ABSTRACT

Counterfeiting is a challenge to companies, customers and markets all over the world. Besides the economic damage which affects in particular the companies and countries that use advanced production and manufacturing processes based on intensive research and development to produce high quality goods, safety standards are omitted. These standards protect usually the customer from goods which are dangerous or hazardous to health. Product piracy prevention is often followed by the application of RFID tags to supervise supply chains. The lack of robust counterfeit detection methods created a market for artificial security labels which are used to secure the product itself. The specific conditions of production, manufacturing technologies and materials generate specific features, which identify every product uniquely. The innovation of this text is the detection of these features in an automated fashion through the combination of digital sensing and machine learning, rendering the application of artificial security labels obsolete.

KEYWORDS

Automated Counterfeit Detection, Product Fingerprinting, Pattern Recognition, Sensor Fusion, Classification
ing and piracy” [2] of 2008 estimates a total loss of 250 billion dollars in the year 2007. This report covers the analysis of international trade in counterfeit and pirated products, but these estimates do not include domestically produced and consumed counterfeit and pirated digital products being distributed via the Internet. If these were also considered, the magnitude of counterfeiting and piracy worldwide could be several hundred billion dollars more in 2007. Furthermore, if we compare these numbers to the amount of cases reported in Figure 1, they probably doubled in 2011. The effect of counterfeiting and piracy is an intermission of innovation and thus impairment of economic growth. The economic damage affects in particular countries that use advanced production and manufacturing processes based on intensive research and development to produce high quality goods.

Another very important argument to enable the differentiation between brand products and their counterfeits is safety. It is stated in the OECD report that the products counterfeiters and pirates produce and distribute are often of minor quality and can even be dangerous and health hazards. Common standards that ensure the safety of products can be ignored by product pirates and the used materials can be dangerous.

With the magnitude of counterfeiting and piracy in mind, these reports emphasize the need for more effective enforcement to combat the counterfeiting and piracy on the part of governments and businesses alike. A key component for this enforcement is the development of new methods for automated counterfeit detection.

The review of copyright infringement of registered trademarks and products is not easy to implement. Due to the high number of pending trademarks and constantly added new applications it is very difficult for the executive bodies, such as customs, to register violations of trademark rights immediately and in a comprehensive manner. The awareness to all registered brands and products is for the executive organs not possible and therefore necessarily, trademark infringement remains unnoticed. The current scenario for products entering a market in a foreign country is displayed in Figure 2. Here it is shown how customs officials usually handle the inspection of products at the border. First the goods arrive at a specific check point, usually via sea- or airfreight. If the customs officer notices some anomaly in the paperwork, he will check the cargo containers. As discussed earlier the officer is often not an expert for the shipped product, so he could not detect a counterfeit. Instead the company producing the genuine product is contacted to send their own expert, which can verify the product. This is a time-consuming and expensive process, therefore most containers in question often remain unnoticed.

To overcome these limitations in the checkup routine an automated expert-system is neces-
sary that can support the customs officials, as shown in Figure 3. Given that the officer could verify the shipped cargo by himself while the company issues the authentication system for their products. This idea was adopted more recently through an application of artificial security features to products. The issues of such security labels are in part the high cost, and additionally the integration into the product. On the other hand high-quality branded products, as the target of counterfeiting, have usually, due to the production processes and materials used, and in view of its processing machinery and equipment, a grade of high quality. The specific conditions of production, manufacturing technologies and materials generate specific features, which identify the product uniquely. These features may be detected multimodal by man, including tactile (plasticity, elasticity, thermal conductivity, surface structure), visual (shape, colour, surface texture, transparency), olfactory (smell) or acoustic (sound) perceptions. In general, only the person familiar with the manufacture of the product can combine these inherent characteristics in their entirety so that it can differentiate the genuine product from a clear counterfeit. The innovation of this text is the detection of these features in an automated fashion through the combination of digital sensing and machine learning, rendering the application of artificial security labels obsolete. As shown in Figure 4, more than 60% of counterfeit products are shoes, bags and clothing. Therefore two properties of a product have been identified as the most promising ones suitable for identification: the olfactory and the optical features.

2 STATE-OF-THE-ART-TECHNOLOGY

Common automated counterfeit detection methods require nowadays additional security features at the product itself. Several methods have been developed, but main advantages and disadvantages remain similar. Additional security features require further steps in production to add these features to the product. This raises expenses, manufacturing time and development efforts, which is clearly a disadvantage. On the other hand the security is enhanced and an original brand is easy to detect in an automated fashion, since there is a specific feature to look for. But this could also be a main disadvantage, if the security feature itself is easy to reproduce and could be added to any forged product. Another challenge is to link the security label to the brand product in a way it cannot be removed or stolen. This way product pirates could label their counterfeits easily as an original with an original security label.

