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MULTISENSORY DATA FUSION FOR QUALITY ASSESSMENT OF FRUITS AND VEGETABLES

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ABSTRACT

Multisensory data fusion is one of the vibrant technologies, in which the data from several sources is acquired and processed together in order to get unified output. Data fusion systems are now widely used in various areas such as sensor networks, robotics, video and image processing, quality analysis of different products, intelligent system design etc. Quality of fruits and vegetables consumed, contributes to health of human being. Generally, a team of trained sorters can do the manual quality analysis of fruits and vegetables by identifying its size, colour, smell, stiffness, skin texture etc. It takes much time and due to the subjectivity of individual team members, no uniform analysis would be possible by this way. The repetitive task of smelling may lead to the infection and/or irritation to the graders leading to degradation of the quality of grading. Use of Multisensory data fusion will be the good solution to get more correct and quick quality assessment of fruits and vegetables. In this technique, the acquired data of size, colour, smell, stiffness, and skin texture are fused using low level fusion to assess its quality. Data imperfection, spurious data, conflicting data, inconsistent data etc. are some of the issues that make data fusion a challenging task. There are a number of mathematical theories available to represent data imperfections, such as probability theory, fuzzy set theory, possibility theory, rough set theory, and Dempster–Shafer evidence theory (DSET). This paper presents the application of multisensory low level data fusion for quality assessment of fruits and vegetables using data of its colour and skin texture obtained from a machine vision camera and odour data obtained from an e-nose. The data collection system used in the study is described in detail along with the pre-processing and data fusion algorithms. Results obtained show usefulness of the technique for quality assessment of fruits and vegetables. It is reported in literature that studies that are focused on the fusion of digital images invariably showed improvements with respect to the results obtained using single data sources. The results obtain in present study indicate that the data fusion applied to machine vision and e-nose data complement well with each other and give positive correlation with the quality.

Keywords: *Data Fusion, Sensors, E-nose, Machine Vision, Artificial Intelligence, Fuzzy Logic.*

Introduction

Most of the time data from a single sensor is not sufficient to provide unique output, even with very effective algorithms, and even if the problem at hand is well defined and limited in scope. Acquiring data (information) from different sensors and fusing it is one of the possible solutions, which the people are now exploring from some of the decades. The idea behind data fusion involves exploring different kinds of data in order to extract more reliable and useful information about the areas being analysed. There are still many challenges like Data imperfection, spurious data, conflicting data, inconsistent data etc. that prevent a more widespread adoption of multisensory data fusion. Basically the term "data fusion" can be defined as "the process of combining data from multiple sources to produce more accurate, consistent, and concise information than that provided by any individual data source"[2].

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The data fusion techniques are divided into three categories:

- Low level data fusion, in which different types of data (raw or pre-processed) are simply concatenated into a single matrix. It used in the analyses where data is of the same nature and properly normalized.
- Mid level data fusion, in which features are first extracted from different types of data and then concatenated into a matrix. This category is most useful where data can be treated in such a way that it generate features that are compatible and complementary.
- High level data fusion, in which classification and regression algorithms are applied separately to each type of data and then the outputs generated by each model are combined, being more appropriate when data sources are too distinct to be combined at an earlier stage.

The level of fusion to be adopted is not a straightforward choice. The majority of studies employ low-level fusion, arguably because this is a more straightforward and computationally lighter approach [2]. Some studies seem to indicate that higher fusion levels tend to produce better results. The best data fusion approach depends on the application and the data attributes considered. The selection of an appropriate method should be conducted using independent data validations. In this paper the data of Guava acquired from e-nose and machine vision [4] is used for assessment of its quality using low level fusion.

Methodology

- **Electronic Nose**

Electronic Nose (e-nose) is basically the ‘Smell detection Electronic Instrument’. It was designed to mimic the smelling operation of animals. It was designed by using pattern recognition techniques for classification of detected odor by gas sensors [5]. Latter on it was developed using various techniques and now are available commercially for different applications. The comparative study of human nose and e-nose is given in the form of block diagram in fig. 1.

