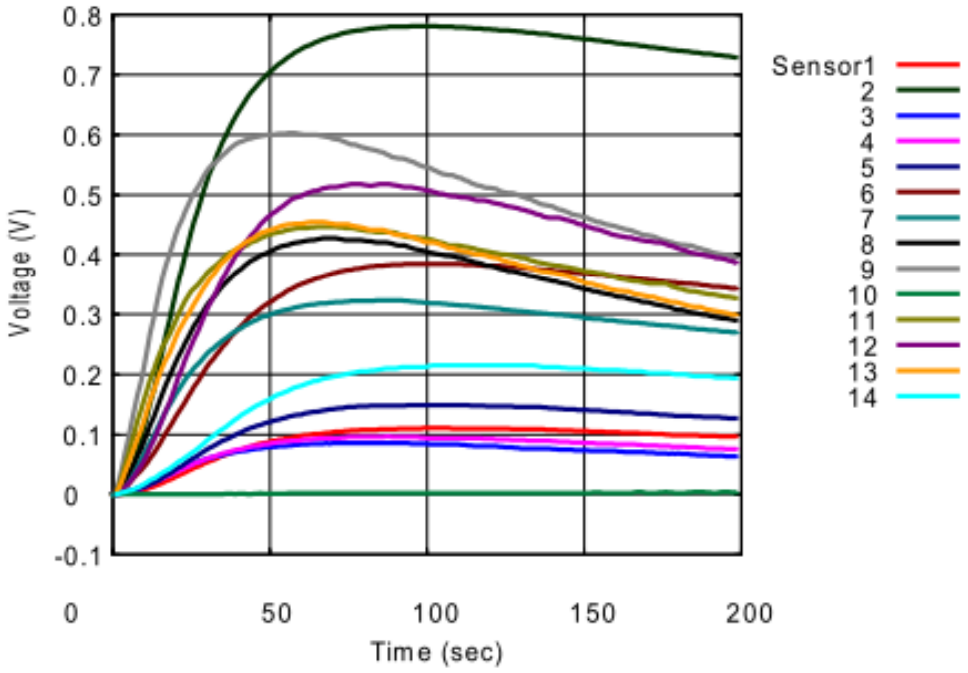
QCM Sensors



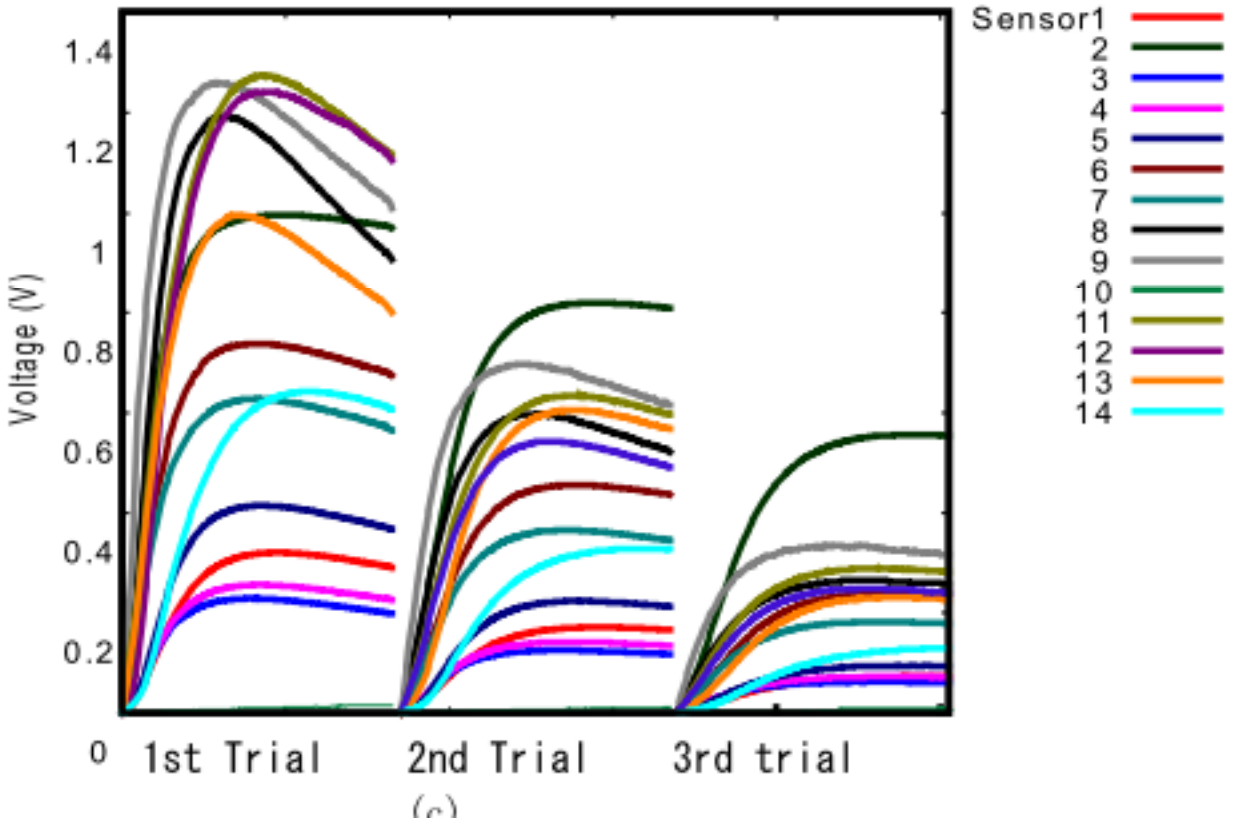
Smell Data by MOGS



Smell Data by MOGS after Filtering



Variation with Densities of Smell

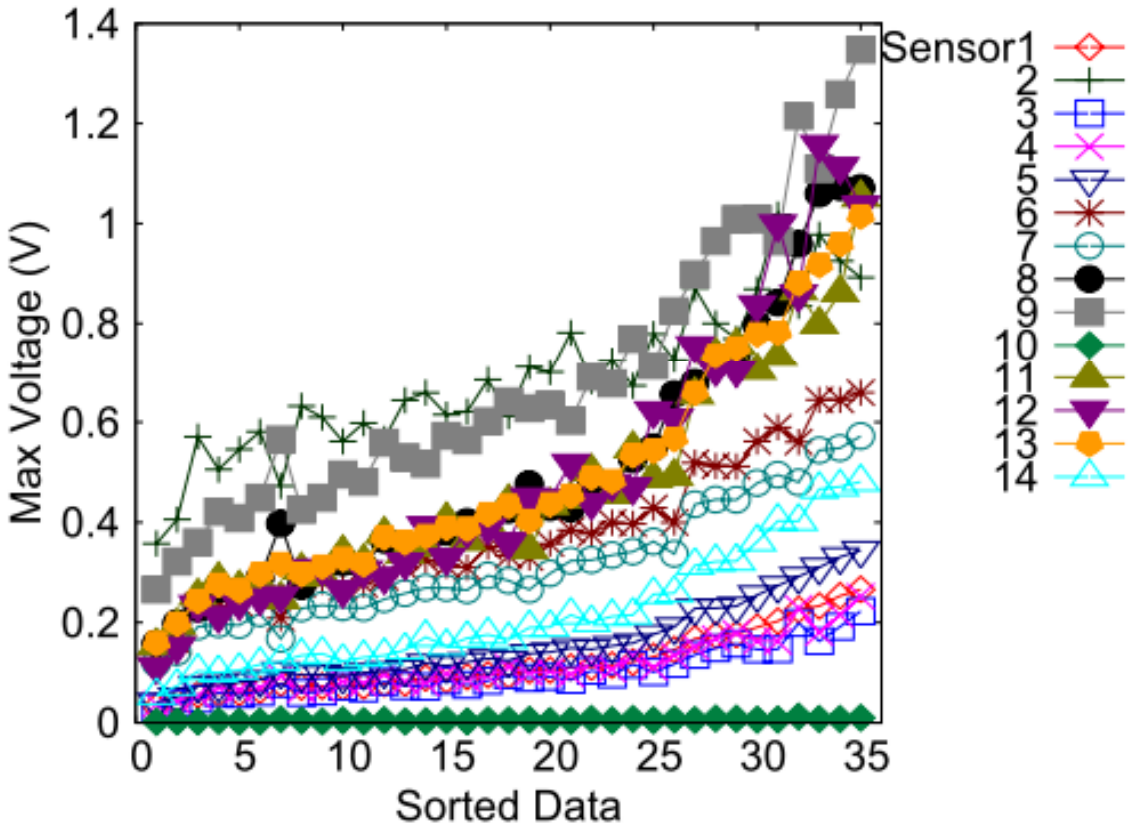


List of Tested Materials

