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ROBOTIC SURFACE MATERIAL RECOGNITION SYSTEM USING SENSOR NETWORK

Salih Ertuğrul GÖKCAN[1], Nihan KAHRAMAN[1*]

[1] Yıldız Technical University, Faculty of Electrical and Electronics Engineering, Dept. of Electronics and Communications Engineering, İstanbul, Türkiye

Keywords

Surface material, Recognition, Machine learning, Pattern recognition, Data fusion, Multi-sensor.

Abstract

Object recognition usually includes colour, shape and material types. This paper presents a methodology for surface material recognition by a tool which is tapped on an object for robotic applications. Recognition of a surface material can be explored by scratching the tip of the tool over the surface. To classify surface types, many different sensors such as acceleration, force, reflectance, image and audio were used via automated robot movements. For this purpose, 28 different surface materials including such as metals and papers were used. It should be emphasized that the properties of surface materials are also different. 22 different classifiers were trained with these surfaces using Matlab Classification Learner Application. The data which is collected ten times from sensors were examined also in different combinations. First, all data (combination of acceleration, force and reflectance) except image and audio data was observed. Then; only image, only audio and dual combinations of all data subsets were evaluated. In the end, classification accuracy of fused data including all sensors was compared to the rest of the results. The proposed fusion of all features provides a classification accuracy of 98.2% in our experiments when combined with a Bagged Trees classifier.

SENSÖR AĞI KULLANARAK ROBOTİK YÜZEY MALZEME TANIMA SİSTEMİ

Anahtar Kelimeler

Yüzey malzeme tanıma, Makine öğrenmesi, Nesne tanıma, Veri füzyonu, Çoklu sensör.

Öz

Nesne tanıma genellikle renk, şekil ve malzeme tiplerini içerir. Bu çalışma, robotik uygulamalarda kullanılmak amacıyla üzerinde çeşitli sensörler bulunduran kontrollü bir araçla birleştirilmiş yüzey materyali tanıma yöntemi sunmaktadır. Yüzey tiplerini sınıflandırmak için, otomatik robot hareketleri ile hızlanma, kuvvet, yansıma, görüntü ve ses gibi birçok farklı sensör kullanılmıştır. Çalışmada taş, ahşap yüzey, kumaş, plastik, metal ve kâğıt gibi farklı yapıdaki malzemeleri içeren 28 yüzey malzemesi kullanılmıştır. Matlab Sınıflandırıcı Uygulaması kullanılarak bu yüzeylerle 22 farklı sınıflandırıcı eğitilmiş ve sonuçlar analiz edilmiştir. Veriler sensörlerden farklı zamanlarda ve farklı kombinasyonlarda toplanmıştır. İlk olarak, görüntü ve ses verileri hariç tüm veriler (hızlanma, kuvvet ve yansıtma kombinasyonu) gözlemlenmiş; daha sonra sadece görüntü, sadece ses ve bu verilerin ikili kombinasyonları değerlendirilmiştir. Sonuçta, tüm sensörler dâhil olmak üzere birleştirilmiş verilerin sınıflandırma doğruluğu, sonuçların geri kalanıyla karşılaştırılmıştır. Tüm özelliklerin önerilen birleşimi ve Torbalı Ağaç sınıflandırıcısı yöntemi kullanıldığında 98.2% oranında bir sınıflandırma doğruluğu elde edilmiştir.

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Yazar Kimliği / Author ID (ORCID Number)

S.E. Gökcan, 0000-0002-1510-1782
N. Kahraman, 0000-0003-1623-3557

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* İlgili yazar / Corresponding author: nicoskun@yildiz.edu.tr, +90-212-383-5884

1. Introduction

Material classification became a very popular topic in last years. It has many applications areas. Each application uses different features or feature combinations. However, using all features has many difficulties under same conditions. This work investigates the performances of algorithms and features. Firstly, hardware setup was fixed to collect data from surfaces. Machine learning algorithms were trained with data after signals were processed. Finally, algorithms were tested with test data and results were given.