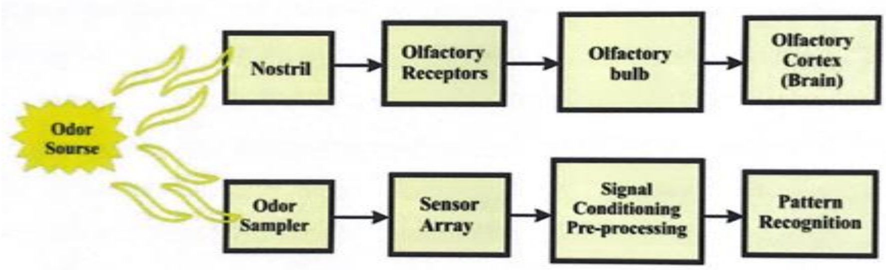

Fig. 1: Block Diagram of Working of Human Nose and E-nose [4]

In human odor identification system as shown in fig. 1. Olfactory receptor are the biological sensors which senses the odor, the olfactory bulb is a switching centre connecting the nose to the olfactory cortex of a brain. When odorant gas molecules come in contact with the chemo sensory smell receptor, electrical stimuli is generated. Such generated stimuli is processed by neurons and passed to the Central Nervous System through olfactory nerves. The Interpretation of smell begins by relating it to the past experiences. A pattern recognition process then takes place in order to identify / classify the odor. Odor sensation depends on its concentration at the olfactory receptors[5].

As was stated earlier, the electronic nose is designed to mimic the human nose. The olfactory receptors are replaced by an array of electronic gas sensors. The signals produced by gas sensors are pre-processed and by way of pattern recognition the received odor is identified. Such identified odor is one of the attribute used to find the quality of the fruit / vegetable.

The selection of sensor in the designed e-nose depends on the nature of analyte to be identified, the nature of sample evaluation etc. The ideal sensors to be added in e-nose should have high sensitivity to chemical compounds, low sensitivity to humidity and temperature, medium selectivity, high stability, high reproducibility and reliability, dynamic and long lasting and easy to calibrate.

Using signal conditioning circuit the output of sensor array was brought to the appropriate level so that the signal processing for pattern recognition will be done properly. By the array of sensors used, large amount of data is generated which needs to be reduced for required information collection. It is done by way of signal pre-processing. Techniques used for pre-processing are weighting, standardizing and normalising sensor responses. The goal of signal pre-processing is to extract relevant information from the sensor responses and prepare the data for pattern analysis. Such pre-processed signals with exact required information are then fed for pattern recognition which gives the details of odor (smell) evolved from the fruit / vegetable. Different odor have different pattern which is recognised in the final stage of e-nose. In this paper the pattern recognition was done using Artificial Neural Network (ANN).

Machine Vision

Machine vision system mimics the human vision using digital camera, computer and image processing tools. Machine vision technique is used to provide imaging based inspection and analysis of data. Machine vision and image processing techniques are contributing a lot in quality inspection. The basic machine vision system consists of lighting system, camera and computer with an image acquisition board. The following figure 2 shows the various components of machine vision system [4].

