DESENVOLVIMENTO DE UMA UNIDADE DE CLASSIFICAÇÃO ROBOTIZADA – DESENVOLVIMENTO DE UM ALGORITMO DE RECONHECIMENTO DE MATERIAIS DE OBJETOS

DEVELOPMENT OF A ROBOTIC SORTING NODE – DEVELOPMENT OF AN ALGORITHM FOR THE RECOGNITION OF MATERIALS OF OBJECTS

РАЗРАБОТКА РОБОТИЗИРОВАННОГО СОРТИРОВОЧНОГО УЗЛА – РАЗРАБОТКА АЛГОРИТМА РАСПОЗНАВАНИЯ МАТЕРИАЛОВ ОБЪЕКТОВ

KRECHETOV, Ivan V.[1*]; SKVORTSOV, Arkadiy A.[2]; POSELSKY, Ivan A.[3]; PALTSEV, Sergey A.[4]; LAVRIKOV, Pavel S.[5]; KOROTKOVS, Vladislavs[6]

[1,2] Moscow Polytechnic University, Department of Scientific Research and Development, 38 Bolshaya Semenovskaya Str., zip code 107023, Moscow – Russian Federation
(phone: +7 495 223-05-23)

[3] Moscow Polytechnic University, Department of Automated Technical Systems, 38 Bolshaya Semenovskaya Str., zip code 107023, Moscow – Russian Federation
(phone: +7 495 223-05-23)

[4] Profina Oy, 33 Ratakatu Str., zip code 53100, Lappeenranta – Finland
(phone: +09 231 692)

[5,6] RU.Robotics, 13 Rubzov Lane, zip code 105082, Moscow – Russian Federation
(phone: +7 927 486-25-18)

** Corresponding author*
e-mail: krechetov_ivan@mail.ru

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RESUMO

Com o desenvolvimento da tecnologia computacional, tornou-se possível resolver uma série de problemas decorrentes dos processos da vida, para facilitar, acelerar, melhorar a qualidade do resultado. O objetivo deste trabalho é estudar as densidades espectrais dos sinais refletidos na zona infravermelha próxima e desenvolver um sistema para reconhecer tipos de materiais para utilizar como parte de uma unidade de classificação robotizada ao realizar as operações em objetos que se movem em uma correia transportadora. Foram analisados os métodos para identificar o material de um objeto, bem como algoritmos para identificar e reconhecer objetos através do processamento de dados de um sistema de visão automatizado. O trabalho mostra alta precisão de 94,12% de identificação de polímeros plásticos. O algoritmo de classificação de material desenvolvido destina-se ao processamento dos dados do sistema combinado de visão automatizado como parte de soluções de software e hardware e uma amostra experimental de uma unidade de classificação robotizada.

Palavras-chave: *identificação de materiais, sistema de visão automatizado, espectrômetro, classificação de resíduos.*

ABSTRACT

With the development of computing technology, it became possible to solve a number of problems arising in the course of life, to facilitate, accelerate, improve the quality of the result. The purpose of this work is

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to study the spectral densities of the reflected signals in the near infrared zone and to develop a system for recognizing types of materials for use as part of a robotic sorting node when performing operations on objects moving on a conveyor belt. Methods for identifying the material of an object, as well as algorithms for identifying and recognizing objects by processing data from a computer vision system, are considered. High accuracy is shown in 94.12% identification of plastic polymers. The developed material classification algorithm is intended for processing the data of the combined machine vision system as part of software and hardware solutions as part of an experimental sample of a robotic sorting node.

Keywords: *material recognize, machine vision system, spectrometer, waste sorting.*

АННОТАЦИЯ

С развитием вычислительной техники стало возможным решить ряд задач, возникающих в процессе жизнедеятельности, облегчить, ускорить, повысить качество результата. Целью данной работы является исследование спектральных плотностей отраженных сигналов в ближней инфракрасной зоне и разработка системы распознавания типов материалов для использования в составе роботизированного сортировочного узла при выполнении операций над объектами, движущимися на конвейерной ленте. Рассмотрены способы идентификации материала объекта, а также алгоритмы выделения и распознавания объектов посредством обработки данных от системы машинного зрения. В работе показана высокая точность в 94.12% идентификации пластиковых полимеров. Разработанный алгоритм классификации материала предназначен для обработки данных комбинированной системы машинного зрения в составе программно-технических решений и экспериментального образца роботизированного сортировочного узла

Keywords: *идентификации материала объекта, система машинного зрения, спектрометр, сортировка отходов.*

INTRODUCTION

The market currently presents two main types of complexes for sorting solid household waste: automated and using manual sorting. The division into automated and manual ones is conditional here since in both cases, manual labor is used, but at different scales. The main difference is the use of manual sorting at the stage of selecting useful fractions (paper / cardboard, plastic, wood, textiles, glass, metals), which can be recycled and are valuable in terms of profit and the possibility of building a business in the field of sorting solid waste (Paulraj *et al.*, 2016; Bakirova, 2011).