In this work, 28 different surfaces were classified using support vector machine (SVM), k-nearest neighbor (KNN), bagged trees and discriminant machine learning algorithms. These machine learning algorithms are most used supervised classifiers for this type of classification according to literature review. Training phase was evaluated with these 28 objects. Testing data was 20% of all data set and they were not used during training phase. Classification was evaluated using different combinations of audio, image and other sensors data with 22 different classifiers. There are some very similar and very different objects in this dataset. First, all data (combination of acceleration, force and reflectance) except image and audio data was observed. Then; only image, only audio and dual combinations of all three data subsets. In the end, classification accuracy of fused data including all sensors was compared to the rest of the results. The proposed fusion of all features provides a classification accuracy of 98.2% in our experiments when combined with a Bagged Trees classifier.

This paper is organized as follows; Section 2 gives the mini literature survey about the scope. Section 3 and Section 4 gives brief information about hardware setup and how the database is obtained respectively. The results are discussed in Section 5 and finally concluded in Section 6.

2. Background

Haptics has many usages in different areas like multimedia Cho vd. (2014), material classification Bharati vd. (2001), biomedical Sgambelluri vd. (2007) and teleoperating systems (Strese vd., 2015). For different applications, there are some different methods to measure the surface properties. Surfaces can be classified with acceleration signal, reflection data, audio data or image. In Chen vd. (1998), a non-contact method that uses the difference between surfaces reflection coefficients was used. It was showed that their method had advantages to previous techniques which used intensity, color and polarization properties. The results had a good accuracy and showed the potential capabilities. As shown in the work, materials can be classified with a non-contact system. In Wolff (1990), it is well-explained why the reflectance data is good for classification of metal and dielectric materials. It was pointed out that this method could be used in computer vision since 20th century. After many years, in Wang vd. (2009), it is still indicated as fundamental building block of many important computer vision algorithms. According to the Lemp vd. (2005), reflectance can change under different light conditions. In early ages, laser scanning and hyperspectral data were used to derive the geometrical shape of objects. Laser data was used to classify roofs with an image captured from above.

Image based classification can be used as non-contact method for some applications. In Omer and Fu (2010), the aim is classifying winter road surface conditions using images with low cost cameras which were mounted on regular vehicles. Some features were extracted from images and used as input for SVM. The accuracy ratios of the results are over 80%. More than 400 images were used in that study. Data set was divided into two parts and 70% of them was used for training where the rest of the data was used for testing.

Images can give very useful information about the surfaces and can be used with other features in parallel (Gao vd., 2016; Zheng vd., 2016). Although it is a strong method, it cannot work properly in bad light conditions. Likewise, reflectance data can be affected from light conditions (Weinmann vd., 2014). This problem and similar problems should be considered when using reflectance or image features. Reflectance coefficient of different colors can be different even if they are from the same surface (Tappen vd., 2005). This problem can be solved by using contact acceleration or force data but it is not enough for full object recognition.

It is possible to classify surfaces with the data obtained via a tool which contacts the surface. Mostly, accelerometers and force sensors are mounted to this tool (Strese vd., 2015; Zheng vd., 2016; Romano vd., 2012). If the tool is tapped or dragged over a surface with a contact, accelerometers can capture the vibrations that occurred on the tool because of the friction between surface and tool (Strese vd., 2017). Acceleration signal carries important information about the surface material properties (Zheng vd., 2016). In Strese vd. (2015), it is indicated that kinaesthetic haptic devices cannot deliver the high-frequency vibrations to remote user in a teleoperation system. Using the features based on hardness and roughness was advised by authors. These features can be extracted from contact acceleration data. In Romano vd. (2012), it is shown that using acceleration sensors is very helpful to extract microscopic features. The surfaces in the paper can be classified as wood, paper, rough plastic, canvas, denim and vinyl. Success of sensing of these surfaces are not equal.

