CIRCULAR ECONOMY OF POST-CONSUMER TEXTILE WASTE: CLASSIFICATION THROUGH INFRARED SPECTROSCOPY

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ABSTRACT (2000 chars with spaces)

The textile and fashion industry is amongst the most resource-intensive and polluting industries, thus impacting the natural environment. During the last decades, there has been an increase in the manufacturing of textiles. Europe consumes large amounts of textiles and clothing due to the current "buy-and-throw-away" culture, so it is crucial to minimize the environmental footprint of the textile and fashion industry. To this end, fashion and textiles should be part of a circular economy, thus extending the life of textiles and clothes, while retaining textile fibers within a closed circuit. There is a need of increasing textile recycling and reuse to minimize the production of virgin textile fibers. However, textiles are mostly sorted manually, thus to process huge volumes of materials and reduce the associated costs, automated sorting systems are required. This paper presents an approach for the sensing and classifying parts of an automatic waste-textile-sorting machine. To this end, the infrared spectra of the textile samples is analyzed and, by applying suitable statistical multivariate methods specially designed to solve classification problems, 100% classification accuracy of unknown fiber samples is reached. The results allow predicting that textile-

fibers can be automatically classified with 100% accuracy at high speed, with no need to apply any prior analytical treatment to the textile samples.

Keywords: textile fibers, textile sorting, multivariate analysis, Infrared spectroscopy, classification, pattern recognition

NOMENCLATURE

ATR	Attenuated total reflection
CV	Canonical variate
CVA	Canonical variate analysis
CNN	Convolutional neural network
ELM	Extreme learning machine
FT-IR	Fourier transform infrared
IR	Infrared
k-NN	*k* nearest neighbors
LDA	Linear discriminant analysis
MLP	Multi-layer perceptron
NIR	Near infrared
PC	Principal component
PCA	Principal component analysis
PLS	Partial least squares
SIMCA	Soft independent modeling of class
SVM	Support vector machines

1. INTRODUCTION

Circular economy is a new concept to help the society's change towards a more sustainable economy. This change needs to re-think and re-design production and consumption patterns to avoid environmental impacts and maintain natural resources as long as possible in the technosphere (Gaustad et al., 2018; Simon, 2019).

The current linear model (extraction of resources, production, use and landfilling) is not sustainable, as the resources are limited and there is an ever growing demand (Suárez-Eiroa et al., 2019). Opposite to this linear system, the aim of the circular economy is to provide maximum utility and value of products, components, and materials (The Ellen MacArthur Foundation, 2012).

Efforts on deeper implementation of circular economy are nowadays made in several industrial activities, such as packaging (Navarro et al., 2018; Civancik-uslu et al., 2019), agriculture and food (Principato et al., 2019; Teigiserova et al., 2019) or textile (Esteve-Turrillas and de la Guardia, 2017; Yousef et al., 2019).

The textile and fashion industry is amongst the most polluting and resource-intensive industries due to the great consumption of water, energy and chemicals, thus affecting the natural environment. The growth of the global population has led to an overall increase in the manufacturing of textiles. European countries consume large amounts of clothes and textiles as a result of the current "buy-and-throw-away" culture. Thus, clothing represents the fourth most environmentally harmful consumption area, after housing, transport and food (NCM, 2015). Therefore, this trend should be reversed for the sake of economy and environmental aspects. It is mandatory to minimize the environmental and social footprint related to Europe's textile production and consumption while improving its sustainability (Roos et al., 2015). To achieve these objectives, much work is required at regional, national, and international levels so that textiles must be part of a circular economy, in order to extend product life and preventing hazardous substances. This strategy should allow using textiles again and again as part of a toxic-free cycle (Reichel et al., 2014).

According to Shen et al. (Shen et al., 2010), 63% of textile fibers are derived from petrochemicals, thus giving rise to greenhouse gas emissions due to production and use. The remaining 37% includes cotton (24%), a plant requiring large amounts of water (Micklin, 2007) and pesticides (FAO-ICAC, 2015), which contribute to toxic pollution (Bevilacqua et al., 2014). Thus, the recycling of cotton is also extremely important (Esteve-Turrillas and de la Guardia, 2017).

Processes such as dyeing (Terinte et al., 2014), finishing or printing, produce toxic emissions as well (Swedish Chemicals Agency, 2014), and the manufacturing processes related to textiles usually rely on the use of fossil energy, thus generating greenhouse gas emissions (Roos et al., 2015). According to the Swedish Chemicals Agency, textile production includes around 2,450 different chemicals, 1,150 of which being classified as hazardous, so they are of potential risk for the environment and consumers during the use of the textiles (Swedish Chemicals Agency, 2014).

As said, water use, greenhouse-gases emissions, toxic chemicals and waste are the main environmental problems that the textile industry needs to face (Allwood, 2006).

To significantly reduce the environmental and social footprint of the Europe's textile industry, radical changes are required, especially in the way in which textiles and clothes are designed, produced, traded, used and recirculated (Sandin and Peters, 2018). Fashion and textiles should be part of a circular economy, thus allowing textiles and clothes life to be extended, to retain textile fibers within a closed circuit, so that they can be used again and again (Dahlbo et al., 2017).

Research publications (Hole and Hole, 2019) support the fact that textile recycling and reuse in general reduce environmental impact compared to landfilling and incineration. Therefore, there is a growing regulatory interest to increase textile reuse and recycling, which is consistent with the

European Union directive on waste (DIRECTIVE 2008/98/EC, 2008). Better reuse and recycling of textiles can lessen virgin textile fibers production (Spathas, 2017).

Textile reuse involves different strategies, including trading, swapping, borrowing, renting or inheriting. This can be facilitated by flea markets, second hand shops, garage sales, charities, online marketplaces or clothing libraries among others.

Textile recycling usually involves a reprocessing stage of pre- or post-consumer textile waste for being used in new products, both textile or non-textile. Routes for textile recycling can be classified as chemical (depolymerization of polymeric fibers or dissolution of natural fibers), mechanical (pretreatment) or thermal (conversion of PET pellets, chips or flakes into fibers by melt extrusion) (Spathas, 2017).

Nowadays low recycling rates are achieved from post-consumer textile waste (Sandin and Peters, 2018). Large proportions of used natural or synthetic materials are often discarded as waste, going to landfills instead of processed for reuse or recycling. This is mainly due to lack of specific collection for post-consumer textile waste, the complexity to separate the different discarded textile materials and the costs associated to sorting important volumes (Dahlbo et al., 2017).

Currently, textiles are sorted mostly manually. However, this has many drawbacks, including high cost, low speed operation and the impossibility of a full automation, which is required to process huge volumes of materials (Nørup et al., 2019).

Although some sorting machines are found in the market, conventional methods and systems for sorting are usually incapable to classify different textile materials, or they require inputs from well-trained operators, being time consuming to operate, or excessively expensive to maintain.