Currently, the Finnish company ZenRobotics has advanced greatly in the field of robotic sorting. This company introduced a recycling system that automatically sorts construction and demolition waste.

The sorting lines on the market have an identical design: a conveyor belt, to which waste distributed in one layer is fed. Above the tape is an optical system that recognizes the substances that make up the waste elements. At the end of the conveyor belt, air nozzles have installed that transfer the recognized waste elements to different containers using a stream of compressed air (Wienke *et al.*, 1996; Rinnan *et al.*, 2009).

However, all such systems have a common drawback – the need to pre-crush incoming waste, which increases the number of small, non-sorted elements. The use of robotic manipulators will allow sorting waste without the need for their crushing, since the manipulator, unlike the pneumatic system, has a significantly higher load capacity with similar performance. The purpose of this work is to develop an algorithm for recognizing types of materials for subsequent implementation as part of a newly developed robotic sorting node.

In general, optical spectrometry in the near infrared region is based on the use of radiation with a wavelength of 700nm to 2500nm. However, for waste sorting problems this range is limited: from 1000nm to 2000nm. The molar absorption coefficient of the substance for the indicated wavelengths is very low, which provides the advantage of using this range – high radiation penetrating ability. As a consequence, IR spectrometry can be used to determine the composition of a substance without its special preparation (Gordetsov, 2010). Halogen incandescent bulbs or LEDs are used as the emitter, which provides a much longer service life. CCD arrays and detectors based on gallium-indium arsenide are used as a detecting receiver.

The key parameter for successful recognition of a substance is the signal-to-noise ratio received by the receiver of the sum signal. The following factors significantly affect this parameter:

1. Stickers on the bottles. The thickness of the walls of various plastic containers is usually about 0.3 mm and the radiation of the near infrared range (BID) penetrates through, forming a high-quality reflected signal. Stickers, often made from another material, have a thickness of 0.01-0.02 mm. The radiation passes through them, with the result that the reflected signal is a mixture of signals from the sticker and from the container itself. This mixture can vary greatly in proportions, depending on how tightly the label fits the surface of the container. For reliable recognition of materials in such cases, requires a high signal-to-noise ratio and special processing algorithms that allow you to select a useful signal.

2. Multilayer bottle walls. The next factor – the multilayer walls of the bottles, has a much greater impact on the quality of recognition of substances. In the manufacture of containers with multilayer walls, polyamide sheets placed between two PET layers are most often used. The peculiarity is that these sheets have a thickness of 0.02 mm and are under the surface of the material. A similar factor is the use of mixtures of two different polymers for the manufacture of containers. Both cases are extremely difficult to recognize and at the moment there is no industrial technology for sorting such materials that provide an acceptable result.

3. Plastic films. Films are the main area in which it is possible to achieve higher levels of recycling. The most commonly used materials for their manufacture are polyethylene, polypropylene, and polyvinyl chloride. The thickness of the films is usually from 10 microns to 15 microns and most often they are folded and dirty. Polymer films are sorted in two stages, first, the films themselves are separated from the total waste stream, and then separated by substances: polypropylene and polyvinyl chloride should be separated from polyethylene. Since these materials are very light, to ensure high sorting performance, they need special sorting lines. For example, films should be distributed over a very large area of the conveyor and pressed against its surface by a stream of air.

4. Biological waste. Organic or food waste is not the scope of BID-sorting methods. Water in large quantities is part of the organic, actively absorbs infrared radiation. Therefore, the analysis of such objects as vegetables or fruits, with a water content of more than 50% is difficult. To ensure IR transparency, the food industry uses another part of the near infrared range: from 700nm to 1100nm. At the same time, for the further processing of organic waste in bioreactors and methane production, low content of the paper in them is necessary.

5. Paper. Mostly paper is made from cellulose, but other formulations are also found. Different types of paper differ in the content of lignin (in the mechanical, or chemical processing of raw materials for paper production), the content of fillers (waxing, changing the brightness and color of the paper in the mass), as well as the content of surface dyes and inks. For example, oil inks for offset printing, or water-based for flexographic printing.

6. The tree. Wood has the same chemical composition and must be separated from the paper. Moreover, natural wood is more valuable than processed wood, which includes components such as varnishes, paints, and adhesives.