Furthermore, scan-time parameters such as force and velocity may affect the acceleration signal while recording a contact data on free-hand systems. In Strese vd. (2017) proposed subset of six features, selected from the described sound, image, friction force and acceleration features, leads to a classification accuracy of 74% in their experiments when combined with a Naive Bayes classifier. According to this paper, when a human strikes a rigid tool over an object surface, the applied force and the scan velocity typically vary during the surface exploration and between subsequent exploration sessions.

If there is a possibility to use these data together, it can be useful to increase the accuracy of classifiers. For example, it cannot be possible to use contact data to classify the road condition from a regular vehicle (Omer and Fu, 2010). Also, for high temperature environments, it can be very dangerous for materials. On such these types of applications, non-contact data types can be combined like reflectance and image.
There are some studies which use both visual and haptic data for classification or other applications (Gao vd., 2016; Zheng vd., 2016; Strese vd., 2017; Palluel-Germain vd., 2007). These studies extract features from an image and use them with haptic features. Image features are very helpful to increase the efficiency of system. In Gao vd. (2016), visual and haptic features were used both separately and combined. For some situations, visual features increased the accuracy whereas haptic data seems better than visual data. It is indicated that the combined model improves performance. By the way, there are some situations which combined data has lower accuracy than visual or haptic data.

In Palluel-Germain vd. (2007), a visuo-haptic device was used to teach handwriting to kindergarten children. Fluency was analysed by kinematic parameters like velocity, velocity peaks and number of breaks during writing six cursive letters. According to the results, children could write faster with more continuous movements. These types of applications can help to improve some personal skills.

In Zheng vd. (2016), a fully connected convolutional neural network was used for material classification. There were 69 objects from 9 divisions like stones, wooden surfaces, meshes, glossy surfaces, rubber-type surfaces, fibers, foams, foils & papers and textiles. A comparison was made between haptic, visual and hybrid classification using images which were taken in a static position. According to the results, using haptic and visual data together improves performance. Hybrid classification performance are over 95%. Despite that, most of other classification results are under 90%. Three of them are close to hybrid classification performance but still hybrid classification results are better. Unlike from Gao vd. (2016), in Zheng vd. (2016), combined or hybrid classification results are better than other ones for all types of materials. Visual classification has a disadvantage. Its running time is longer than haptic classification (Zheng vd., 2016). It can affect real-time applications performance.

3. Hardware Setup

In this work, the focus is material classification using a robotic system which includes AL5D robot arm. As shown in Figure 1, it is a 4 Degree of Freedom (DOF) robot arm like a human arm. Therefore, it can also perform some exploratory movements like human. They are not so complex movements but they satisfy the requirements to measure some reasonable data from surface with sensors. There is an important point while manipulating the robot arm for exploratory movements. Using inverse kinematics cannot be a good choice since two or more servo motors move. Speed and torque control can be lost at this kind of situation. It can be performed on another work focused on robotic movements. In this work, manipulating robot arm is a tool and moving only one of four servos give desired movements.

Raspberry Pi was selected as microcontroller unit for this work because its processor and memory performances are quite good to satisfy all computing requirements in this work. Also, it has enough pins and USB ports to add external components.

All sensors are mounted to the end position of the robot arm. Figure 2 shows the sensors from four different sides.

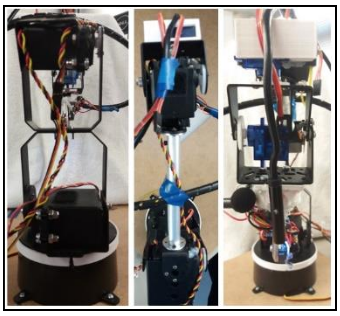

Figure 1. Robot Arm from Different Views

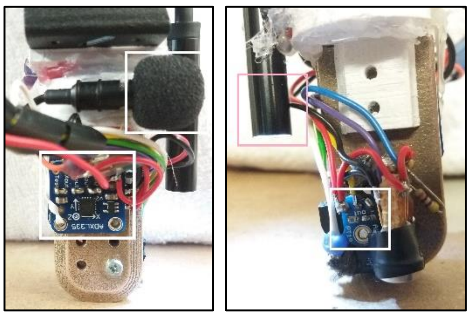

Figure 2. Tool photos

3.1. Sensors

In this work, three sensors which are acceleration, force and reflectance were used to extract features from surfaces. The acceleration sensor, ADXL335, can measure dynamic results from motion, shock or vibration.