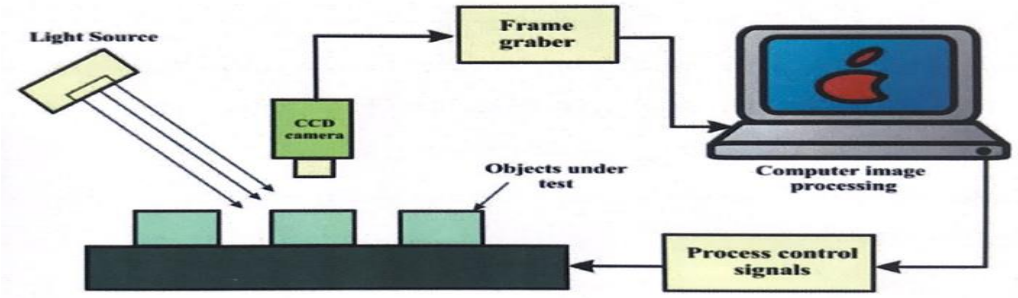

Fig. 2: Components of Machine Vision System

The machine vision system used to produce data for fruit or vegetable quality analysis is assembled with the motor driven conveyer belt to carry fruit or vegetable serially in front of camera. The light source is used to put light appropriately on the object. When the object comes in front of CCD camera, it receives light from the object surface and convert it into electrical signals. The frame grabber grabs images continuously with defined time intervals and send to the computer for further processing. After taking sufficient number of images the conveyer belt pushes the next fruit in front of camera through process control signals and same process continues. The captured images are processed in order to extract several relevant features i.e. colour, size, skin texture etc. of an object.

Various image processing algorithms are used to estimate the parameters of quality assessment. The mostly used and accurate classification techniques are fuzzy logic, Artificial Neural Network (ANN), support vector machine, genetic algorithm technique and histogram based method. Image processing involves a series of steps which can broadly divided into three levels: Low level processing, Intermediate level processing and High level processing as shown in below figure 3 [4].

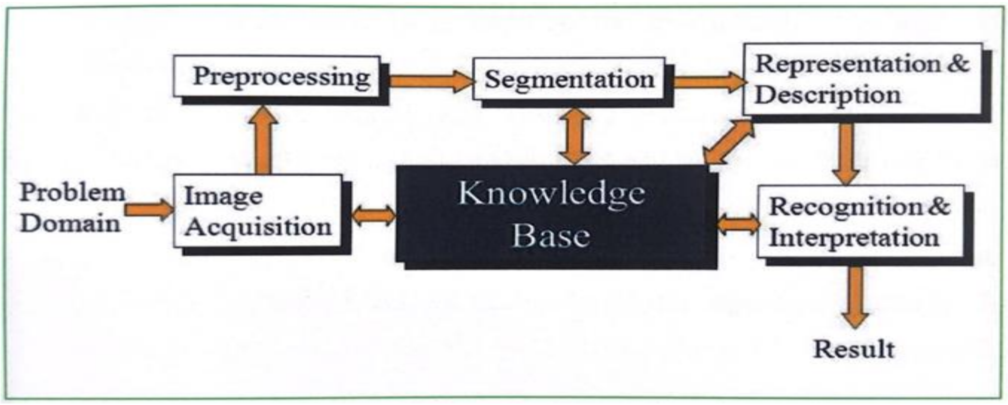

Fig. 3: Block Diagram of Image Processing [4]

Low level processing includes image acquisition and pre-processing. Image acquisition is the transfer of electronic signal from the sensing device into numeric form. Image preprocessing refers to the initial processing of the raw image data for correction of geometric distortions, removal of noise, gray level correction and correction of blurring.

Intermediate level processing involves image segmentation, image representation and description. Image segmentation is one of the most important steps in the entire image processing technique. Its main aim is to divide an image into regions that have strong correlation with objects or areas of interest.

High level processing involves recognition and interpretation using statistical classifiers or multilayer neural networks of the region of interest. These steps provide the information necessary for the process control for quality sorting and grading.

The interaction with knowledge database at all stages of the entire process is essential for more precise decision making and is seen as an integral part of the image processing process. Algorithms such as Neural Networks, Fuzzy logic and genetic algorithms are some of the techniques of building knowledge bases into computer. Neural Network and Fuzzy logic operations have been implemented successfully with computer vision in the food industry[4].

Result and Discussion

The fruits can be sorted according to the quality and maturity level before its transportation using fusion of data obtained from e-nose and machine vision technique. Quality analysis of fruits and vegetables are done succesfully using the data of their smell, shape, size, colour and skin texture.