LITERATURE REVIEW

The most popular method in this area is spectroscopy. Spectroscopy is the science of the interaction of electromagnetic radiation with various substances. In this method, there are several main areas (Ball, 2001):

- optical spectroscopy (OS);
- infrared spectroscopy (IR);
- ultraviolet spectroscopy (UFS);
- terahertz spectroscopy (THzS);

Infrared spectroscopy is a section of spectroscopy operating in the infrared frequency range. With the passage of infrared radiation through a substance, the molecules are excited. At the same time, there is a decrease in the intensity of the light that has passed through this object. Absorption does not occur in the entire spectrum of the irradiating radiation, but only at frequencies whose energy corresponds to the excitation energies of the vibrations in the molecules. Consequently, the frequency of maximum absorption of IR radiation indicates the presence in the sample molecules of the corresponding functional groups.

In the article (Paulraj *et al.*, 2016), the authors investigated and experimentally tested the hybrid sensor system to accurately determine the metal grade in the incident stream of solid particles of waste. The system includes an infrared and electromagnetic unit around the central tube and counts both the total number of particles and only metal particles.

The article (Bakirova, 2011) presents the study of polymers at leading universities in the UK using IR and UV spectrometry. In (Gordetsov, 2010), IR spectroscopy of biological fluids and tissues was examined to detect changes in their composition.

In (Brown and Lo, 1998), the authors presented a complex algorithm for the classification of hydrocarbons based on the use of decomposition by the principal component method as input data for a neural network based on radial basis functions and showed a classification accuracy of up to 95%.

With the help of genetic algorithms (Lavine *et al.*, 2002), it is possible to select a set of features (wavelengths) for optimal class separation on the graph of the signal decomposition into principal components.

The method of partial least squares (Helland, 1990; Van Den Broek *et al.*, 1996)has long been used in mathematical statistics when calculating a regression model for the secondary processing of data obtained using the principal component method (Gao *et al.*, 2018). When using a neural network of direct distribution (Van Den Broek *et al.*, 1998), the accuracy of recognition of plastics types was obtained up to 95%, the recognition of non-plastic materials – up to 80%. The study also carried out studies of the influence of humidity and temperature on the stability of the algorithm (Formalev *et al.*, 2016; Kakhramanov *et al.*, 2017).

The neural network based on the adaptive resonance algorithm (Wienke *et al.*, 1996) has shown effective work in classifying several types of plastics if the class boundaries are pronounced. For strongly blurred classes, its effectiveness was insufficient. Improving the stability of the operation of the spectrum recognition algorithm in the near infrared zone can be achieved (Rinnan *et al.*, 2009) by pre-digital processing of the measured signal for scattering correction (Paraforos *et al.*, 2018). When spectral processing of signals, high speed can be achieved by reducing the dimension of the original data, so the optimal spectral ranges can be calculated using genetic algorithms (Van Den Broek *et al.*, 1997).

Depending on the number of types of plastic being sorted, the simplest approach (Scott, 1995) (PET sorting (PET) and PVC (PVC)) can be used based on the ratio of absorption coefficients in a narrow region of the spectrum.

MATERIAL AND METHODS:

To recognize the material of an object, we use spectroscopy in the near infrared region. The infrared region of the spectrum is divided into several ranges:

- 0.8–2 µm region – near infrared region;
- 2–40 µm region – middle (fundamental) infrared region;
- area up to 200 microns – far infrared.

Since the most powerful radiation in the infrared range in the near infrared region, this method is suitable for the analysis of complex organic molecules. The radiation source is usually a tungsten halogen lamp. A halogen lamp generates a polychromatic radiation spectrum, which is converted into monochromatic radiation of one or several wavelengths using a rotating replaceable light filter. Monochromatic radiation is directed to the sample surface using a flat mirror, hits the sample, the molecules of which begin to oscillate at certain frequencies and absorb part of the light (Prietl, 2017; Tamás, 2018; Gitelman *et al.*, 2018). Another part of the world is reflected. The reflected radiation is collected by a parabolic mirror, which redirects it to the photo detector. The detected radiation is transferred by the detector into a proportional electrical signal, after processing of which data on the spectral characteristics of the materials are given (Sánchez *et al.*, 2003; Esatelles *et al.*, 2018).

After receiving the spectrum of the detected object, the initial filtering of the FIR filter is performed using the moving average method and the determination of the extremum. The wavelength corresponding to the extremum of the spectral density of the reflected signal corresponds to a certain type of material. The spectrometer used in this work is a small-sized spectrometer DLPNIRnano, manufactured by Texas Instruments. Unlike many other spectrometers, this model is not built on a linear, but on a matrix detector, i.e. a two-dimensional image is obtained at the sensor output. The detector has a high sensitivity in the range from 900nm to 1700nm. Spectrum measurement was carried out through the DLP NIRscan Nano GUI application and then saved to CSV (Comma-Separated Values) files.