Force sensing resistor measures the pressure on the resistor. Resistance value changes if a pressure is applied directly to the sensor. Its output is analog like accelerometer so it was connected to analog digital converter.

Reflective sensor was used to measure reflected signals from objects. Its value depends on surface and distance. A reflective infrared sensor (within 3 cm) was used for this work.

3.2. Camera

A USB webcam mounted to the robot arm with other sensors was used in this work to obtain visual features for classification. During experiments, a problem was occurred about resolution. The object can be stand in different heights. With a fixed focus webcam, it is not a good idea to capture an image from an unknown distance at the beginning of the process. To avoid this problem, the image was captured after contact with surface. By this way, all images had the same sharpness and brightness.

Since the webcam has a flashlight which is always open, there is no problem about darkness. However, it caused a brightness problem around center of the image. Fortunately, it does not affect all image pixels. Therefore, we have extracted visual features from another part of the images.

Figure 3. Used part of images for feature extraction

3.3. Microphone

In this work, a microphone which records 44.1 kHz audio signals was used to record audio signals while the tool is scratching and tapping. Since Raspberry Pi does not have an audio input, the microphone was connected to Raspberry Pi via a sound card.

4. Surface Database

In order for the robot tool to perform necessary movements to collect data, rigid and non-deformable materials were used for this work. At the tapping phase, since the tool hits the surface three times, it can damage the surface if it is fragile. At the scratching phase, the tool scratches on the surface with a bit pressure. If the surface is deformable like sponge, the tool cannot execute the scratching movement. Therefore, it cannot record meaningful data.

The database consists of 28 different surfaces such as stones, wooden surfaces, fabrics, plastic, metal, papers etc. These surfaces have different opaqueness, hardness and roughness properties. Some of the objects are in different colors or the different tones of a color. In addition, some of them do not have a homogenous colour histogram. Figure 3 shows some samples from the database.

Audio, image and sensors raw signals were captured via the tool. They were processed to make them ready for classifiers. In this section of the paper, these processes were explained.

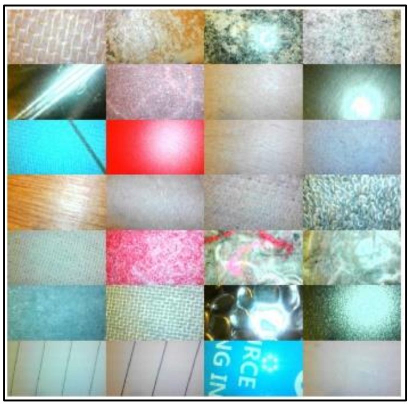

Figure 4. The surface data set

4.1. Audio Data

The fast Fourier transform is a computational tool which facilitates signal analysis such as power spectrum analysis and filter simulation by means of digital computers (Cochran vd., 1967). It can represent signals in frequency or time domain. Especially, it is very useful to extract features from audio signals. Also, it can be applicable for one dimensional signals.

Audio signal was recorded with a microphone over a sound card. It has a fixed frequency, 44.1 kHz. Using audio signal raw data makes the input size of classifiers larger. Therefore, fast Fourier transform was used for preprocessing of the audio signals. It gives a symmetric signal between 0 and 44100. Although using the half of signal is enough, it is still large for classifiers input. Therefore, we have reduced the signal to 10% using sampling method. Finally, the size of audio data was decreased to 2205 for each movement. Raw signals and processed signals are given for some surfaces in Figure 4 and Figure 5.

