

DISTANCE-BASED FEATURE SELECTION FOR LOW-LEVEL DATA FUSION OF SENSOR DATA

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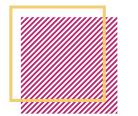




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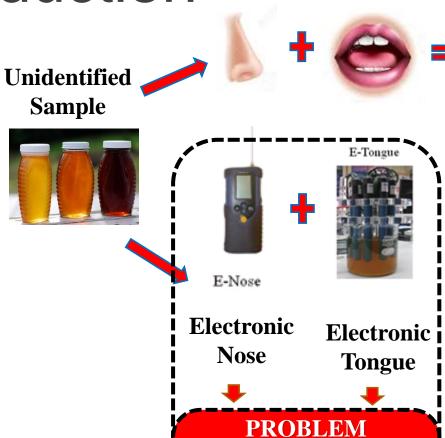


Introduction



Conventional testing method in food & beverage manufacturing

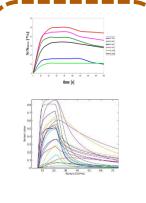
Artificial sensors to mimic trained human panel



Multi Sensor Data
Fusion -

which model is appropriate to be applied?

Human Panel/ Trained Expert



Brain

Data Analysis System

PROBLEM
Conventional
Feature
Extraction

Identified Sample



Drawback:-

- Discrepancy due to human fatigue/stress
- Time consuming
- Expensive & impossible for online monitoring



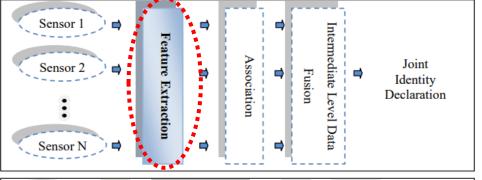
ntroduction (Joint Directors of Laboratories (JDL) Data Fusion Framework – Hall, 1992)

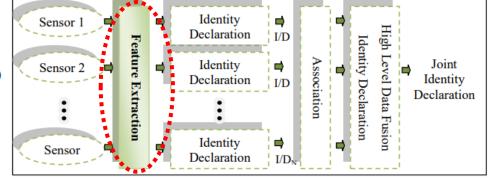
Low Level Data Fusion (a)

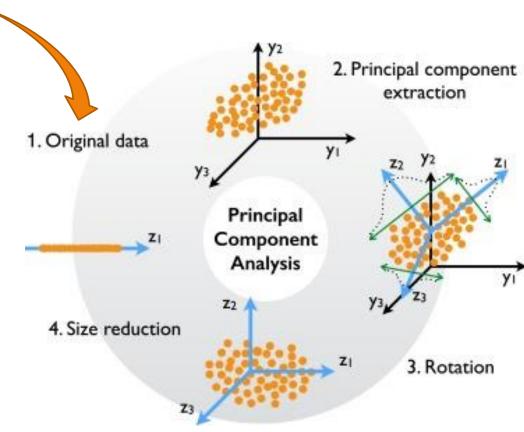


Intermediate Level Data (b) **Fusion**

High Level Data Fusion







The resulting linear combinations of features are difficult to interpret especially when specific features are of interest.

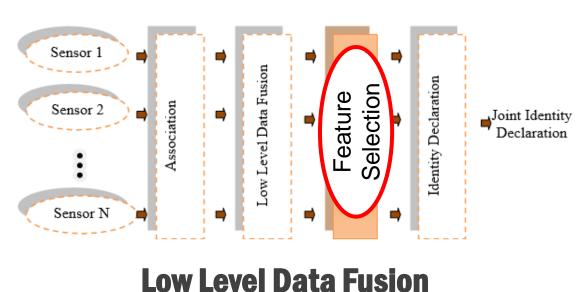


Objectives



To <u>propose a new approach to replace the feature extraction phase with</u> <u>feature selection method</u> for the low-level data fusion of two sensor devices i.e. electronic nose and electronic tongue.

A distance-based feature selection using <u>unbounded Mahalanobis distance</u> <u>criterion</u> is applied for <u>classification of multi-class problem</u>.