Table 2. Kinds and number of samples used the classification.

Tea			Coffee		
Label	Materials	No. of samples	Label	Materials	No. of samples
A	English tea	20	A	Mocha coffee1	35
B	green tea	20	B	Mocha coffee2	35
C	barley tea	20	C	Mocha coffee3	35
D	oolong tea	20	D	Kilimanjaro coffee	35
			E	char-grilled coffee	35

Sorted Data of Maximum Values



Sorted Data for Coffee

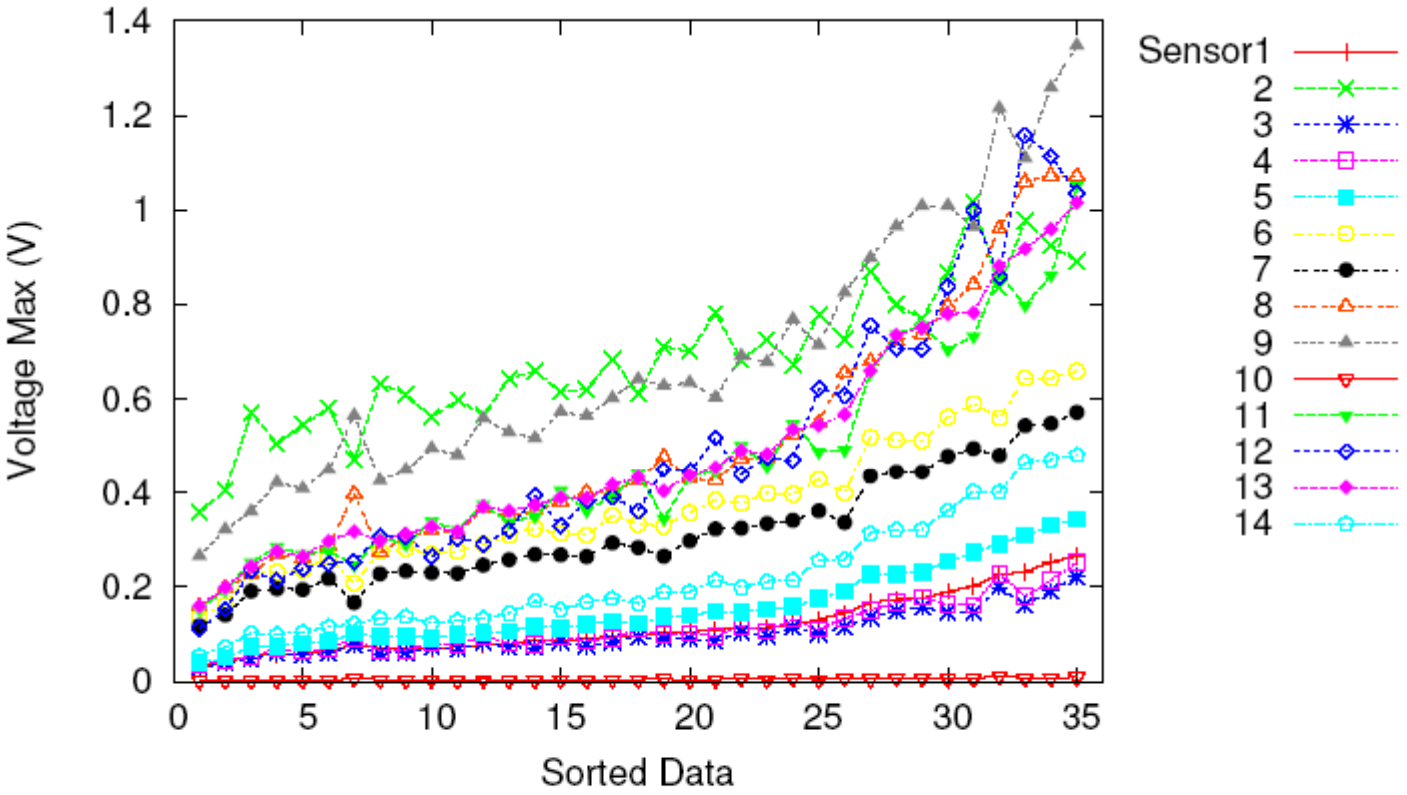
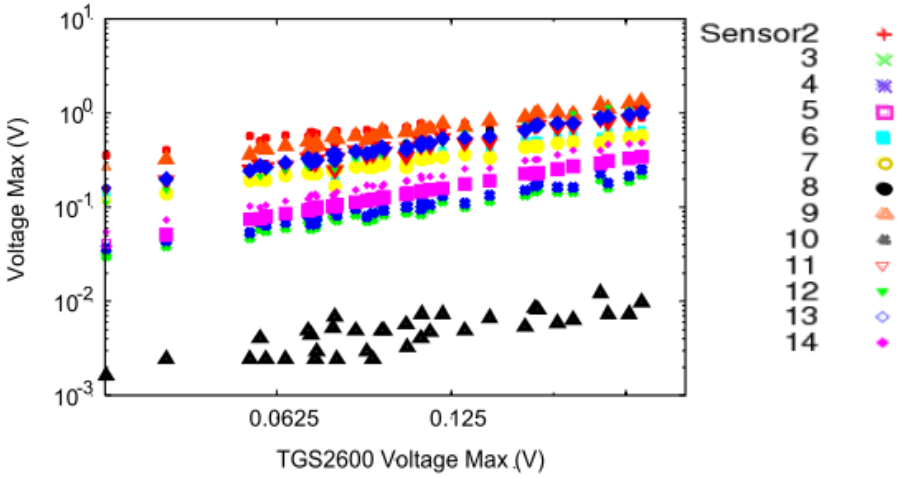
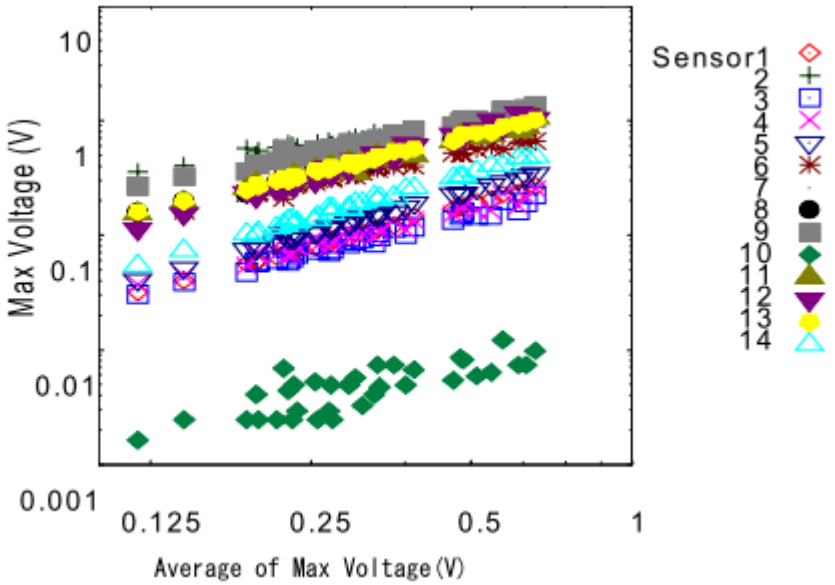