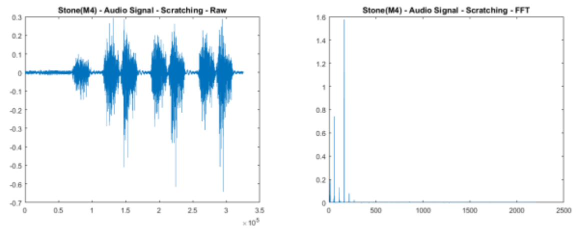

Figure 5. Audio Signal Processing for Scratching Movement

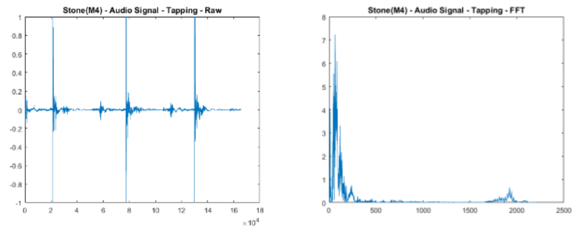

Figure 6. Audio Signal Processing for Tapping Movement

4.2. Image Data

In this work, a pre-trained convolutional neural network (AlexNet) is used to extract features from surface images. These images are in 1280x720 resolution. Since the flashlight does not affect the upper left part of image, that part can be used for neural network input. This means that a 227x227 sized sub image can be used from the original one. Its fully connected layer was selected to extract features and it gives a feature vector that has a size of 4096. It is directly used as classifier input.

4.3. Sensor Data

There are three sensors used for feature extraction. All of them are analog sensors and connected to the Raspberry Pi via an analog digital converter. Output of the analog digital converter is 10-bit so the samples are between 0 and 1023.

There are 1023 features from the accelerometer for each axis. Totally, there are 6138 acceleration features for both scratching and tapping movements in 3D. Their histogram counts were used as classifiers input. Force data and reflection data were collected from only scratching movement. Their input sizes are 1023 for each.