There is one publication in the literature (Peets et al., 2017) stating that with the spectral data of ATR-FTIR jointly with the application of PCA it was not always possible to distinguish cellulose-based fibers (cotton, linen and sometimes viscose) and it was only partly possible to distinguish silk and wool. In another publication (Xing et al., 2019), a system for classifying wool and cashmere fibers based on fractal, parallel-line algorithm, and K-mean clustering algorithms is proposed based on digital photographs of such fibers, obtaining identification rates between 85% and 97.5%. A recent paper (Zhou et al., 2019) identified different types of fibers from the NIR spectrum by applying PCA, SIMCA and LDA with only two classifiers, although it was difficult to distinguish between wool and cashmere fibers. In (Chen et al., 2019) NIR spectroscopy is applied to perform a quantitative determination of fiber components by applying PLS and ELM algorithms, showing that ELM can generate better predictive models than PLS, with a similar computational cost. In (Liu et al., 2019) waste textile fibers are classified from the NIR spectrum by applying SVM, MLP and CNN algorithms, showing that CNN performs better than the others with classification rates between 92% and 98%.

The aim of the present work is to contribute in the sensing and classifying parts of an automatic textile-sorting machine. It is done by using a more accurate mathematical modeling based on the data from the IR spectrum, by applying state-of-the-art multivariate methods well suited for this purpose, while improving the robustness of the model by analyzing a large number of textile samples from different origins. The novelty of the method proposed here is the use of ATR-FTIR spectra of the samples for textile recycling purposes (only one previous paper is found in the literature) and the combined statistical multivariate algorithms, which are very powerful supervised models not yet applied to this type of samples.

This paper is focused to develop a fast and accurate method for a direct and non-invasive sorting and classification of different textile fibers used for clothing, which include natural, artificial and synthetic fibers, from the spectral data obtained from the FTIR spectra of such samples, with no need of any prior analytical treatment. The results of this paper are focused towards the automation of textile-waste-materials sorting process. For this purpose, textile samples are analyzed by using an ATR-FTIR spectrometer, with no previous sample pretreatment, and thus, this system does not need the addition of any chemical or reagent. Therefore, the proposed system is simple and fast to apply. It is known that FTIR spectral data typically includes thousands of data points, one per wavenumber analyzed, and thus, multivariate mathematical methods are required to operate with this large number of points. Such methods include feature reduction algorithms and classifiers, the first ones designed to concentrate the relevant analytical information of the whole data set in a few latent variables, which also let partially removing most of the noise included in the original spectral data (Riba et al., 2020). To calculate the reduced set of latent variables, the principal component analysis (PCA) algorithm is applied followed by the canonical variate analysis (CVA) algorithm. Next, the nearest neighbor (kNN) classifier is applied, this algorithm providing as many output normalized variables within the range 0 - 1 as types of textile fibers or classes defined in the problem, thus assigning an incoming textile sample to the class having the highest output value.

This combined methodology (ATR-FTIR spectra and PCA+CVA+kNN mathematical treatment) applied to sorting post-consumer textile-waste is described for the first time in the literature.

2. METHODOLOGY

This section describes the experimental details and methodology used to prove the accuracy and usefulness of the approach proposed in this paper.

2.1. Samples collection and identification

This paper deals with 350 textile samples coming from different companies' catalogs and supplied by Fitex technology center. The whole set of samples includes 200 samples from natural fibers (50 cotton, 50 linen, 50 wool and 50 silk samples) and 150 samples from artificial and synthetic fibers (50 viscose, 50 polyamide and 50 polyester samples). Artificial fibers are the ones obtained by transformation of natural products (i.e., viscose comes from cellulose), while synthetic fibers are obtained from oil derivatives.

With the aim of including the maximum variability in the group of samples studied, different colors (light and dark) and presentations (yarn or fabric) are included. For a quick identification, each sample is coded including catalog origin, color and presentation form (yarn or fabric).

To check the performance of the mathematical methods, the whole set of samples was split into two subsets, i.e., the calibration and prediction subsets in the proportion 50%-50%, as shown in Figure 1.

Artificial and synthetic fibers (150)
- Polyamide (25 calibration + 25 test)
- Polyester (25 calibration + 25 test)
- Viscose (25 calibration + 25 test)

Natural fibers (200)
- Cotton (25 calibration + 25 test)
- Linen (25 calibration + 25 test)
- Wool (25 calibration + 25 test)
- Silk (25 calibration + 25 test)

Figure 1. Summary of the 350 textile samples used in this work.

2.2. ATR-FTIR methodology

Middle infrared electromagnetic radiation, within the wavenumber range 4000 - 400 cm^{-1}, is energetic enough to cause transitions between rotational and vibrational levels of the molecular bonds. Due to the high selectivity of the radiation absorption in the middle infrared because of the molecular bonds, this region of the spectrum is widely used in both qualitative and quantitative analysis.

ATR measurements take advantage of the behavior of the IR radiation beam, by passing through two media with different refractive indices. In such systems, the IR beam passes through a crystal, which is transparent to the IR radiation and has a high refractive index, at an angle of incidence greater than the critical angle. When the beam reaches the crystal-sample interface, it is almost completely reflected, and only a small fraction of the beam crosses the interface and penetrates the sample slightly. The beam is attenuated in the regions of the infrared spectrum in which the sample absorbs energy. The beam returns to the crystal and leaves at the opposite end of the crystal, and then focus to the detector (McGill et al., 2014). The use of this technique will allow a rapid scanning or acquisition of textile samples without any pretreatment.

The FTIR spectra of the textile samples analyzed in this work, were acquired by means of a PerkinElmer Spectrum One (S/N 57458, Beaconsfield, UK) spectrometer equipped with an ATR module. The spectra are recorded in the wavenumber range 4000–650 cm^{-1}, with a resolution of 1 cm^{-1} by averaging four scans to minimize noise effects. Therefore, each original spectral signal includes 3351 spectral points. Subsequently, the spectra are converted to the first and second derivative modes, in order to improve the classification performance of multivariate classification models applied to identify the different textile samples.

2.3. Mathematical classification approach

To solve classification or identification problems from complex datasets, different mathematical and statistical algorithms are available. In such problems, the whole sample set is commonly split into two subsets, i.e., the subsets including the calibration and prediction samples. This approach allows both, calibrating or training the models and to evaluate the behavior and accuracy of the classification model from different samples than those used during the calibration stage (see Figure 2). Due to the 3551 wavenumbers constituting the variables measured for each ATR-FTIR spectrum of the textile samples requires to apply appropriate feature extraction/reduction methods. Such algorithms are designed to compress the essential discriminating information included in the raw spectra in a reduced number of latent variables, while removing most of the noise incorporated in raw spectra to optimize the discriminating power.

Among the feature extraction algorithms, PCA, CVA (Riba et al., 2020), ECVA (Riba et al., 2013) or SVM highlight (Riba et al., 2012). However, supervised feature extraction methods, i.e. those requiring an expert to choose the class tags of the calibration samples, which allocate each sample to its pertinence class, are always preferred due to their superior discriminating power.