Fig. 3. Sorted data according to the concentration levels from a coffee odor in Experiment II

Sorted Data by Log Scale





Linear Regression for Fig. 3

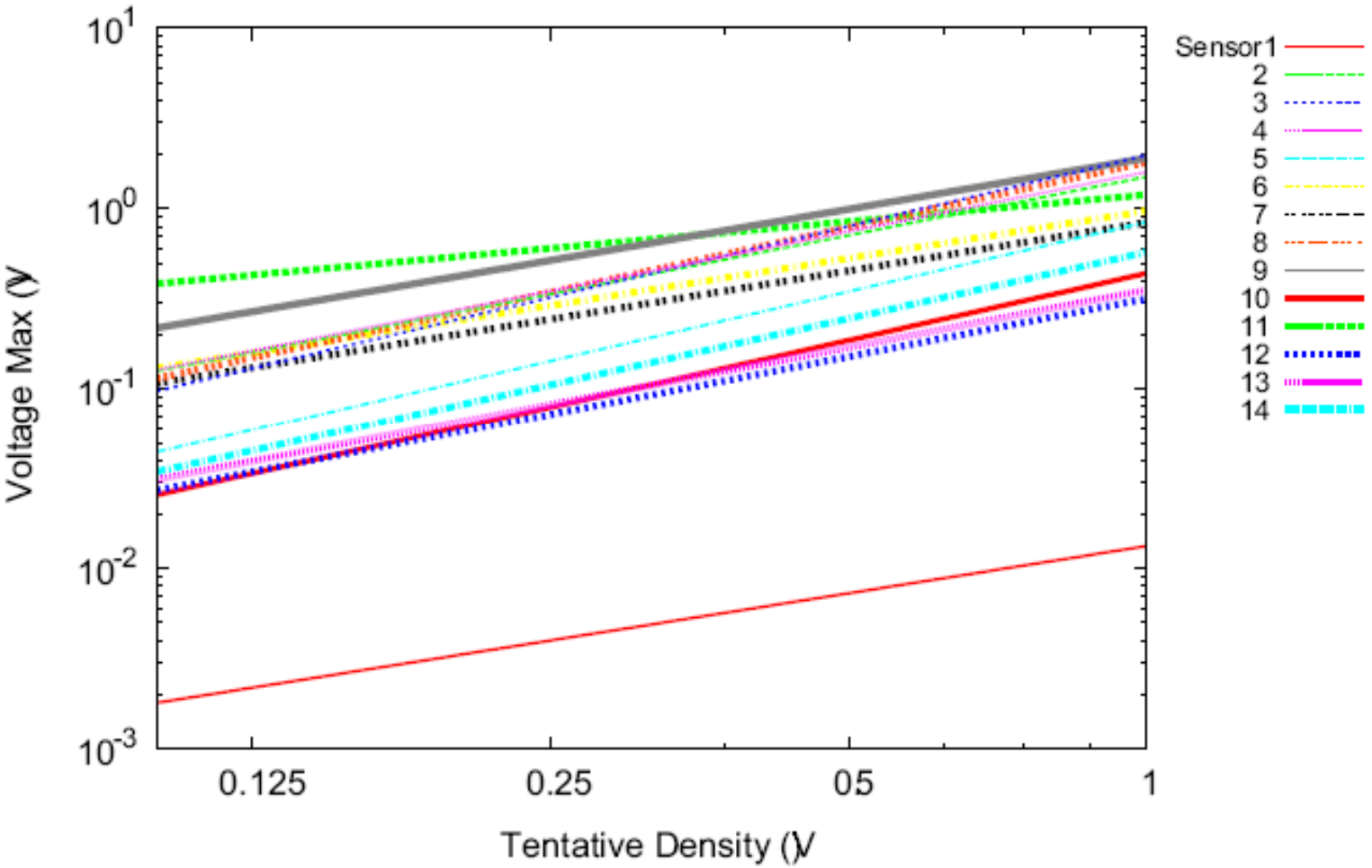


Fig. 4. Linear regression lines in Experiment II

Classification Results

Table 3. Classification results for Experiment I

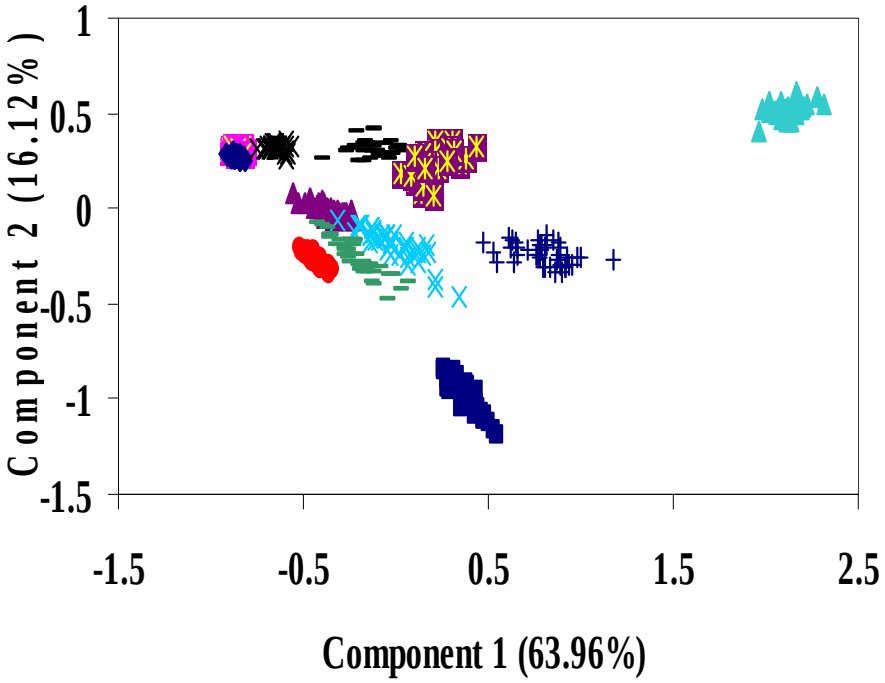
odor data	Classification results(96.15%)					
	A	B	C	D	Total	Correct %
A	500	0	0	0	500	100.0%
B	0	494	6	0	500	98.80%
C	0	71	429	0	500	85.80%
D	0	0	0	500	500	100.0%

Table 4. Classification results for Experiment II

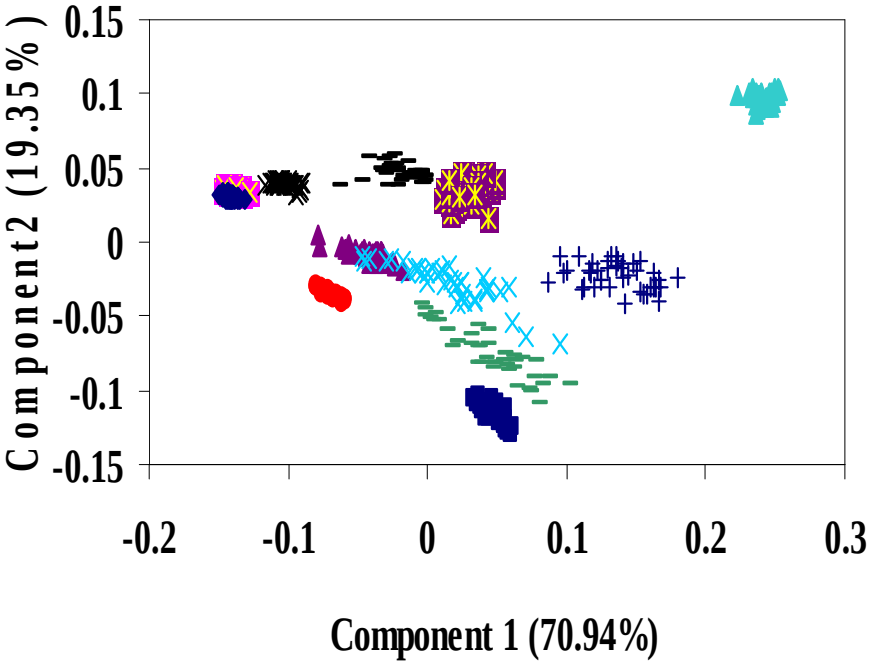
odor data	Classification results(88.80%)						
	A	B	C	D	E	Total	Correct%
A	1190	253	29	27	1	1500	79.33%
B	225	1237	9	10	19	1500	82.47%
C	142	7	1325	26	0	1500	88.33%
D	9	14	3	1437	37	1500	95.80%
E	0	18	0	11	1471	1500	98.07%