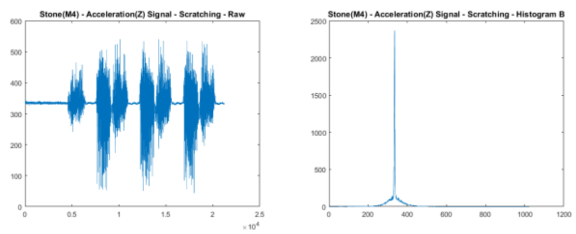

Figure 7. Accelerometer Signal Processing for Scratching Movement

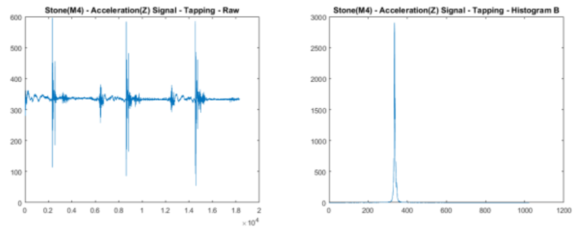

Figure 8. Accelerometer Signal Processing for Tapping Movement

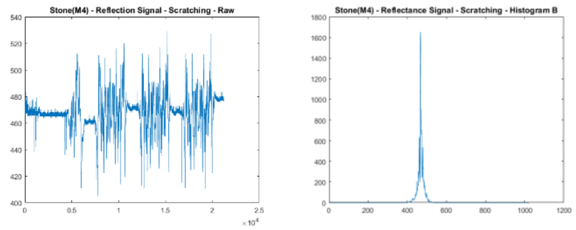

Figure 9. Reflectance Sensor Signal Processing for Scratching Movement

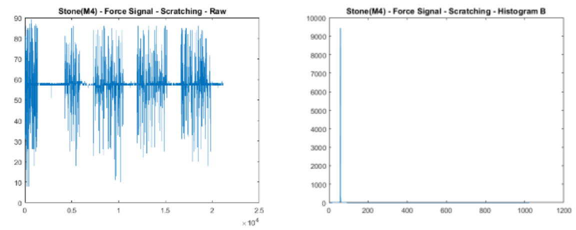

Figure 10. Force Sensor Signal Processing for Scratching Movement

5. Classification Results

In this work; SVM, KNN, Bagged Trees and Discriminant Analysis were used via Matlab Classification Learner Tool as classifiers for obtained data. All classifiers were trained with 224 records from 28 objects. 4-fold cross validation were used as validation method. 56 records from the same 28 objects were used for test.

While the classification accuracy was calculated, the effect of each properties obtained in both movements was examined separately and in combination.
In the first three subsections 5.1, 5.2 and 5.3 the classification accuracy of the sensor, image and audio data are analyzed separately while the rest of subsections explain fused classification accuracy results.

5.1. Only Sensor Data

Classifiers were trained and tested with only sensor features. Accelerometer, force sensing resistor and reflection sensor data were used as input. Table 1 shows the accuracy results of only sensor data where the best is Bagged Trees.

Table 1. Results with Only Sensor Data

CLASSIFIER	ACCURACY
Linear Discriminant	93.8%
Quadratic Discriminant	71%
Linear SVM	65.2%
Medium Gaussian SVM	83.5%
Fine KNN	94.2%
Cosine KNN	81.7%
Weighted KNN	80.8%
Boosted Trees	84.8%
Bagged Trees	96.4%
Subspace Discriminant	92.9%

5.2. Only Image Data

Classifiers were trained and tested with only image features. Table 2 shows the accuracy results of only image data where the best is Subspace Discriminant. Although the surface classification using the images captured by the camera is highly successful, there may be a decrease in the results in dark environments or in environments where the light surface is misleading.

Table 2. Results with Only Image Data

CLASSIFIER	ACCURACY
Linear Discriminant	98.2%
Quadratic Discriminant	98.2%
Linear SVM	94.6%
Quadratic SVM	94.6%
Coarse Gaussian KNN	94.6%
Fine KNN	96.4%
Cosine KNN	89.3%
Weighted KNN	98.2%
Bagged Trees	96.4%
Subspace Discriminant	100%

5.3. Only Audio Data

Classifiers were trained and tested with only audio features coming from tapping and scratching movements. Although it seems to be inadequate, classification can be performed with this data when the surface is rough and light is insufficient.

There are two audio files. One is from tapping movement and the other one is from scratching movement. Both were used as input for classifiers separately. As seen from Table 3, tapping audio data has more accuracy than scratching audio data for all classifiers. The maximum accuracy with tapping audio is 80% and the maximum accuracy with scratching audio is 70%. If these two data are combined, the best accuracy is 83.9%.

Table 3. Results with Only Audio Data

CLASSIFIER	TAPPING	SCRATCHING	COMBINED
Linear Discriminant	76.3%	67%	79.9%
Quadratic Discriminant	76.3%	44.6%	72.8%
Linear SVM	76.8%	56.3%	75.4%
Quadratic SVM	77.2%	62.9%	76.8%
Cubic SVM	71.9%	57.1%	69.2%
Coarse Gaussian SVM	65.6%	50.4%	70.1%
Fine KNN	72.3%	55.4%	70.5%
Cosine KNN	66.5%	58%	75.4%
Bagged Trees	78.6%	51.3%	73.2%
Subspace Discriminant	80.8%	70.1%	83.9%

5.4. Image and Audio Data

Image and audio data were used together to classify the objects. Table 4 shows the results.

Table 4. Results with Image and Audio Data

CLASSIFIER	ACCURACY
Linear Discriminant	98.2%
Quadratic Discriminant	92%
Linear SVM	96.4%
Quadratic SVM	95.5%
Fine KNN	96.9%
Cosine KNN	92.4%
Weighted KNN	90.2%
Bagged Trees	96.9%
Subspace Discriminant	98.7%
Subspace KNN	98.7%

5.5. Sensor and Image Data

Sensor and image data were used together to classify the objects. This scenario can be useful for noisy environment. Table 5 shows the results.