This work applies the supervised CVA algorithm in the feature extraction and reduction step because it is among the most widely applied algorithms for this purpose. However, due to the large number of measured wavenumbers in each spectrum, this algorithm requires a previous dimensionality reduction, which is achieved by means of the PCA algorithm. CVA provides a limited number of latent variables, known as canonical variates or CVs, i.e., the number of CVs equals the number of classes (types of fibers) minus one. However, CVA requires input data containing more samples than the number of measured variables. Since the input spectral data includes 3351 wavenumbers per sample, and the number of samples dealt with is 350, this requirement is not fulfilled, thus requiring a previous dimensionality reduction by means of the PCA algorithm.

Finally, once the latent variables are calculated, the next step consists in applying a suitable classification algorithm such as the *k*-NN, which is evaluated in this work due to its simplicity and accuracy. The *k*-NN calculates as many outputs, which are within the [0,1] interval, as classes (types of textile fibers) defined in the problem. The normalized outputs specify the degree of membership of the sample evaluated to each class. Therefore, the sample evaluated is identified as belonging to the class with higher output value, when such value is greater than 0.5. *k*-NN is grounded on the weighted vote of the *k* samples of the calibration set (nearest neighbors whose class is already known) which are closest to the analyzed sample. The *k*-NN algorithm classifies the incoming sample within the class with the highest score. It assigns *k* votes to the nearest neighbor's class, *k*-1 votes to the second nearest neighbor's class, and so on until assigning 1 vote to the farthest neighbor's class. Finally, it sums up and normalizes the votes of all classes, thus assigning the analyzed sample to the class with highest score.

To obtain a robust classification model, the calibration set must include all the variability inherent in the textile samples. To this end, it is required to have an extensive dataset of known fibers, whose origin must be known, since a supervised approach is carried out.

Figure 2 shows the supervised classification process carried out in this work.

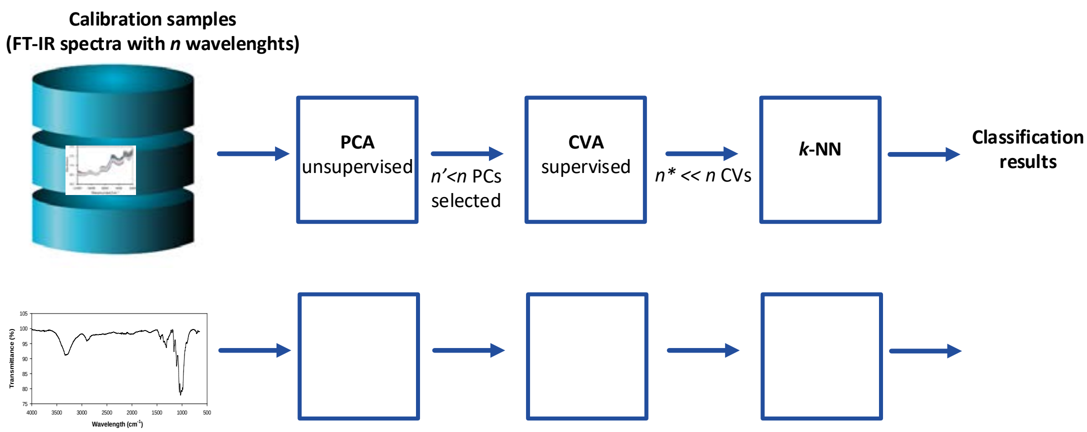


Figure 2. Summary of the classification approach proposed in this work. a) Calibration stage. b) Prediction stage

3. EXPERIMENTAL RESULTS AND DISCUSSION

The recycling of natural fibers differs from that of the artificial or synthetic ones. Whereas the first ones are mainly recycled based on mechanical treatments, the recycling of synthetic fibers is based on chemical treatments. Thus, the first step should separate between natural and artificial or synthetic fibers, while in the following step, the different types of natural fibers should be separated among them and the same for the synthetic ones. This approach is followed in this section.

3.1. ATR-FTIR spectra of the analyzed textile fibers

IR spectra show characteristic absorption bands according to the functional groups in the molecules of the different types of fibers. The most characteristic bands of the different types of fibers studied are presented in Table 1.

Table 1. Most characteristic infrared bands for the studied fibers. Produced from (Peets et al., 2017) and (Vigo, 1994).

Band frequency (cm^{-1})	Type of bond-vibration	Type of fiber
3500-3000	O-H stretching	Cellulosic fibers (N and A)
3500-3000	N-H stretching	Polyamide(S), wool(N), silk(N)
1750-1715	C=O stretching (ester)	Polyester(S)
1680-1630	C=O stretching (amide)	Polyamide(S), wool(N), silk(N)
1570-1515	N-H bending (amide)	Polyamide(S), wool(N), silk(N)
1250-1150	C-O stretching (ester)	Polyester(S)
1100-1000	C-O stretching	Cellulosic fibers (N and A)
730-700	C-H aromatic ring wagging	Polyester(S)

(N) natural fibers; (A) artificial; (S) synthetic

Textile fibers, such as cotton, linen and viscose, show characteristic bands between 3500-3000 cm^{-1}, which are attributed to OH stretching and between 1100 -1000 cm^{-1}, which are assigned to CO stretching (see Figure 3 and 4). The presence of the amide group in fibers such as wool, silk and polyamide generates bending and stretching bands due to NH, as shown in Table 1 and Figures 3 and 4. Regarding polyester fibers, it is worth noting that the characteristic band between 1750-1715 cm^{-1} is assigned to C = O stretching (ester). Although these are the characteristic bands in the IR spectra for such type of functional groups, it has to be said that the IR spectrum is very specific for each molecule because all the surrounding bonds nearby the functional group have their own wavelength-absorption value, which also slightly affect the exact position of the characteristic band.

Thus, the IR spectrum of a molecule is considered to be like its fingerprint, slightly different from the one of another molecule, although it may be difficult to distinguish by simple visual inspection. This is why a supervised mathematic model applied to the spectra is of great help. It is able to highlight the differences between very similar molecules (i.e., cotton, linen and viscose), which need to be separated and, on the other hand, to conceal the differences between molecules which need to be classified in the same group (i.e., different polyester-type of molecules). Supervised mathematic algorithms use the whole IR spectrum, not only the characteristic bands of the functional groups in the molecule.

In Figure 3, it can be seen that cotton and linen natural fibers have very similar spectra (they both are cellulose based). Their differences are difficult to perceive by visual inspection. Something similar happens when comparing the spectra of natural wool and silk fibers.

On the other hand, spectra of artificial or synthetic fibers (Figure 4) have much different shapes, as they correspond to families with a different chemical nature. When comparing, however, cotton and linen spectra (Figure 3) with that of viscose (Figure 4), the similarity between them is clearly observed, as viscose is an artificial fiber derived from cellulose. In addition, wool and silk spectra (Figure 3) have features in common with those of polyamide (Figure 4), due to the presence of the amide group in their molecules. Those similarities between the different families of fibers make it difficult to classify them without treatment through mathematical algorithms, which make use of the complete IR spectra.