For the analysis of the spectral density of the reflected signal in the near infrared zone, samples were taken of various plastic materials (HDPE, PP, PET, PS, PVC), paper/cardboard, wood and textiles (Table 1).

The experimental data were prepared by measuring the reflected signal in the near-infrared zone with a Texas Instruments DLPNIRNANO spectrometer.

To ensure the reliability of the measurements, multiple exposures were made (up to 6 times) of each selected sample with the subsequent averaging of the result. Figure 1 shows the spectral densities of the reflected signal when the sample is irradiated at different distances from the receiving head of the spectrometer. The initial data for the development of a material type recognition algorithm is the normalized spectral density for various types of materials (Figure 2), obtained on the basis of experiments on previously prepared samples.

RESULTS AND DISCUSSION:

3.1. Determination of spectral density extremes

To reduce the size of the original sample, it is advisable to select the spectral regions with characteristic features. In the case of the near-infrared zone, these are the regions (frequencies) of the spectrum with the highest absorption, which is typical of the detection of the chemical composition of the material under study. We calculate the first and second frequency derivatives for the original spectrum of the reflected signal and plot them together with the original signal (Figure 3).

As can be seen from the graph, the following dependencies are characteristic of the local extremum of a signal (Figure 4):

- change the sign of the first derivative (the intersection with zero);
- the intersection of the first derivative with zero from above is typical for the maximum, from below for the minimum.

3.2. Selection of informative features

- As arguments for the classification of materials using the principal component method, we use the values of the frequencies corresponding to the found extremums of the absorption spectral density in the near infrared zone.
- As can be seen from the analysis of the obtained spectral densities of the reflected signal, all materials are characterized by the presence of two frequencies and areas around them with characteristic distinctive features. However, due to the inhomogeneity of the relief of the samples, scanning is performed at an arbitrary angle of incidence of the emitter, in the spectral density there are noises (false extremes), the presence of which significantly complicates further processing and increases the number of false alarms of the peak detector.
- To eliminate noise, we use a filter with the use of a moving average, the output value of which is determined by the following relation Equation 1:

$$y(t) = \frac{1}{n}\sum_{i=0}^{n-1} x_{t-i} \qquad (1)$$

- Where: t – time,
- n – sliding window size,
- x –source signal.

The size of the sliding window also forms a delay line (Figure 5), therefore, in order to preserve the binding of the original data to the frequency values, it is necessary to shift the received signal by the size of the size of the sliding window.

As a result of the peak detector operation, the radiation wavelengths corresponding to the extremes of material absorption were determined for the spectral densities of the reflected signals of the selected samples, the found points can be used to reduce the sample for further processing by the principal component method (Table 2).

As a result of the decomposition of the

input signals by the principal component method (Figure 6), clustered clusters are obtained, which correspond to a certain type of material. For classification, i.e. determining whether a sample of a given spectral density belongs to a particular class, a method can be used based on the Euclidean distance (if the classes are circles) to the center of the class or the Mahalanobis distance, which takes into account the elliptical form of the class.

3.3. Recognition using artificial neural networks

We use hardware artificial neural networks to recognize signals. The neural network architecture is a convolutional neural network with the following parameters:

- Number of layers – 5
- Number of inputs – 227
- Number of Outputs – 8
- Number of neurons –50

We will also study the effect of the number of neurons in the hidden layer on the accuracy of recognition.As a result of the operation of the recognition unit based on the use of neural networks, the following error matrix was obtained (50 neurons of the hidden layer) (Figure 7).

The developed algorithm showed recognition accuracy of 94.12% by the criterion of "plastic – not plastic", while 10 neurons in the hidden layer are enough, which is a good indicator for ensuring high computing performance of 0.68 ms using the Intel Core i7-6700HQ processor. The probability of recognition of various types of plastics is presented in Table 3. As can be seen from Figure 7, the recognition accuracy of individual types of plastics is more than 90%, and the probability of PVC extraction is 100%, which positively affects the safety of further recycling.We represent the plot of recognition accuracy on the dimension of the hidden layer of the neural network (Figure 8).

CONCLUSION:

As shown by the results of the analysis of the spectral density of the reflected signal, the sensor used has sufficient sensitivity to analyze and recognize parameters using the second harmonic of the reflected signal. A key feature of this sensor that influences the configuration of the developed sorting node is a small focal length (about 17 mm), it is recommended to place the sensor directly on the gripping head of the manipulator to achieve the highest recognition quality, or place a group of several sensors parallel to the plane of the conveyor belt so that the flow of objects on the conveyor got into the field of view of the sensor, for example, through a transparent window mounted in the transport plane molecular tape. Placing above the conveyor belt is impossible due to the small focal length. However, it is necessary to take into account the fact that the transparency of the protective window is influenced by several factors: the mechanical impact of the flow of objects can lead to wear of the glass surface, moisture and dirt from objects can also accumulate.