Figure 5 shows examples of different labels which are commonly used on products for different purposes. One purpose is the use as a logical security feature where the security label contains unique information and cannot be copied. Counterfeit detection without artificial security tags is a solution to these problems, if the counterfeit is distinguishable from the original brand.

2.1 Security Labels

The report [3] of the German Engineering Federation shows the latest innovations against
2.2 Product-Inherent Features

The Inherent ID Project adopts a novel approach to protecting high-value products from counterfeiting. The approach is based on the stationary and mobile capture of key product features indissolubly linked with the product which enable its production process to be traced. This not only renders obsolete the application of security tags but also gives enhanced protection against counterfeiting as the inherent characteristics that the high-quality production process impregnate in the genuine product are combined with one another to serve as proof of product identity. They form the basis on which electronic certificates of authenticity can be issued without the need for complicated explicit security markings. Methods for the capture and control of identity characteristics are being elaborated in the Inherent ID project for system integration using intelligent cameras and an electronic nose. The identity characteristics captured by this range of sensors serve both for the product identification and product authentication. At the same time this also offers opportunities for improving documentation of product flows in the supply chain. Full documentation serves as a complement to the inherent characteristics of the authentic product and offers valuable information of verification of the genuine article, thus serving to safeguard against counterfeits. The Project aims to answer the question: Which inherent features allow separation of genuine products from counterfeits in an automated fashion? The motivation of this question is the assumption that genuine products must differ in its properties from its counterfeit, since the product pirate tries to maximize its profit by using material of inferior quality and misusing a trademark of a genuine manufacturer to feint the customer. One result of
the project is that only a combination of features can detect counterfeits at a decent rate for different products.

3 MATERIALS AND METHODS

Optical 2D and 3D characteristics as well as olfactory characteristics are combined with one another to serve as proof of product identity, as shown in Figure 6. They form the basis on which electronic certificates of authenticity can be issued without the need for complicated explicit security markings. The identity characteristics captured by this range of sensors serve both for product identification and product authentication. At the same time this also offers opportunities for improving documentation of product flows in the supply chain. Within the scope of Inherent ID is the successful establishment of a laboratory providing multi-modal measurement equipment comprising multigas sensor array for olfactory analysis, high resolution camera for texture analysis and stereo vision, as well as range cameras for 3D feature extraction. Further research is conducted with the aim for increasing robustness of the sole test methods especially under ambiguous environments, integration into portable devices, implementing sensor data fusion for increased detection ratio, effortless integration into supply chains and developing efficient data models for storage of various features depending on the regarded product.

3.1 Texture Features

The ability to characterise visual textures and extract the features inherent to them is considered to be a powerful tool and has many relevant applications. A textural signature capable of capturing these features, and in particular capable of coping with various changes in the environment would be highly suited to describing and recognising image textures [6]. As humans, we are able to recognise texture intuitively. However, in the application of Computer Vision it is incredibly difficult to define how one texture differs from another. In order to understand, and manipulate textural image data, it is important to define what texture is. Image texture is defined as a function of the spatial variation of pixel intensities [5]. Furthermore, the mathematical description of image texture should incorporate, identify and define the textural features that intuitively allow humans to differentiate between different textures. Numerous methods have been designed, which in the past have commonly utilised statistical models, however most of them are sensitive to changes in viewpoint and illumination conditions [6]. For the purposes of mobile counterfeit detection, it is clear that this would be an important characteristic for the signature to have, as these conditions can not be entirely controlled. Recently a description method based on fractal geometry known as the multifractal spectrum has grown in popularity and is now considered to be a useful tool in characterising image texture. One of the most significant advantages is that the multifractal spectrum is invariant to the bi-Lipschitz transform, which is a very general...
Figure 7: Workflow for generating a textural signature

transform that includes perspective and texture surface deformations [6].

Another advantage of Multifractal Spectra is that it has low dimension and is very efficient to compute [6] in comparison to other methods which achieve invariance to viewpoint and illumination changes such as those detailed in [7], [8]. One of the key advantages of multifractal spectra, which is utilised here is that they can be defined by many different categorisations or measures, which means that multiple spectra can be produced for the same image.