A robust enough mathematical model has to be chosen, to take advantage of all the information provided by the spectra of the samples and to accentuate as much as possible small differences between groups of fibers, thus allowing the classification of different textiles.

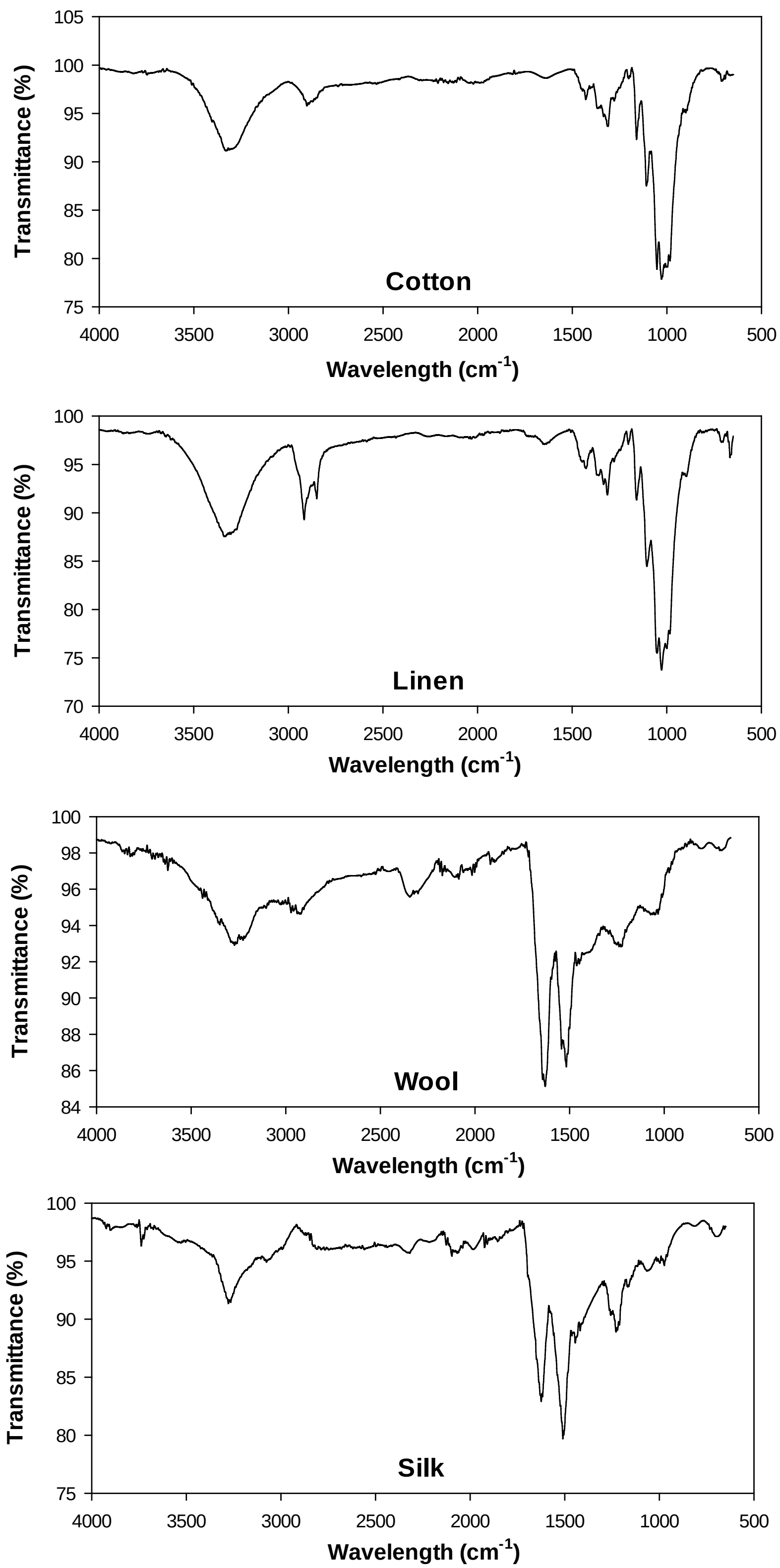


Figure 3. ATR-FTIR spectra of representative natural fibers.