The developed material classification algorithm is intended for processing the data of the combined machine vision system as part of software and hardware solutions as part of an experimental sample of a robotic sorting node (EO RSU). The developed robotic sorting node is intended for further use in the tasks of automating the processes of sorting operations with objects that have several (more than one) characteristics (properties of objects that are important for their classification and/or sorting operations). In the future, the developed solutions should find their application, above all, when conducting sorting operations with components of municipal solid waste at the stage of the waste sorting process cycle for the selection of useful fractions.

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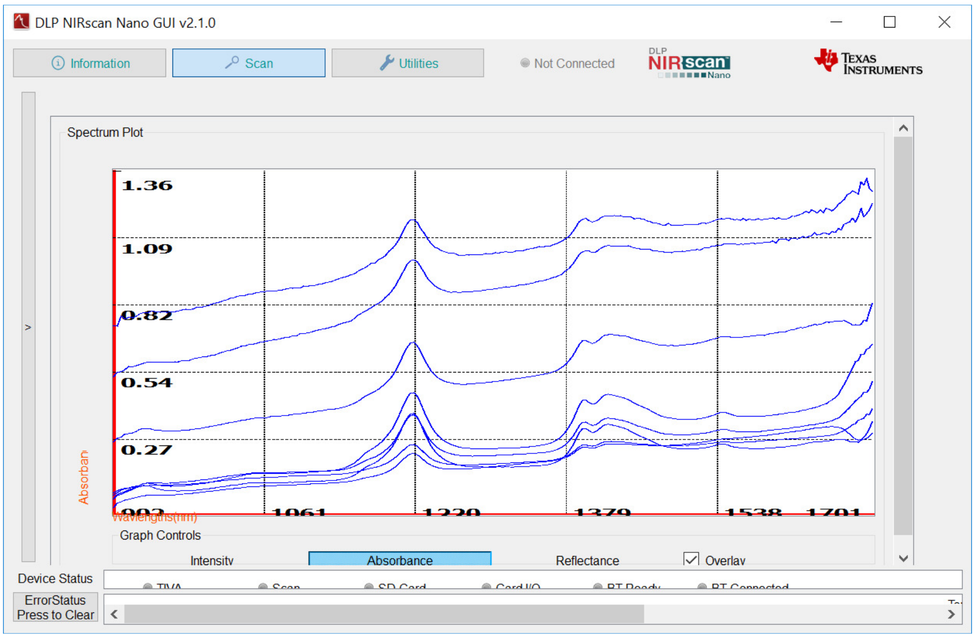

Figure 1. *The dependence of the spectral absorption density for different samples of HDPE plastic at the same distance from the optical system of the NIR spectrometer*