 II_2 $D_{1,3}^2$ $D_{2,4}^2$ $D_{3,4}^2$ $D_{3,4}^2$ $D_{3,4}^2$ $D_{4,4}^2$ $D_{4,4}^2$







Ray and Turner (1992) have introduced <u>unbounded</u> and bounded <u>Mahalanobis distance</u>-based evaluation criteria for multi class classification problem both in the distribution free and Gaussion distribution cases for the recognition of hand-printed numeric characters.

$$\Delta^2 = \left(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2\right)^T \boldsymbol{\Sigma}^{-1} \left(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2\right) \tag{1}$$

Calculate the pair-wise distances among multiclass for a feature

$$D_{ij}^2 = \left(\overline{X}_i - \overline{X}_j\right)^T S_{ij}^{-1} \left(\overline{X}_i - \overline{X}_j\right)$$

(2)

Finding the average distance for a feature

$$D_{U_{x(ip)}}^{2} = \frac{1}{\pi C_{2}} \sum_{i=1}^{\pi} \sum_{j=i+1}^{\pi-1} D_{ij}^{2}$$

$$(3) \longrightarrow D^2_{U_{x(ip)}} \in [0, \infty)$$



Methodology



Array of sensors for *q*=1, 2, ..., 32

1 2 3 4 5 6 7 8
9 10 11 12 13 14 15 16
17 18 19 20 21 22 23 24
25 26 27 28 29 30 31 32

32 Features

Figure 1.2: Illustration for Array of Sensors Attached in an e-nose (32-array)

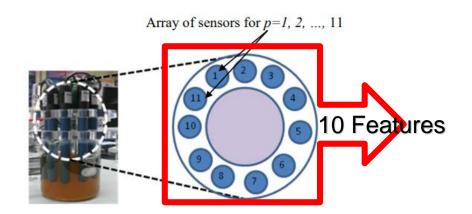
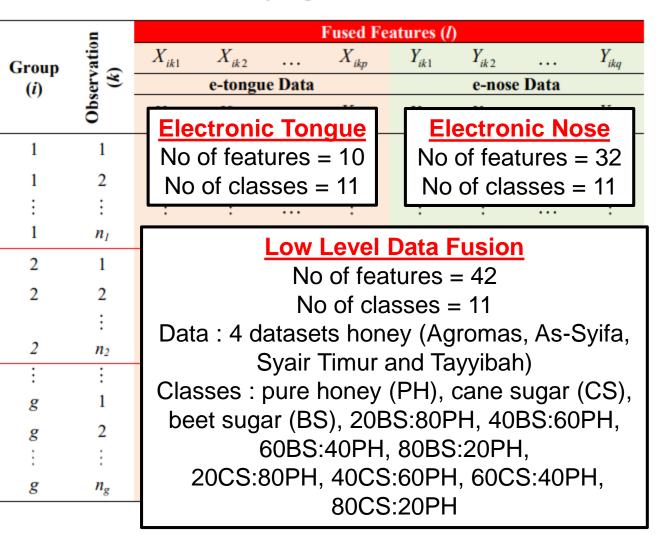
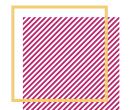


Figure 1.3: Illustration for Array of Sensors Attached in an e-tongue (11-array)

Table 3.1: Illustration of Single Sensor Data and Fused Data





Methodology



Input:

 $\mathbf{X}_{ip} = (\mathbf{X}_{ip_1} + \mathbf{X}_{ip_2})$ - matrix of observation for fused feature set Ranked fused features $\mathcal{F} = \left[D_{U_1}^2 > D_{U_2}^2 > \dots > D_{U_p}^2\right]$ Output:

Initialize $X_{ip} = [X_{i1}, ..., X_{ip_1}, ..., X_{ip2}, ..., X_{ip}]$ Step 1:

For each feature $(X_{ip_1}, X_{ip_2}) \in \mathbb{Z}^p$ Step 2:

> Calculate the unbounded Mahalanobis distance for ${}^{\pi}C_{2}$ pair-wise classes using criterion (3) for each fused feature in \mathbb{Z}^p

$$D_{ij}^{2} = \frac{\left(\overline{X}_{i} - \overline{X}_{j}\right)^{2}}{S_{ij}}, (i = 1, 2, ..., \pi; j = i + 1, ..., \pi - 1; i \neq j)$$

Calculate the average distance for ${}^{\pi}C_{2}$ pair-wise classes using criterion (4) for each fused feature in $X_{ip} \in \mathbb{Z}^p$

criterion (4) for each fused feature in
$$X_{ip} \in \mathbb{Z}^p$$

$$D_{U_{x(ip)}}^2 = \frac{1}{\pi C_2} \sum_{i=1}^{\pi} \sum_{j=i+1}^{\pi-1} D_{ij}^2 \qquad [0, \infty) \text{ unbounded Mahalanobis distance.}$$
iii. Store $D_{U_{x(ip)}}^2$ into $\mathcal{F} = [$

Step 3: End of for loop

Rank D_U^2 (from largest to smallest values) where Step 4:

 $\mathcal{F} = \left[D_{U_1}^2 > D_{U_2}^2 > \dots > D_{U_n}^2 \right]$. Filter \mathcal{F} for best feature subset evaluation.

Single feature calculation

Distances for g groups produce gC_2 group pairs $(g=9)$										
	G_I	G_2	G_3	G_4	G_5	G_6	G_7	G_8	G_9	
G_{I}	9	$D_{1,2}^2$	$D_{1,3}^2$	$D_{1,4}^2$	$D_{1,5}^2$	$D_{1,6}^2$	$D_{1,7}^2$	$D_{1,8}^2$	$D_{1,9}^2$	
G_2	$D_{2,1}^2$	9	$D_{2,3}^2$	$D_{2,4}^2$	$D_{2,5}^2$	$D_{2,6}^2$	$D_{2,7}^2$	$D_{2,8}^2$	$D_{2,9}^2$	
G_3	$D_{3,1}^2$	$D_{3,2}^2$	9	$D_{3,4}^2$	$D_{3,5}^2$	$D_{3,6}^2$	$D_{3,7}^2$	$D_{3,8}^2$	$D_{3,9}^2$	
<i>G</i> ₄	$D_{4,1}^2$	$D_{3,2}^2$	$D_{4,3}^2$	9	$D_{4,5}^2$	$D_{4,6}^2$	$D_{4,7}^2$	$D_{4,8}^2$	$D_{4,9}^2$	
G_5	$D_{5,1}^2$	$D_{5,2}^2$	$D_{5,3}^2$	$D_{5,4}^2$	Q	$D_{5,6}^2$	$D_{5,7}^2$	$D_{5,8}^2$	$D_{5,9}^2$	
G_6	$D_{6,1}^2$	$D_{6,2}^2$	$D_{6,3}^2$	$D_{6,4}^2$	$D_{6,5}^2$	0	$D_{6,7}^2$	$D_{6,8}^2$	$D_{6,9}^2$	
G_7	$D_{7,1}^2$	$D_{7,2}^2$	$D_{7,3}^2$	$D_{7,3}^2$	$D_{7,5}^2$	$D_{7.6}^2$	0	$D_{7.8}^2$	$D_{7.9}^2$	
G_8	$D_{8,1}^2$	$D_{8,2}^2$	$D_{8,3}^2$	$D_{8,4}^2$	$D_{8,5}^2$	$D_{8,6}^2$	$D_{8,7}^2$	0	$D_{8,9}^2$	
G_9	$D_{9,1}^2$	$D_{9,2}^2$	$D_{9,3}^2$	$D_{9,4}^2$	$D_{9,5}^2$	$D_{9,6}^2$	$D_{9,7}^2$	$D_{9,8}^2$	0	



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Table 2: Ranked features for four types of honeys.