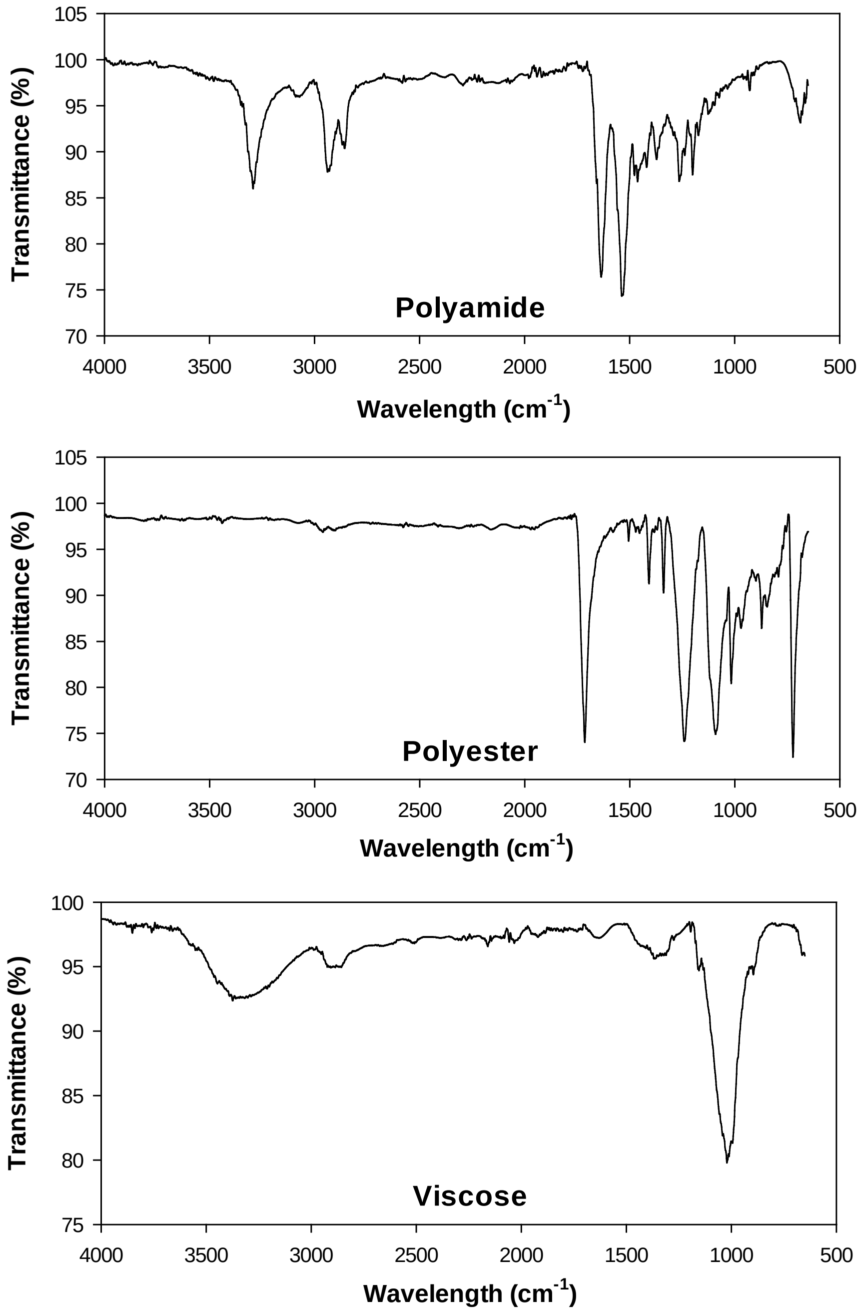
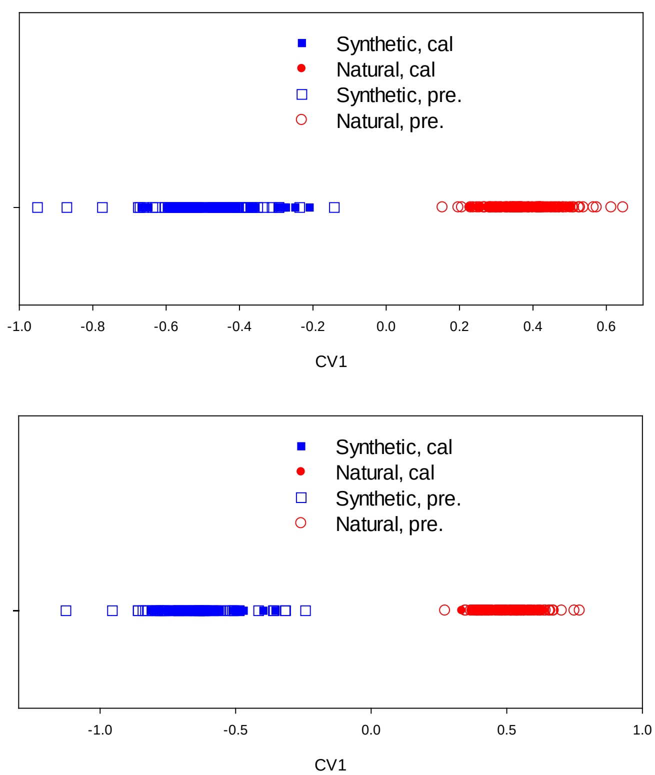


Figure 4. ATR-FTIR spectra of representative artificial or synthetic fibers.

3.2. First study. Classification of natural versus artificial and synthetic fibers

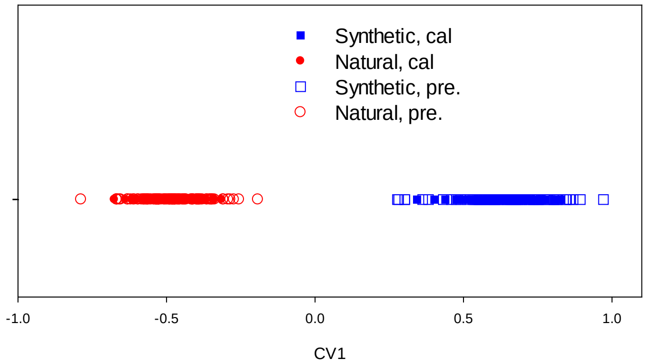
In this first study, the dataset is divided into two subsets, i.e., the calibration and prediction sets. In this study both sets include 50% of the total data, i.e., both the calibration and prediction sets contain half of the data. The calibration set is used to calibrate or train the mathematical methods to solve the classification problem, whereas the remaining data constitute the prediction set, which is used to validate the identification procedure, by using different data than that used during the calibration stage.

A total of 350 samples are analyzed, 200 corresponding to natural fibers (50 cotton, 50 linen, 50 wool and 50 silk samples) and 150 corresponding to synthetic fibers (50 polyamide, 50 polyester and 50 viscose samples). Although viscose is an artificial fiber, for simplification purposes, in this work it is included in the group named synthetic fibers. Therefore, the calibration set includes 175 samples (25 cotton, 25 linen, 25 wool, 25 silk, 25 polyamide, 25 polyester and 25 viscose samples), whereas the prediction set includes the remaining 175 samples. The samples are classified by applying the PCA + CVA + *k*-NN algorithms in this order, obtaining 100% success rate in the classification results provided by the *k*-NN algorithm, whose results summarized in Table 2 are based on the data shown in Figure 5.



a)

b)



c)

Figure 5. a) Classification of natural versus synthetic fibers from the raw FTIR spectral data by applying the PCA (40 PCs, 99.0% variance) + CVA with 175 calibration and 175 validation samples. b) Classification of natural versus synthetic fibers from the first derivative of the FTIR spectral data by applying the PCA (66 PCs, 99.0% variance) + CVA with 175 calibration and 175 validation samples. c) Classification of natural versus synthetic fibers from the second derivative of the FTIR spectral data by applying the PCA (81 PCs, 99.0% variance) + CVA with 175 calibration and 175 validation samples.

Table 2. Classification success rate of natural versus synthetic fibers following the PCA + CVA + *k*-NN approach over the 175 prediction samples

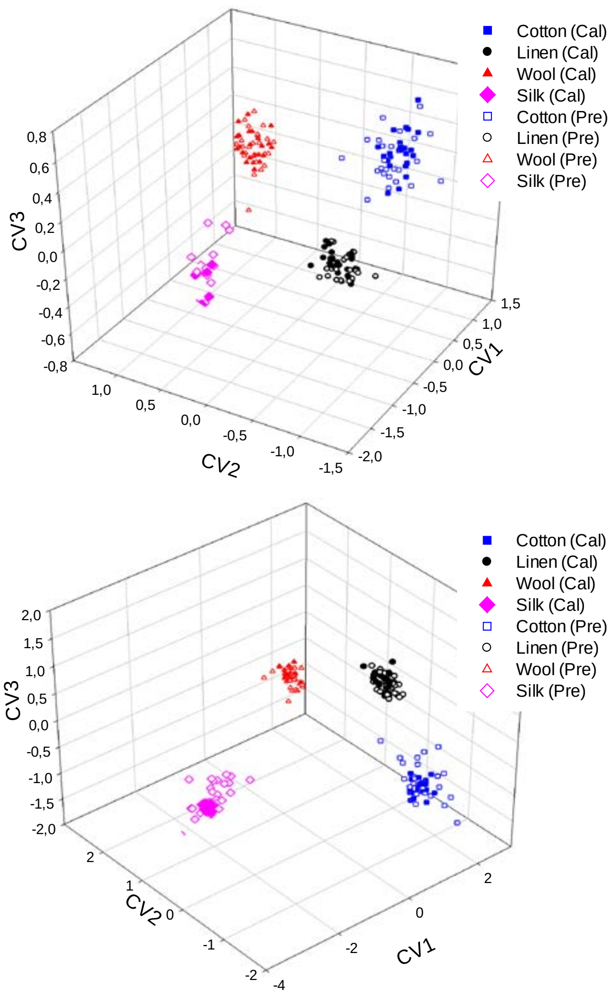
Preprocessing type	*k* = 3	*k* = 4	*k* = 5	*k* = 6
Raw spectral data	175/175	175/175	175/175	175/175
First derivative of spectral data	175/175	175/175	175/175	175/175
Second derivative of spectral data	175/175	175/175	175/175	175/175