Following Table -1 shows the data acquaired by the senors used in the e-nose. There were 8 TGS gas sensors used, TGS 2602. TGS 2600, TGS 2610, TGS 2611, TGS 2620, TGS 822, TGS 813, TGS 832. The data shows good response of sensors for three fruits Guava, Orange and Banana. The variations in minimum and maximum voltage values shows good sensor response. Such varied voltage data of different friuts helps to identify fruit. The data shown in Table-2 helps to find its quality.

Table 1: E-nose Gas Sensor responses for Three Different fruits [4]

Fruit Type	Sensor response	TGS 2602	TGS 2600	TGS 2602	TGS 2611	TGS 2620	TGS 822	TGS 813	TGS 832
Guava	Min	2.26	6.75	2.154	0.178	2.2	5.3	0.278	0.452
	Max	3.5	10.83	3.365	0.267	3.64	8.423	0.588	0.935
Orange	Min	0.796	10.62	0.893	0.111	0.968	7.897	0.3	0.242
	Max	1.127	18.44	1.351	0.178	1.286	11.76	0.45	0.606
Banana	Min	4.021	13.33	4.255	0.34	4.538	16.4	0.842	2.25
	Max	4.234	14.71	4.224	0.37	4.75	17.2	0.895	2.548

In order to check the quality of fruit the sensor output voltage data at different ripening stages are requird. Such data is also obtained by same e-nose sensor array which is shown in Table-2.

Table 2: E-nose Gas Sensor Responses for Quality Check of Guava Fruit [4]

Fruit Class	Sensor response	TGS 2602	TGS 2600	TGS 2602	TGS 2611	TGS 2620	TGS 822	TGS 813	TGS 832
Green	Min	0.05	0.044	0.049	0.02	0.085	0.095	0.048	0.029
	Max	0.186	0.667	0.187	0.115	0.212	0.378	0.10	0.121
Ripe	Min	0.185	0.414	0.209	0.12	0.215	0.326	0.105	0.152
	Max	0.288	0.469	0.257	0.163	0.284	0.444	0.167	0.162
Overripe	Min	0.284	0.644	0.303	0.115	0.339	0.51	0.15	0.121
	Max	0.952	2.846	1.015	0.163	1.097	2.459	0.19	0.265
Spoiled	Min	1.308	3	1.434	0.253	1.58	4.231	0.333	0.287
	Max	1.434	3.571	1.491	0.326	1.615	4.286	0.471	0.533

The colour of Guava fruit samples at different maturity stages were obtained by digital image measurement. The average RGB values were obtained using image tool of Matlab. Below figure 4. shows the analysis of Guava fruit using machin vision. To increase the accuracy of quality analysis of Guava fruit the data acquired by such machine vision technique can be fused.

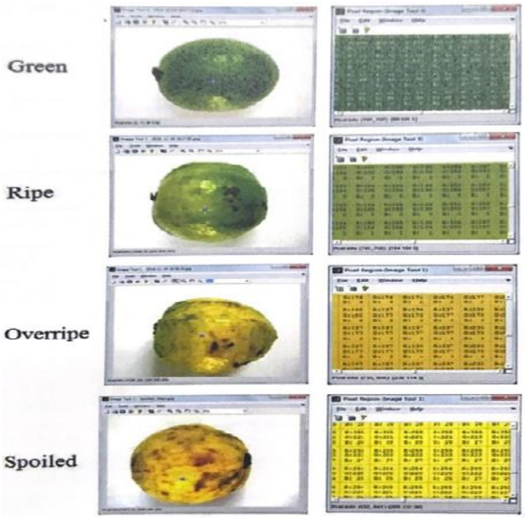

Figure 4: Analysis of Guava Fruit using Machine Vision [4]

The major advantages of data fusion is that it is non-invasive technique of quality analysis with high speed, high accuracy and uniformity. The alternative method is a chemical analysis in which the fruit or vegetable is crushed, by adding necessary chemicals in it the data is acquired. Such acquired data can also be fused along with the data acquired by e-nose and machine vision. The chemical analysis is destructive technique. It has not been used in this project but in future it can be involved in data fusion.

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