Agromas		A	s-Syifa	Sya	ir Timur	Tayyibah			
R	lanke	d Unbounded	Ranked	Unbounded	Ranked	Unbounded	Ranked	Unbounded	
F	Feature Distance		Feature Distance		Feature Distance		Feature Distance		
	N23	11,949.06	N26	1937.62	N29	12593.81	<i>T7</i>	84016	
١.	N5	11,343.20	N5	1872.11	N5	6375.09	T2	17337.5	
	N29	10,027.52	N29	1815.44	N23	6014.23	N29	4120.59	
	N31	4,040.16	N31	1116.44	N31	5832.96	N23	3493.41	
	N9	3,680.18	N15	1086.9	N26	5555.79	N31	2661.3	
	N26	3,482.48	N9	1058.89	N9	4647.56	N5	2235.94	
	N11	3,074.39	N20	994.57	T2	4354.62	N6	2188.87	
	N6	2,418.34	N16	928.61	N11	3749.95	N26	2043.21	
	N20	2,300.65	N23	917.45	N6	3650.01	N9	1883.41	
	N10	1,793.69	T11	888.82	N20	3259.16	N20	1156.73	
	N17	1,778.24	N17	886.27	N17	2369.79	N10	1097.63	
	N15	1,407.55	N13	832.86	N28	2264.82	N17	1052.48	
	N16	1,161.90	N8	800.05	N10*	1997.47	T11	1037.43	
	N28	1,129.29	N21	779.23	NI	1778.03	N22	1029.37	
	N22	1,124.58	1111	755.48	N8	1742.91	N8	1020.89	
	N8	1,094.92	N18	727.66	N18	1742.85	N28	1019.52	
	N18	1,074.86	N28	712.29	N15	1695.26	N18	900.7	
	N13	869.54	N7	626.57	N16	1346.31	N15	870.4	
	N12	770.64	N12	616.34	N22	1207.47	N16	802.34	
	T11	762.64	N10	582.97	N30	1074.31	T9	660.37	
	N30	741.57	N1	580.04	N3	913.47	N11	657.82	
	N4	669.04	N3	545.42	T9	889.88	N12	554.35	
	<i>N</i> 7	646.60	N4	516.91	N12	868.62	N13	544	
	N14	574.10	N14	502.47	N13	842.9	N27	537.6	
	N21	546.70	T2	498.87	N19	826.82	<i>T1</i>	513.37	
	N19	536.86	N2	436.33	N4	818.7	N19	475.41	
	N2	532.30	N22	423.87	N27	761.42	N7	474.97	
	NI	500.41	N25	405.44	N2	700.4	NI	446.23	
	N27	459.53	N19	385.8	N7	687.86	N21	440.02	

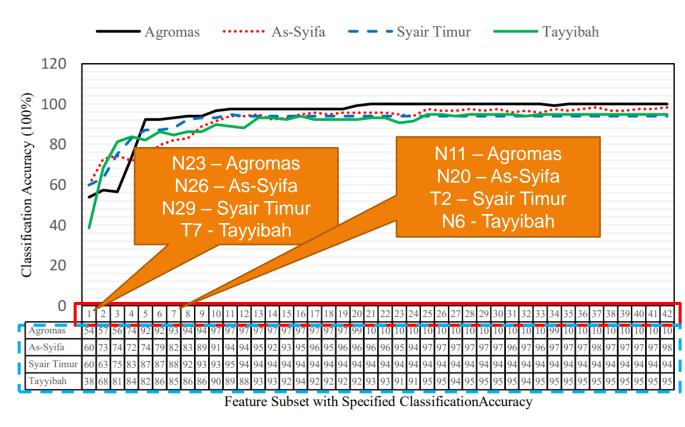


Figure 2: Classification performance of ranked feature subset (inclusion of one ranked-feature)



Conclusion



Feature selection (unbounded Mahalanobis distance) can be used to replace the conventional feature extraction for low level data fusion involving different sensor devices.

The proposed method has shown potential result of classifying pure honey from adulterated honey concentrations.

Unlike feature extraction, distance-based feature selection offers a simple and objective method to identify features that are useful to describe separation between classes which lead to good classification performance.





THANK YOU

INTERNATIONAL CONFERENCE ON COMPUTING, MATHEMATICS AND STATISTICS