Results summarized in Figure 5 and Table 2 show that the PCA + CVA + *k*-NN approach allow classifying between synthetic and natural fiber samples with 100% accuracy.

3.3. Second study. Identification of the different natural fibers

Once the unknown incoming samples have been classified successfully as synthetic or natural, this section classifies the unknown natural fibers into four groups, i.e., cotton, linen, wool and silk. As explained, both the calibration and prediction set consist of 25 samples of each types, that is, 100 samples in total each.

The classification results of the natural fibers (cotton, linen, wool and silk) are summarized in Figure 6 and Table 3.



a)

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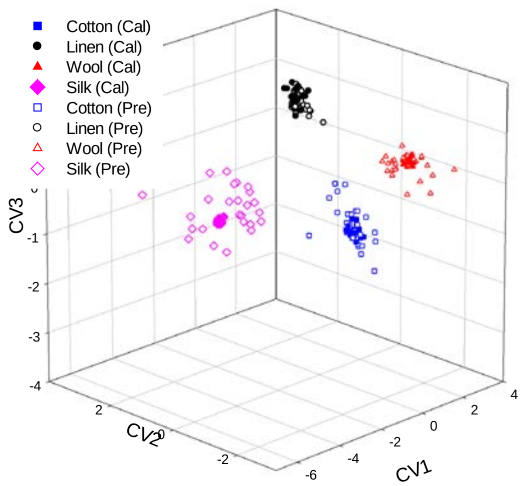


c)

Figure 6. a) Classification of the different natural fibers from the raw FTIR spectral data by applying the PCA (31 PCs, 99.0% variance) + CVA with 100 calibration and 100 validation samples. b) Classification of the different natural fibers from the first derivative of the FTIR spectral data by applying the PCA (63 PCs, 99.0% variance) + CVA with 100 calibration and 100 validation samples. c) Classification of the different natural fibers from the second derivative of the FTIR spectral data by applying the PCA (70 PCs, 99.0% variance) + CVA with 100 calibration and 100 validation samples.

Table 3. Classification success rate of natural fibers (cotton, linen, wool and silk) following the PCA + CVA + *k*-NN approach over the 100 prediction samples

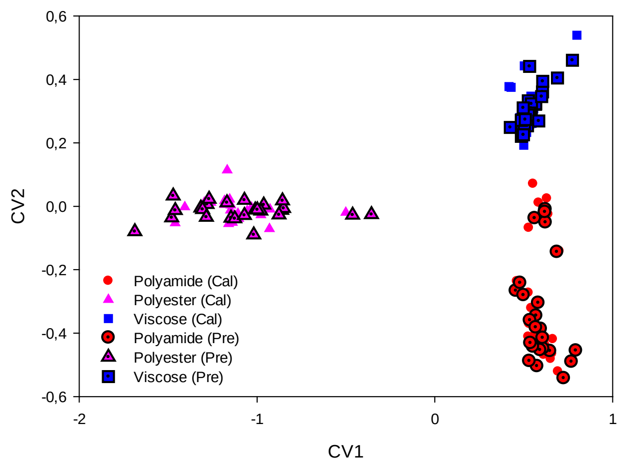
Preprocessing type	*k* = 3	*k* = 4	*k* = 5	*k* = 6
Raw spectral data	100/100	100/100	100/100	100/100
First derivative of spectral data	100/100	100/100	100/100	100/100
Second derivative of spectral data	100/100	100/100	100/100	100/100

Results summarized in Figure 6 and Table 3 show that the PCA + CVA + *k*-NN approach allow classifying between cotton, linen, wool and silk fiber samples with 100% accuracy.

3.4. Third study. Identification of the different synthetic fibers

Once the unknown incoming samples have been classified successfully as synthetic or natural, this section classifies the unknown synthetic fibers into three groups, i.e., polyamide, polyester and viscose. Both the calibration and prediction set consist of 25 samples of each types, that is, 75 samples in total each.

The classification results of the synthetic fibers (polyamide, polyester and viscose) are summarized in Figure 7 and Table 4.



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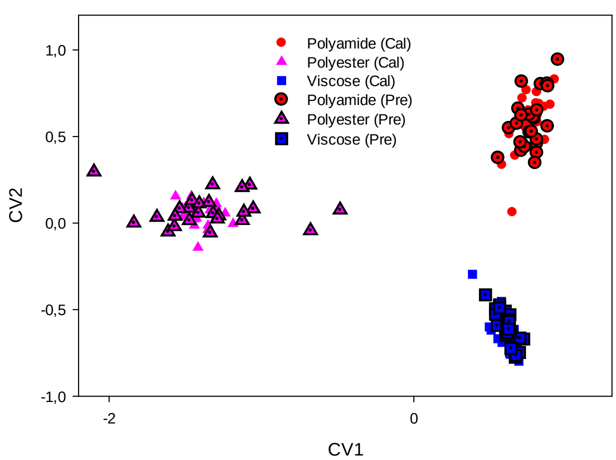

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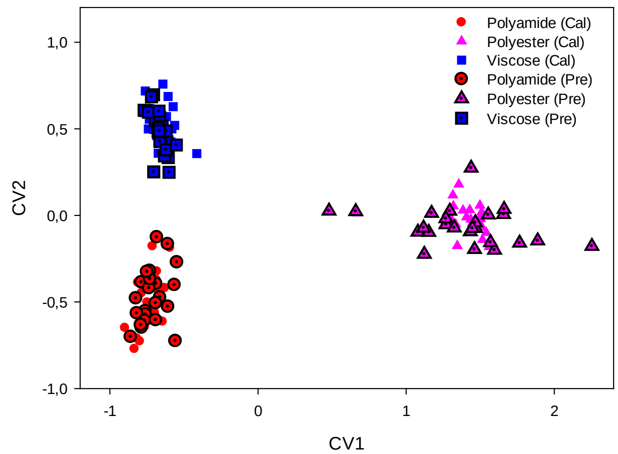

c)

Figure 7. a) Classification of the different synthetic fibers from the raw FTIR spectral data by applying the PCA (6 PCs, 99.0% variance) + CVA with 75 calibration and 75 validation samples. b) Classification of the different natural fibers from the first derivative of the FTIR spectral data by applying the PCA (29 PCs, 99.0% variance) + CVA with 75 calibration and 75 validation samples. c) Classification of the different natural fibers from the second derivative of the FTIR spectral data by applying the PCA (39 PCs, 99.0% variance) + CVA with 75 calibration and 75 validation samples.