PCA of TSD and SSD

Principal Component Analysis of *Full Time Series Data*

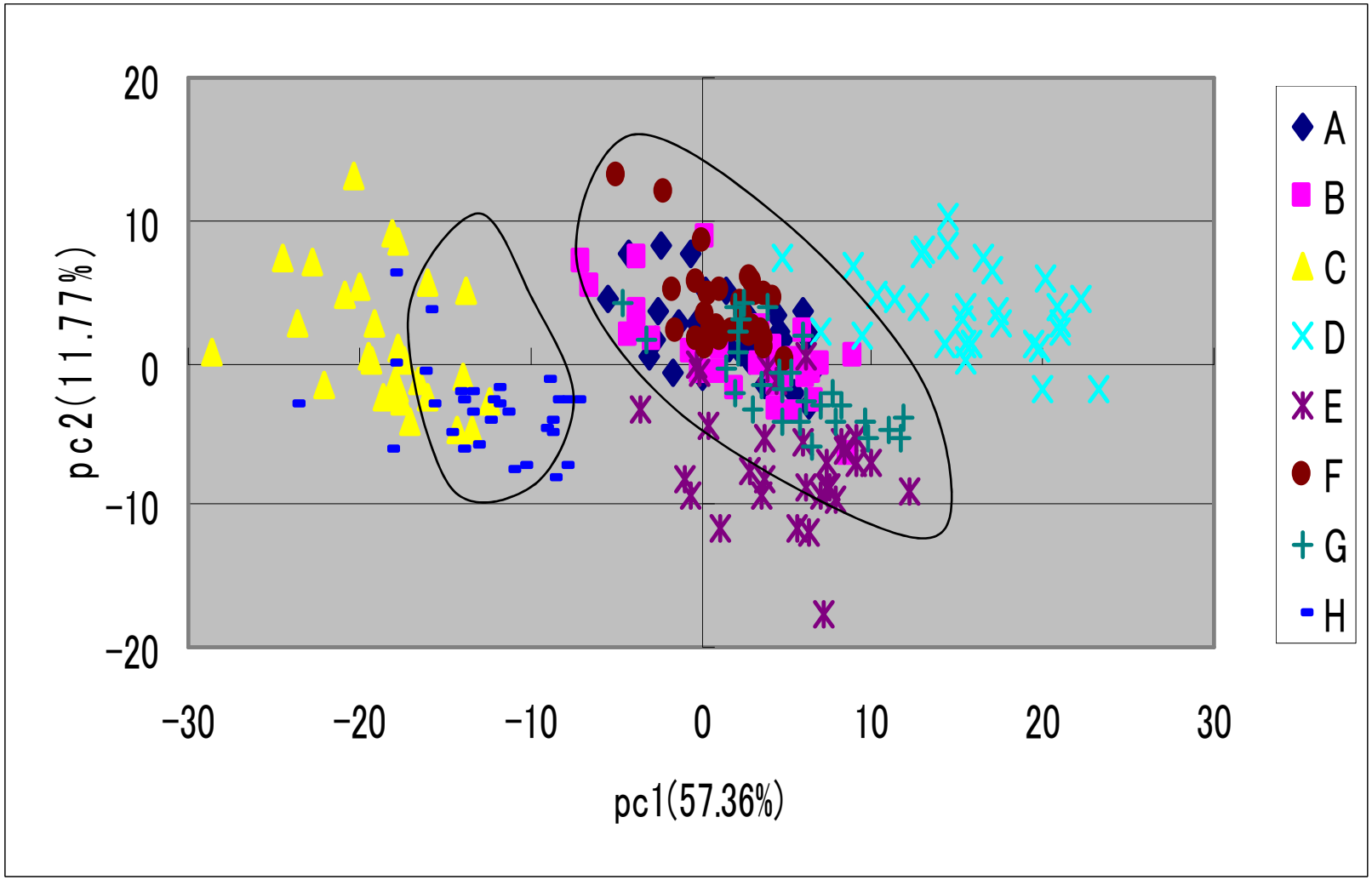


Principal Component Analysis of *Saturation Stage Data*

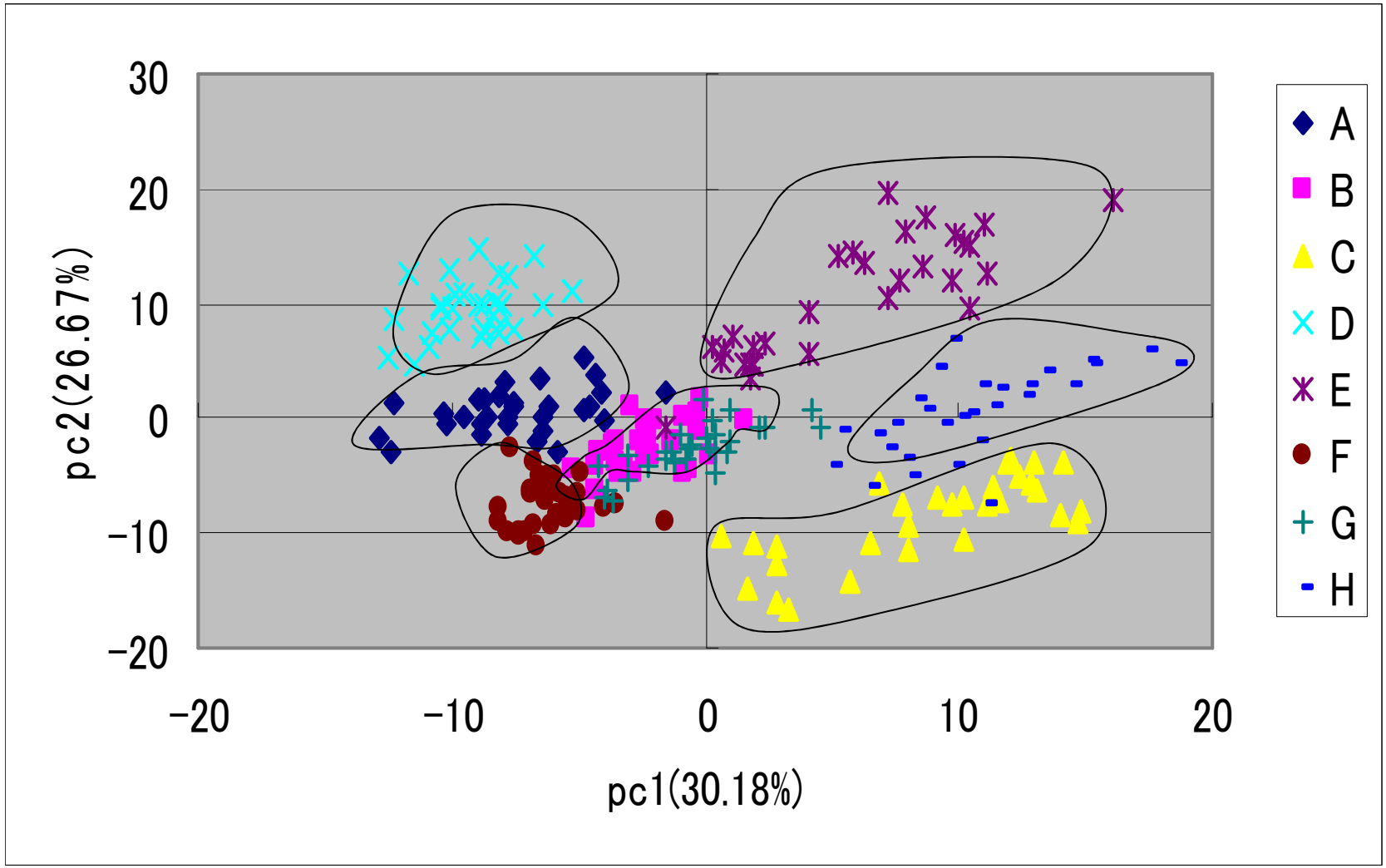


Steam, Candle, Oil, Joss, Flame, Toast, Mos, LPG, Paper, Aroma, Oden, Wood

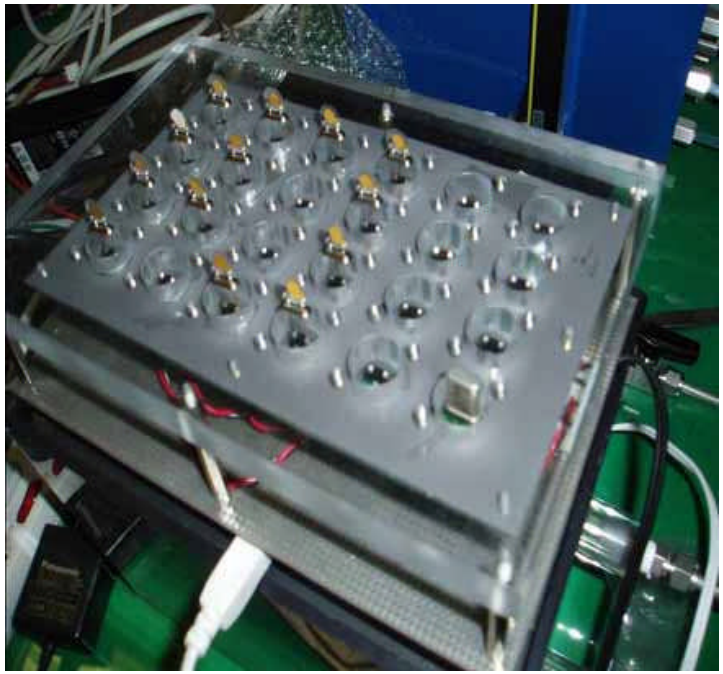
PCA for Measurement Data

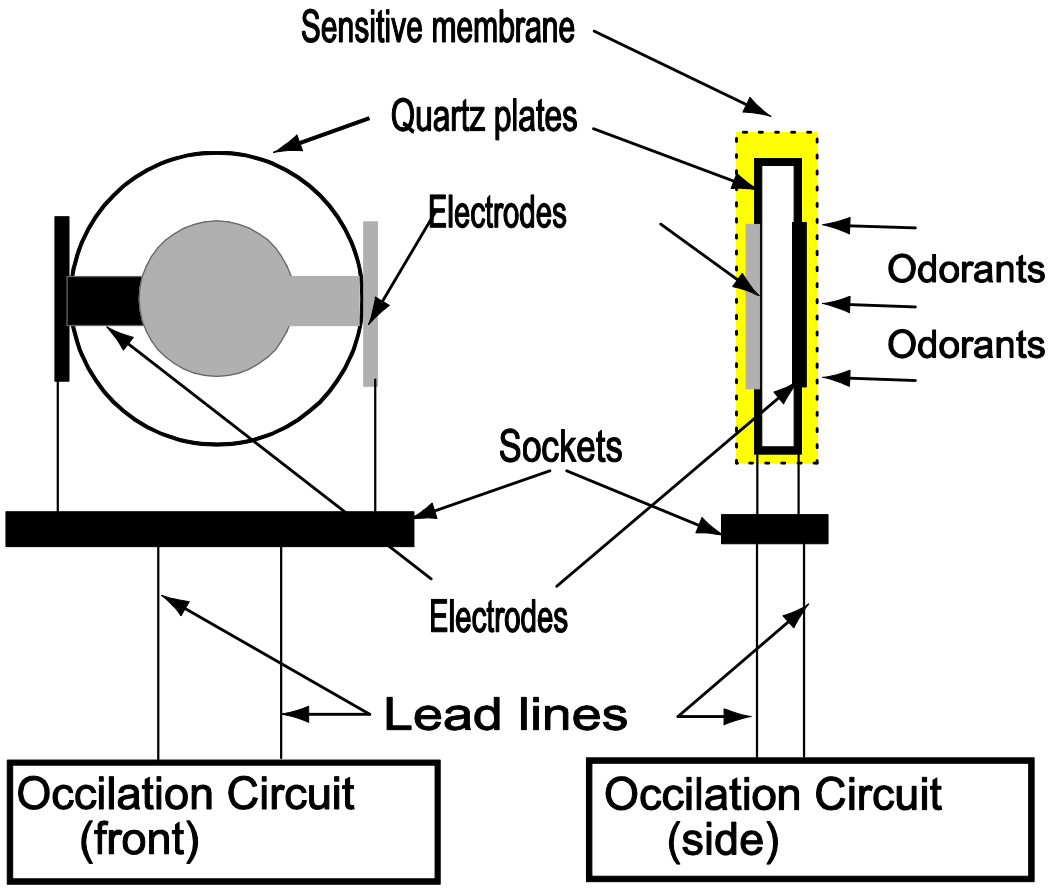


PCA for Normalized Data

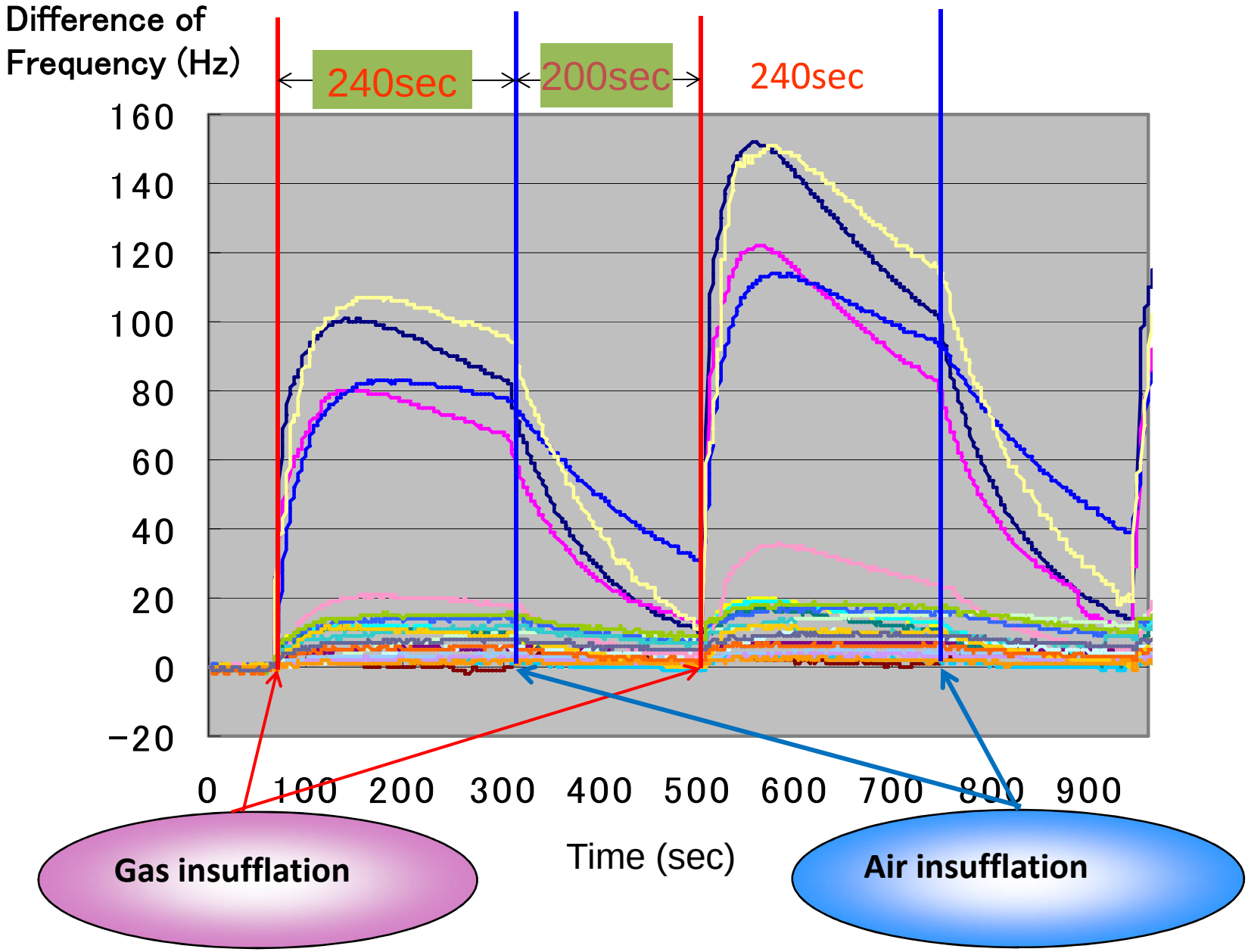


New Type QCM Sensors