Table 5. Results with Sensor and Image Data

CLASSIFIER	ACCURACY
Linear Discriminant	97.8%
Quadratic Discriminant	90.2%
Linear SVM	91.1%
Quadratic SVM	88.8%
Fine KNN	98.2%
Cosine KNN	91.5%
Weighted KNN	93.8%
Bagged Trees	98.2%
Subspace Discriminant	97.8%
Subspace KNN	79.9%

5.6. Audio and Sensor Data

Audio and sensor data were used together to classify the objects. This scenario can be useful under bad light conditions. Table 6 shows the results.

Table 6. Results with Audio and Sensor Data

CLASSIFIER	ACCURACY
Linear Discriminant	92.4%
Quadratic Discriminant	82.1%
Linear SVM	69.6%
Quadratic SVM	67.4%
Coarse Gaussian SVM	81.3%
Fine KNN	88.8%
Cosine KNN	86.6%
Bagged Trees	93.3%
Subspace Discriminant	85.7%
Subspace KNN	79.5%

5.7. Fused Data

In this section, all the sensor, image and audio data used up to now are combined and the effect on the classification result is investigated. Table 7 shows the best eight classifiers.

Bagged Trees algorithm is obtained as the best for training phase with four misclassified samples over 224. Three of misclassified test samples show a large similarity with the original patterns. For this reason, the failure of the classification algorithm can naturally be met. However, the rest of the example does not show any similarity with the classification result. It is given in Figure 10.

The best classifier was tested with 56 unseen records. The records were never used for training. Only two of them were misclassified so the accuracy is 96.4%. Again, one of the paper surface in Figure 11 was classified as the other paper surface. The other misclassified surface was the other side of the black fabric which has small colorful parts. The difference between the sides are a nylon covering. The side which has a nylon covering was classified as another black fabric surface as in training phase. It is given in Figure 12.

Table 7. Results with Fused Data

CLASSIFIER	Image & Audio	Sensor & Image	Audio & Sensor	Fused
Linear Discriminant	98.2%	97.8%	92.4%	97.3%
Quadratic Discriminant	92%	90.2%	82.1%	91.1%
Linear SVM	96.4%	91.1%	69.6%	89.3%
Coarse Gaussian SVM	95.5%	94.2%	81.3%	94.6%
Fine KNN	96.9%	98.2%	88.8%	97.3%
Weighted KNN	90.2%	93.8%	71.4%	92.9%
Bagged Trees	96.9%	98.2%	93.3%	98.2%
Subspace Discriminant	98.7%	97.8%	85.7%	97.3%

Figure 11. Misclassified Sample in Train Data

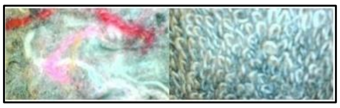

Figure 12. Misclassified Sample (1) in Test Data

Figure 13. Misclassified Sample (2) in Test Data

6. Conclusion

Nowadays, pattern recognition and artificial intelligence is used in different applications. However, some fields need these methodologies as an assistive technique.

In this study, a scenario was dealt with which included systems in which image classification techniques based on surface classification were inadequate. For this purpose, a tool which collects data from the surfaces autonomously with various sensors is used. A 3-axis accelerometer, a reflectance sensor, a force sensor, a USB camera and a microphone were used for data collection. The data was evaluated by different machine learning algorithms with various data combinations. In the case of using the whole data, the performance ratio may not always seem increased, but this allows the system to be used in different environmental conditions. Also, some machine learning algorithms gave their best results when all data used together. According to the results, data fusion should be achieved carefully since it may decrease or increase the accuracy. Furthermore, it should not be forgotten that using the best data may not be available all the time.

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Conflict of Interest

No conflict of interest was declared by the authors.

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