Table 4. Classification success rate of synthetic fibers (polyamide, polyester and viscose) following the PCA + CVA + *k*-NN approach over the 75 prediction samples

Preprocessing type	*k* = 3	*k* = 4	*k* = 5	*k* = 6
Raw spectral data	75/75	75/75	75/75	75/75
First derivative of spectral data	75/75	75/75	75/75	75/75
Second derivative of spectral data	75/75	75/75	75/75	75/75

Results summarized in Figure 7 and Table 4 show that the PCA + CVA + *k*-NN approach allow classifying between polyamide, polyester and viscose fiber samples with 100% accuracy.

3.5. Challenges of this new technique and comparison with the literature

As shown in Table 5, there is only one author (Peets et al.,2017; Peets et al., 2019) using FTIR textile-spectra (like in the present study) for identification of different textile fibers and mixtures. Nevertheless, these papers use a very simple mathematical treatment (PCA), thus not being able to differentiate among very similar textile fibers (i.e., cotton/linen/viscose).

On the other hand, there are 4 papers in the literature using NIR spectra to classify textile samples, three of them for recycling purposes (Liu et al., 2019; Zhou et al., 2018; Zhou et al, 2019). Nevertheless, only Zhou et al., 2019 are using advanced mathematical algorithms being able to achieve 100% recognition rate (same as the present described technique), but they do not include cotton/linen/viscose (which are the most difficult to distinguish).

Table 5. Comparison of results with the previously published in the literature.

Reference	Types of textile fibers	Aim	Type of spectrum	Mathematic algorithms	Recognition rate (%)
(Peets et al., 2017)	11 + mixtures	Quality control	ATR-FTIR	PCA	No distinction among: cotton/linen/viscose Nor wool/silk
(Peets et al., 2019)	16 + mixtures	Quality control	FTIR	PCA	No distinction among: cotton/linen/viscose
(Chen et al., 2019)	4 + mixtures (wool, polyester, nylon, polyacrilonitrile)	Quality control	NIR	PLS or ELM	ELM better predictions
(Liu et al., 2019)	2 + mixtures (polyester, wool)	Textile recycling	NIR	SVM, MLP + CNN	92-98%
(Zhou et al., 2018)	6 no linen, nor viscose	Textile recycling	NIR	SIMCA	97% (cotton/polyester 90%)
(Zhou et al., 2019)	7 no linen, nor viscose	Textile recycling	NIR	PCA, SIMCA, LDA	100%
Present paper	7	Textile recycling	ATR-FTIR	PCA, CVA + k-NN	100%

The present technique has shown better results than the described up to now in the literature, thus being a promising option.

Nevertheless, further work must be performed before implementation in real sorting machinery, like producing the specific software to be implemented and to make the IR-spectra-database robust enough to be able to correctly classify dirty-wet textile-waste entering the recycling system. In addition, after sorting the textile by type of fiber a second sorting by color will be needed (i.e. black-colored cotton-fibers all together), thus reducing additional dyeing.

One possible drawback of the present FTIR technique, for its automation at industrial scale, is the contact needed between the sensor and the textile, to register its IR spectrum and compare with the database for classification. A strict maintenance protocol of the sensor would be advisable.

4. CONCLUSIONS

Today, only a small portion of the textiles is reused or recycled and they are mostly sorted manually. This paper has proposed an automatic sensing and sorting approach focused to increase textile recycling and reuse for minimizing the production and trade of virgin textile fibers which tries to contribute to minimize the environmental problems that the textile and fashion industry is facing. The sorting approach proposed in this work is based on the ATR-FTIR spectrum of the textile samples, which once acquired is processed by means of several algorithms, including the PCA, CVA and *k*-NN mathematical methods.

Experimental results presented in this paper, which are based on 350 textile samples (from companies' catalogs), have shown that the incoming unknown fiber samples can be automatically classified with 100% accuracy and high speed, with no need to apply any prior analytical treatment to the textile samples. These excellent results prove that the methodology suggested in this work can be a valuable tool for sorting textile fibers for further reuse and recycling.

The present promising technique needs further development before its implementation to actual sorting machinery (i.e., software developing, sorting fiber blends, additional sorting by color and a more robust IR database including dirty-wet textiles from postconsumer waste).

The sorting approach proposed in this paper can be fully automatized for future industrial application, thus allowing to process large volumes of materials and reduce the costs associated to the sorting processes.

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6. REFERENCES

Allwood, J.M., 2006. Well dressed? : the present and future sustainability of clothing and textiles in the United Kingdom. University of Cambridge, Institute of Manufacturing, Cambridge.

Bevilacqua, M., Ciarapica, F.E., Mazzuto, G., Paciarotti, C., 2014. Environmental analysis of a cotton yarn supply Chain. J. Clean. Prod. 82, 154–165. https://doi.org/10.1016/j.jclepro.2014.06.082

Chen, H., Tan, C., Lin, Z., 2019. Quantitative Determination of the Fiber Components in Textiles by Near-Infrared Spectroscopy and Extreme Learning Machine. Anal. Lett. https://doi.org/10.1080/00032719.2019.1683742

Civancik-uslu, D., Puig, R., Voigt, S., Walter, D., Fullana-i-palmer, P., 2019. Resources , Conservation & Recycling Improving the production chain with LCA and eco-design : application to cosmetic packaging. Resour. Conserv. Recycl. 151, 104475. https://doi.org/10.1016/j.resconrec.2019.104475

Dahlbo, H., Aalto, K., Eskelinen, H., Salmenperä, H., 2017. Increasing textile circulation—Consequences and requirements. Sustain. Prod. Consum. 9, 44–57. https://doi.org/10.1016/j.spc.2016.06.005

DIRECTIVE 2008/98/EC, 2008. DIRECTIVE 2008/98/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 19 November 2008 on waste and repealing certain Directives (Text with EEA relevance).

Esteve-Turrillas, F.A., de la Guardia, M., 2017. Environmental impact of Recover cotton in textile industry. Resour. Conserv. Recycl. 116, 107–115. https://doi.org/10.1016/j.resconrec.2016.09.034

FAO-ICAC, 2015. Measuring Sustainability in Cotton Farming Systems: Towards a Guidance Framework.