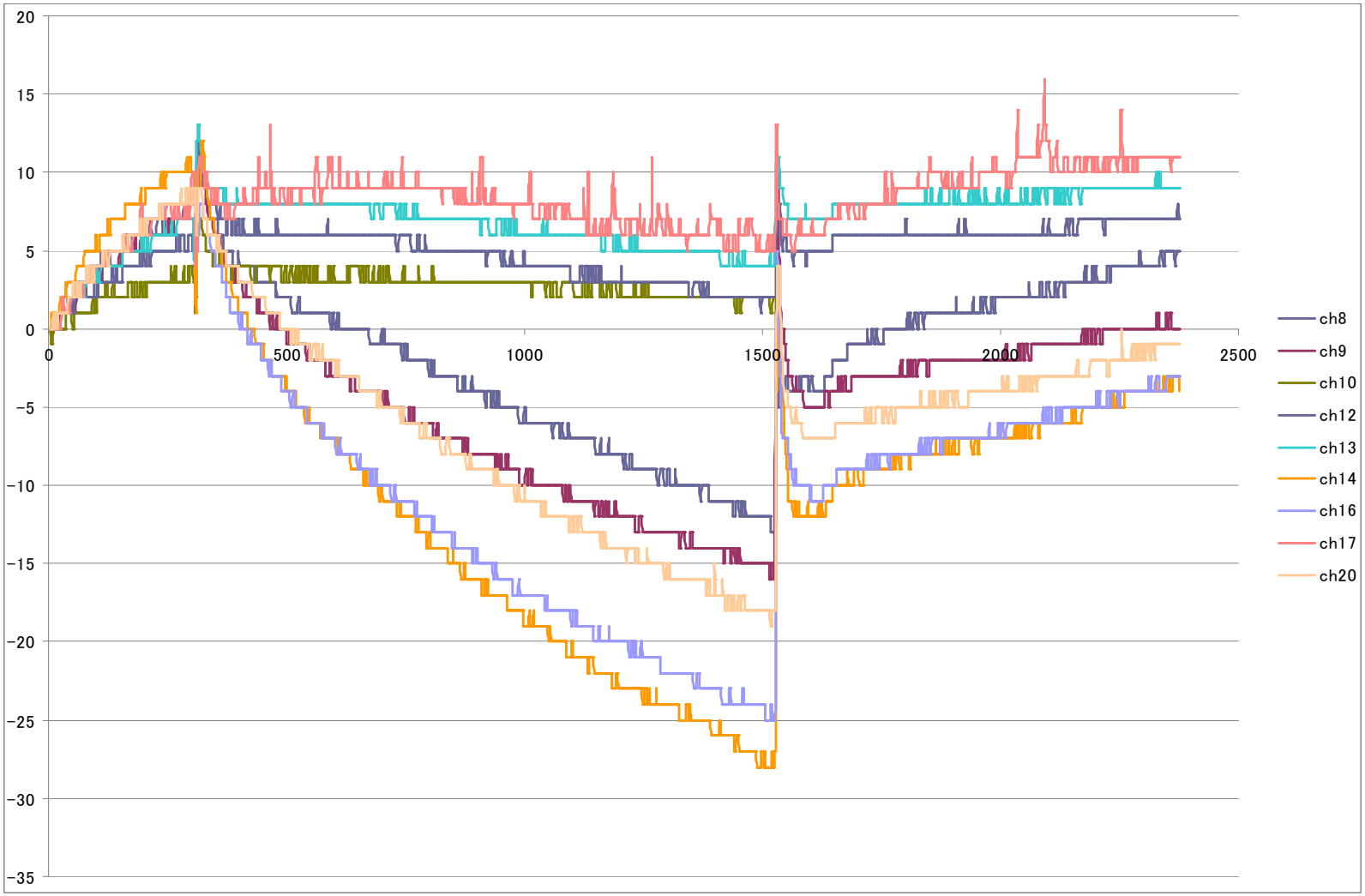




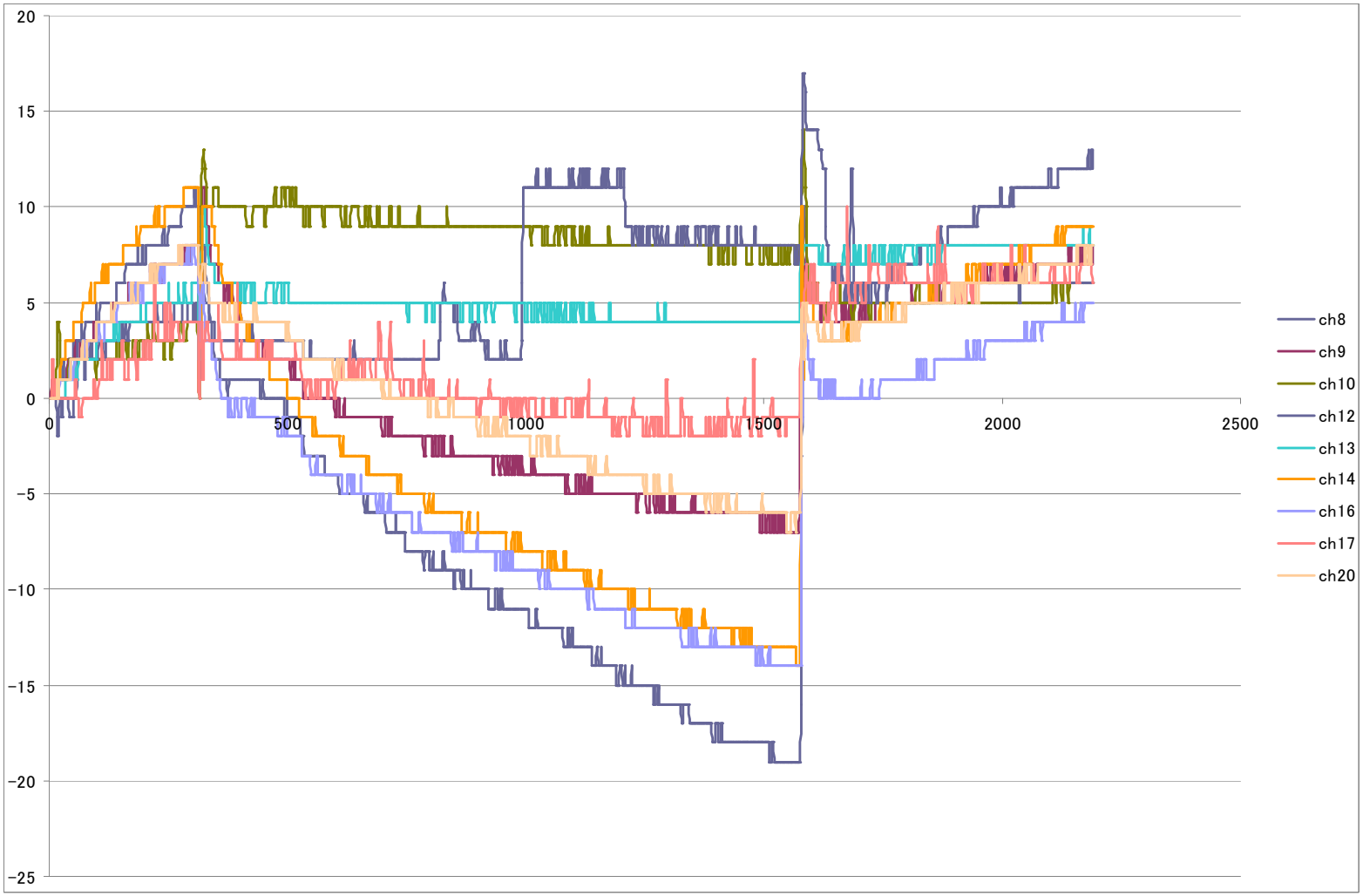
Smell Data by QCMs



Ethanol


20
15
10
5
0
−5
−10
−15
−20
−25
−30
−35
0
500
1000
1500
2000
2500
ch8
ch9
ch10
ch12
ch13
ch14
ch16
ch17
ch20

vanilla essence



New Types of MOGS

Table 1. List of MOGS used in the Experiment from FIGARO Technology Inc.

Sensor No.	Sensor model	Main detecting gas
1	TGS2600	tobacco, cooking smell
2	TGS2602	hydrogen sulfide, VOC, ammonia
3	TGS2610	LP gas, butane, propanel
4	TGS2611	methane
5	TGS2620	alcohol, organic solvent
6,7	TGS826	ammonia, amine compounds
8,9	TGS816	methane, propane, butane(flammable gas)
10	TGS821	hydrogen gas
11	TGS832	chloro fluoro carbon gas
12	TGS825	hydrogen sulfide
13	TGS830	chloro fluoro carbon gas
14	TGS822	alcohol, organic solvent

Future Research

- Mixed odors classification
- Smell communication
- Odor control
- Thick house detection
- New TV with smell, smell switches
- Small size smell detector to mobile communication

Conclusions

- MOGS and QCM sensors were shown to measure odors
- Layered types and Competitive types of neural networks are effective
- Fruitful applications to up-grade the information quality

Thank you for your attention!

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Best Paper Awards 2008

"Intelligent Electronic Nose Systems with Metal Oxide Gas Sensors for Fire Detection",

Michifumi Yoshioka, Toru Fujinaka, Sigeru Omatu,

International Journal On Advances in Intelligent Systems, Volume 2, Number 1, pp. 268 – 277, 2009