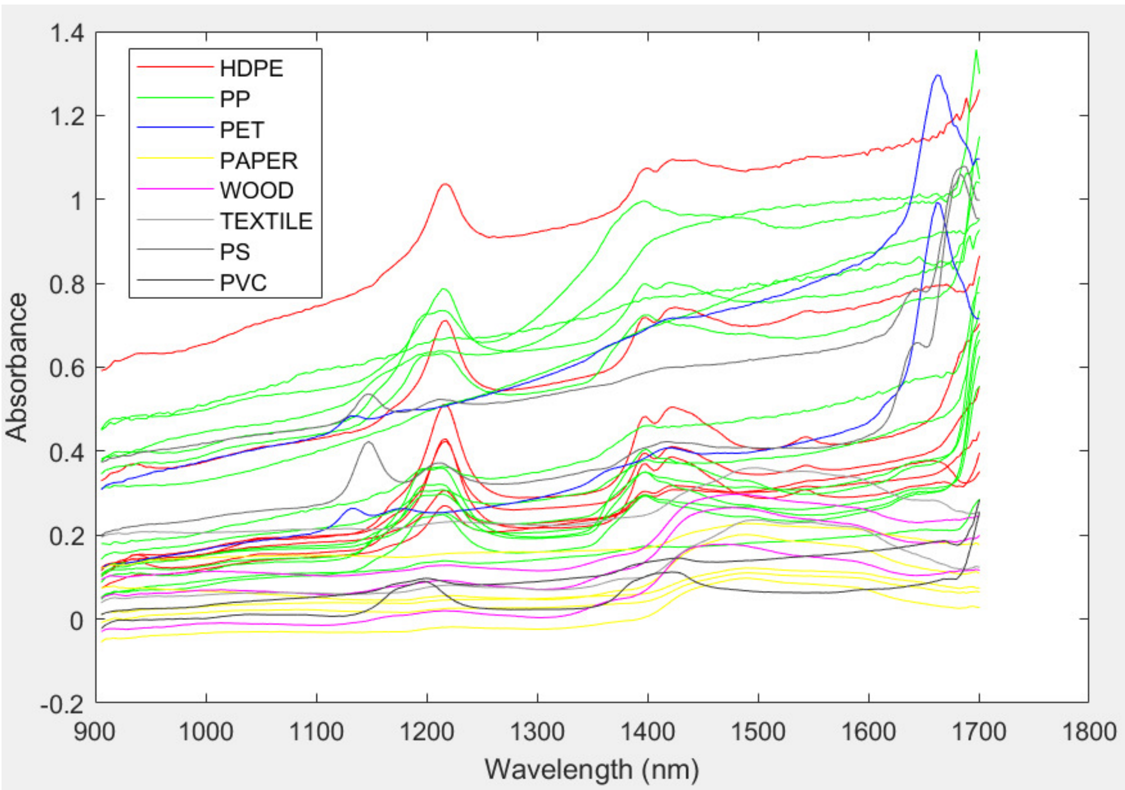

Figure 2.*Normalized absorption spectral density for various types of materials*

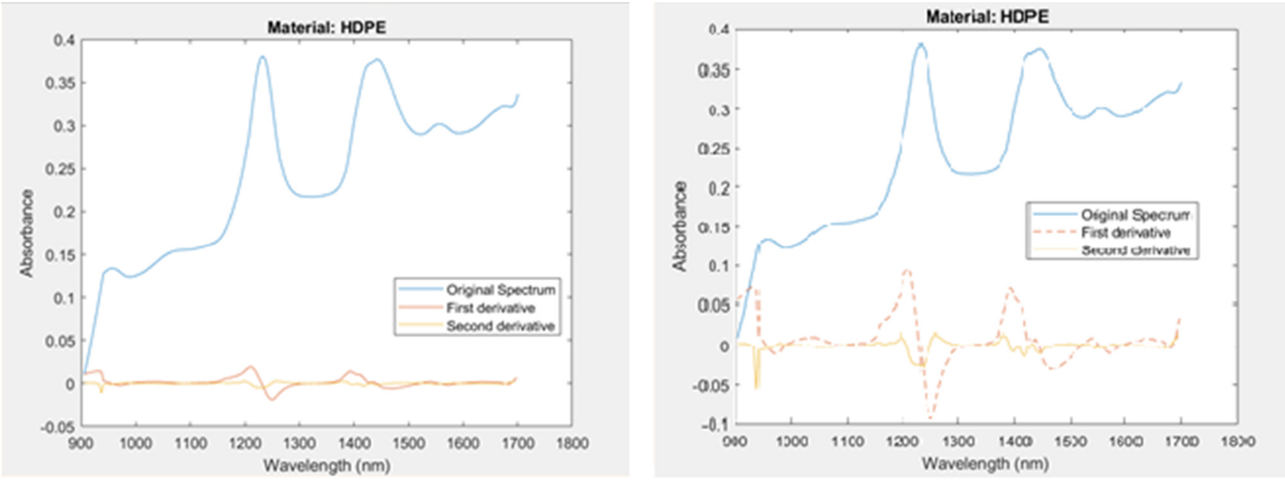

Figure 3*. The preliminary stage of the peak detector*

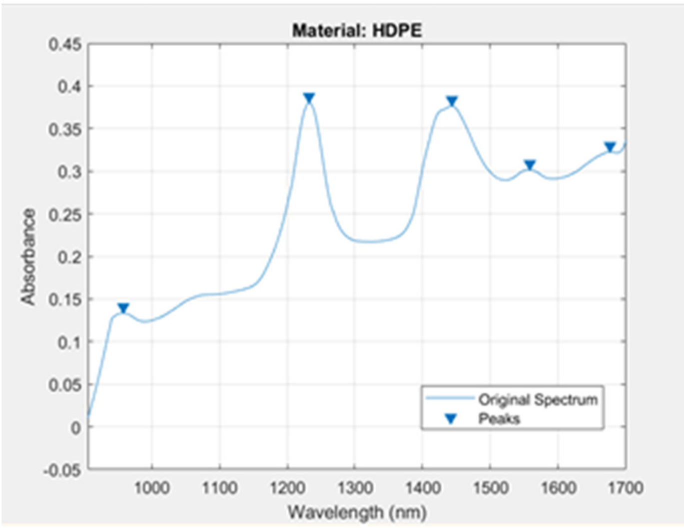

Figure 4.*Peak Detector Result*

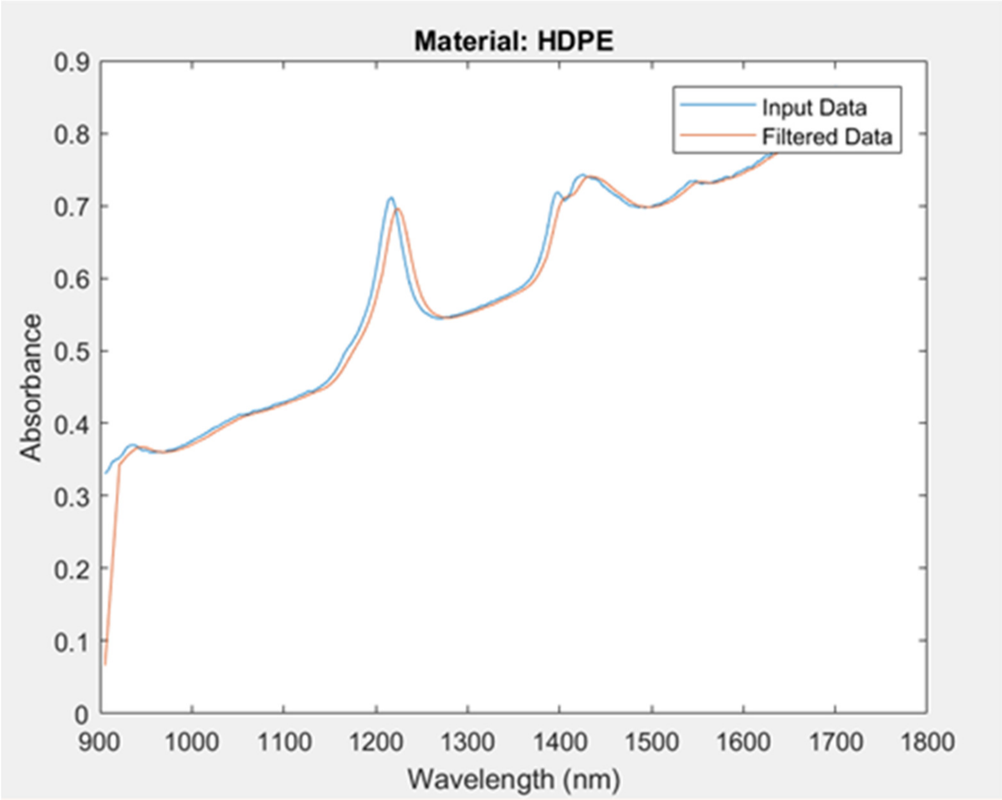