Gaustad, G., Krystofik, M., Bustamante, M., Badami, K., 2018. Circular economy strategies for mitigating critical material supply issues. Resour. Conserv. Recycl. 135, 24–33. https://doi.org/10.1016/J.RESCONREC.2017.08.002

Hole, G., Hole, A.S., 2019. Recycling as the way to greener production: A mini review. J. Clean. Prod. 212, 910–915. https://doi.org/10.1016/J.JCLEPRO.2018.12.080

Liu, Z., Li, W., Wei, Z., 2019. Qualitative classification of waste textiles based on near infrared spectroscopy and the convolutional network. Text. Res. J. https://doi.org/10.1177/0040517519886032

McGill, R.A., Stievater, T.H., Pruessner, M.W., Holmstrom, S.A., Nierenberg, K., McGill, R., Nguyen, V., Park, D., Kendziora, C., Furstenberg, R., 2014. Infrared molecular binding spectroscopy realized in sorbent coated microfabricated devices, in: Next-Generation Spectroscopic Technologies VII. SPIE, p. 910107. https://doi.org/10.1117/12.2050819

Micklin, P., 2007. The Aral Sea Disaster. Annu. Rev. Earth Planet. Sci. 35, 47–72. https://doi.org/10.1146/annurev.earth.35.031306.140120

Navarro, A., Puig, R., Martí, E., Bala, A., Fullana-i-Palmer, P., 2018. Tackling the Relevance of Packaging in Life Cycle Assessment of Virgin Olive Oil and the Environmental Consequences of Regulation. Environ. Manage. 62. https://doi.org/10.1007/s00267-018-1021-x

NCM, 2015. Well dressed in a clean environment, Nordic act. ed, Well dressed in a clean environment. Nordic Council of Ministers. https://doi.org/10.6027/anp2015-764

Nørup, N., Pihl, K., Damgaard, A., Scheutz, C., 2019. Evaluation of a European textile sorting centre: Material flow analysis and life cycle inventory. Resour. Conserv. Recycl. 143, 310–319. https://doi.org/10.1016/j.resconrec.2019.01.010

Peets, P., Kaupmees, K., Vahur, S., Leito, I., 2019. Reflectance FT-IR spectroscopy as a viable option for textile fiber identification. Herit. Sci. 7. https://doi.org/10.1186/s40494-019-0337-z

Peets, P., Leito, I., Pelt, J., Vahur, S., 2017. Identification and classification of textile fibres using ATR-FT-IR spectroscopy with chemometric methods. Spectrochim. Acta Part A Mol. Biomol. Spectrosc. 173, 175–181. https://doi.org/10.1016/J.SAA.2016.09.007

Principato, L., Ruini, L., Guidi, M., Secondi, L., 2019. Adopting the circular economy approach on food loss and waste: The case of Italian pasta production. Resour. Conserv. Recycl. 144, 82–89. https://doi.org/10.1016/j.resconrec.2019.01.025

Reichel, A., Mortensen, L.F., Asquith, M., Bogdanovic, J., European Environment Agency, C., 2014. Environmental indicator report 2014 : environmental impacts of production-consumption systems in Europe. EUR-OP.

Riba, J.-R., Canals, T., Cantero, R., 2013. Recovered Paperboard Samples Identification by Means of Mid-Infrared Sensors. IEEE Sens. J. 13, 2763.

Riba, J.-R., Canals, T., Cantero, R., 2012. Comparative Study of Multivariate Methods to Identify

Paper Finishes Using Infrared Spectroscopy. IEEE Trans. Instrum. Meas. 61, 1029.

Riba, J.-R., Cantero, R., García-Masabet, V., Cailloux, J., Canals, T., Maspoch, M.L., 2020. Multivariate identification of extruded PLA samples from the infrared spectrum. J. Mater. Sci. 55, 1269–1279.

Roos, S., Sandin, G., Zamani, B., Peters, G., 2015. Environmental assessment of Swedish fashion consumption Five garments-sustainable futures. Stockholm (Sweden).

Sandin, G., Peters, G.M., 2018. Environmental impact of textile reuse and recycling – A review. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2018.02.266

Shen, L., Worrell, E., Patel, M.K., 2010. Environmental impact assessment of man-made cellulose fibres. Resour. Conserv. Recycl. 55, 260–274. https://doi.org/10.1016/j.resconrec.2010.10.001

Simon, B., 2019. What are the most significant aspects of supporting the circular economy in the plastic industry? Resour. Conserv. Recycl. 141, 299–300. https://doi.org/10.1016/j.resconrec.2018.10.044

Spathas, T., 2017. The Environmental Performance of High Value Recycling for the Fashion Industry LCA for four case studies. Chalmers University of Technology, Gothenburg.

Suárez-Eiroa, B., Fernández, E., Méndez-Martínez, G., Soto-Oñate, D., 2019. Operational principles of circular economy for sustainable development: Linking theory and practice. J. Clean. Prod. 214, 952–961. https://doi.org/10.1016/J.JCLEPRO.2018.12.271

Swedish Chemicals Agency, 2014. Chemicals in textiles – Risks to human health and the environment, Report from a government assignment. Report 6/14. Stockholm.

Teigiserova, D.A., Hamelin, L., Thomsen, M., 2019. Review of high-value food waste and food residues biorefineries with focus on unavoidable wastes from processing. Resour. Conserv. Recycl. 149, 413–426. https://doi.org/10.1016/j.resconrec.2019.05.003

Terinte, N., Manda, B.M.K., Taylor, J., Schuster, K.C., Patel, M.K., 2014. Environmental assessment of coloured fabrics and opportunities for value creation: Spin-dyeing versus conventional dyeing of modal fabrics. J. Clean. Prod. 72, 127–138. https://doi.org/10.1016/j.jclepro.2014.02.002

The Ellen MacArthur Foundation, 2012. Towards a circular economy - economic and business rationale for an accelerated transition. Greener Manag. Int. 97.

Vigo, T.L., 1994. Textile Processing and Properties: Preparation, Dyeing, Finishing and Performance, Textile Sc. ed. Elsevier.

Xing, W., Xin, B., Deng, N., Chen, Y., Zhang, Z., 2019. A novel digital analysis method for measuring and identifying of wool and cashmere fibers. Meas. J. Int. Meas. Confed. 132, 11–21. https://doi.org/10.1016/j.measurement.2018.09.032

Yousef, S., Tatariants, M., Tichonovas, M., Sarwar, Z., Jonuškienė, I., Kliucininkas, L., 2019. A new strategy for using textile waste as a sustainable source of recovered cotton. Resour. Conserv. Recycl. 145, 359–369. https://doi.org/10.1016/J.RESCONREC.2019.02.031

Zhou, C., Han, G., Via, B.K., Song, Y., Gao, S., Jiang, W., 2018. Rapid identification of fibers from different waste fabrics using the near-infrared spectroscopy technique. Text. Res. J. https://doi.org/10.1177/0040517518817043

Zhou, J., Yu, L., Ding, Q., Wang, R., 2019. Textile Fiber Identification Using Near-Infrared Spectroscopy and Pattern Recognition. Autex Res. J. 19, 201–209. https://doi.org/10.1515/aut-2018-0055