***Figure 5**.Filtering signals using a sliding window*

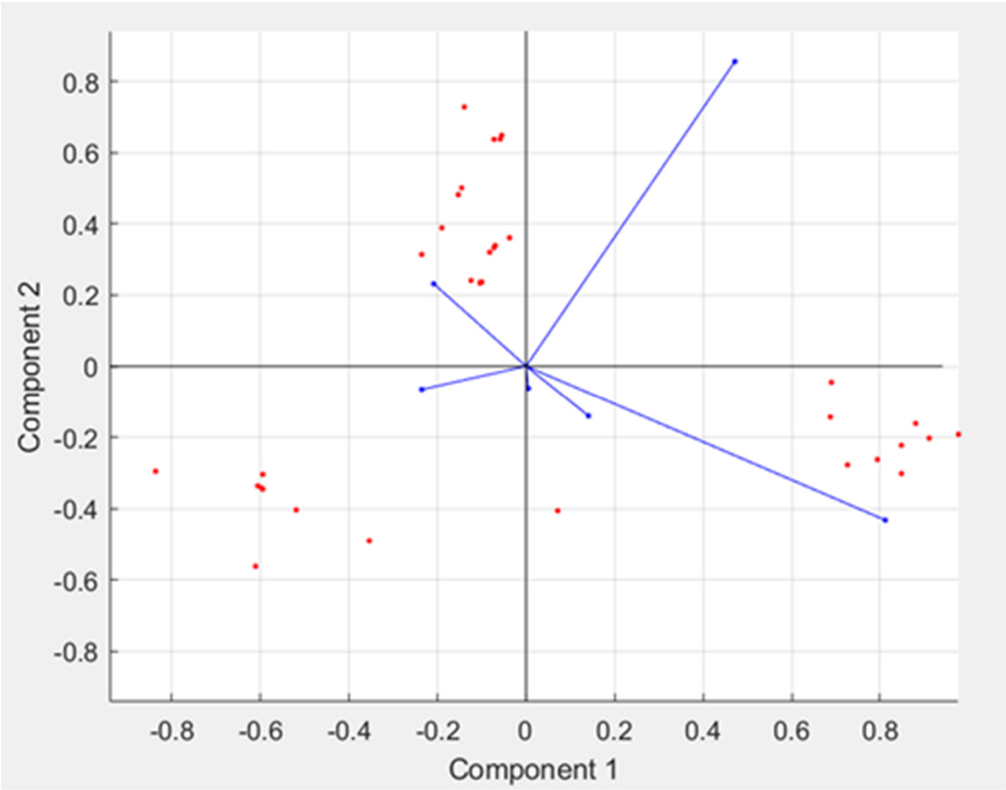

***Figure 6.** Decomposition of plastic polymers in two main components*

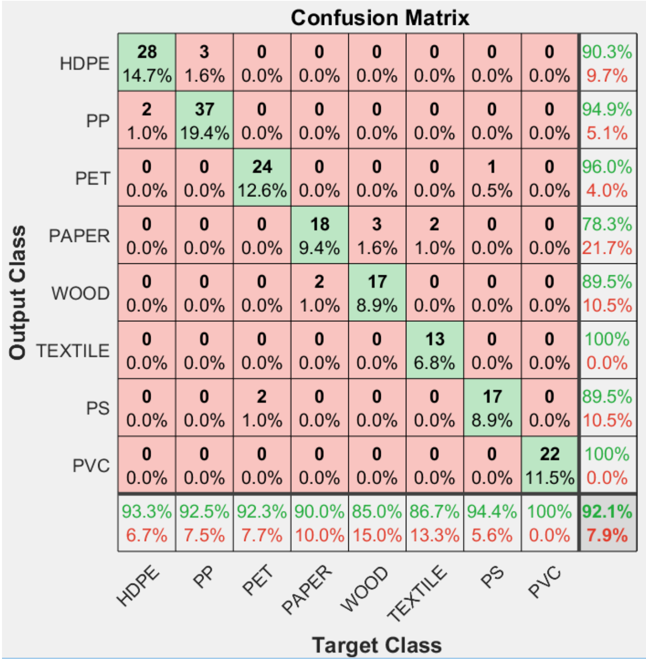

Figure 7. *Error matrix*

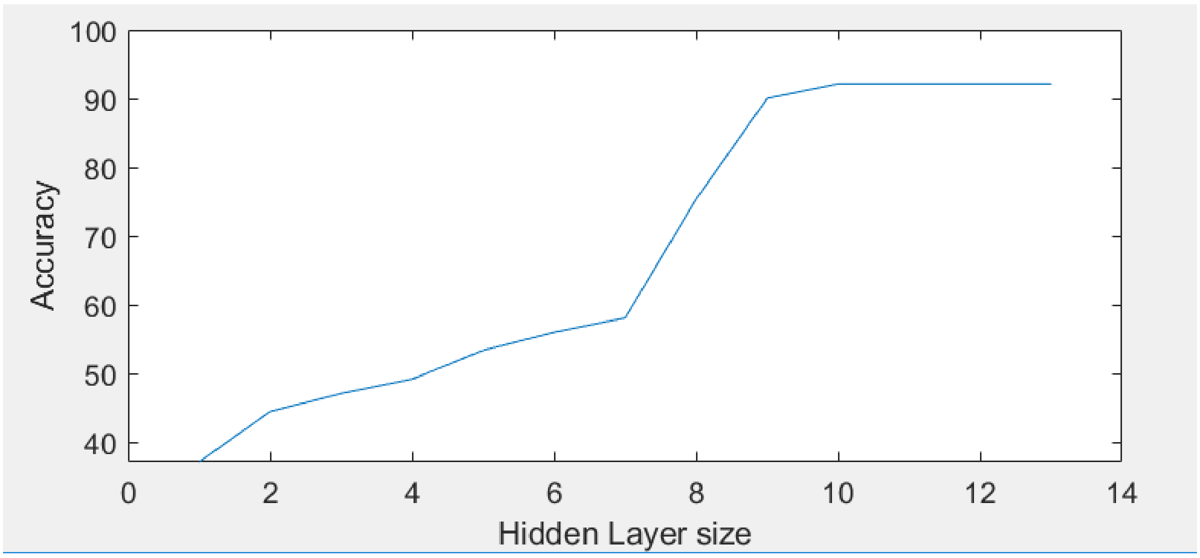

Figure 8. *The influence of the dimension of the hidden layer on the overall recognition accuracy*

Table 1. *Samples*

Material	Number of samples
HDPE	30
PP	40
PET	26
PS	18
PVC	22
Paper / cardboard	20
Textile	15
Wood	20

Table 2. *Key points of the spectrum*

No.	Wavelength, nm
1	958
2	1120
3	1162
4	1232
5	1443
6	1509
7	1558
8	1680