This is achieved through the use of filtering, whereby certain filters are applied to enhance
certain aspects of the texture, to create a new measure. Certain measures are more or less invariant to certain transforms, and the combination of a number of spectra achieves a greater robustness to these. The workflow is depicted in Figure 7 and an example is given in Figure 8.

3.2 Shape Features

Since manual detection is often done visual by customs officials, visual features are also important for any automatic detection mechanism. Besides detecting features through two dimensional image processing, three dimensional data capture is necessary for counterfeit detection, because it provides important additional information.

To capture a real-world object in three dimensions a 3D scanner, or range camera, can be used. The basic principles of 3D scanners available on the market are triangulation, time-of-flight or interferometric approaches, whereas each principle has its advantages or disadvantages. For a profound insight into that
topic refer to [9]. We use a mobile structured-light 3D scanner for our application, but in general any three dimensional data acquisition method can be used to capture a real-world object. But while using different kinds of scanning techniques the results may vary.

One distinguishable feature of brand products is the shape itself. Shape matching is a well studied topic and several publications can be found over the last 15 years. Despite many different approaches available, most practical applications still use the 1992 introduced Iterative Closest Point Algorithm (ICP) [10] or its optimized variants to match objects. This is due to the fact that most newer approaches are neither easy to implement nor able to run at a reasonable speed for the use in commercial software.

One major challenge for three dimensional object capture is the huge amount of data that has to be processed. The 3D scanner we use has an accuracy of 20 to 50 $\mu m$ and generates around 300,000 vertices per object. Assuming a point per point matching algorithm with $O(n^c)$ and $c > 1$ growth rate and a calculation time of 1ms per point match, it would take nearly 3 years to calculate a match of two objects.

Feature-based approaches have become very popular since some years in image analysis (2D) due to robustness and less computational effort compared to other approaches. In shape matching (3D) feature-based approaches have been introduced more recently and are gaining popularity in shape retrieval applications for the same reasons. The major difference among these is whether the approach uses global or local features. A global feature describes the whole object, while local features only describe parts or details of an object. In [11] an overview of shape matching principles and algorithms can be found.

Many shape matching approaches use digital human made data like the Princeton-Shape-Benchmark [12] or the SHREC datasets [13] to evaluate their algorithms. Scanned data from real world objects is different to artificially-made data in a sense that holes\(^1\) and variations between two scans of the same object can appear. The SHREC datasets have indeed several categories with different 3D models to mirror these real-world challenges, but the categories are examined separately and models are artificially-made too. For that reason we created our own database using 3D scanners and our students shoes. Figure 9 shows some examples of our scans. We scanned some shoes with different scanners to get a more complex testing database. Furthermore different types of noise were applied to the scanned models as shown in Figure 10. Approaches using global features are not suit-

\(^1\)Holes are areas on the scanned object where the used scanning technique has troubles to capture data.
able for counterfeit detection, where minor details of an object can be highly important. Therefore only approaches detecting local features were taken into consideration. Our automatic local-feature-based matching algorithm consists of two major parts: a feature detector and a feature descriptor. The classification is done later after the texture and odour features are combined with the shape features through feature fusion.

Feature Detector

The feature detector finds points of interest on a given mesh which are usually extrema in a specific mathematical notation. In two-dimensional approaches well known techniques like corner detection are used. In three dimensions new approaches based on two-dimensional image processing algorithms that use feature-based approaches have been developed. Examples are the Harris-3D-feature detector [14], several portations of the SIFT-algorithm to three dimensions [15, 16] or the 3D equivalent of SURF [17]. Other approaches use for example Heat-Kernel-Signatures [19] or maximally stable extremal regions (MSER) [18] to detect features.

For counterfeit detection we use a Scale Space approach to detect keypoints [9]. The Scale Space is usually constructed by repeatedly applying a filter to a given mesh.

\[ L(x, y, z, \sigma) = F(x, y, z, \alpha) \ast M(x, y, z) \]

whereas \( M \) ist the mesh and \( F \) ist the filter-kernel. The difference of the resulting meshes is then examined for extremas. As filter-kernel a finite difference approximation of the Laplace operator

\[ G(x, y, z, \alpha) = \frac{1}{n} \sum_{i=1}^{n} \alpha_i P_i \]

was used, where \( \alpha_i \) is a weighting factor and \( P_i \) are the neighbors of the regarded point. The advantage of this smoothing approach is that each point keeps its relative position, keeping the shape itself of the whole object, as shown in Figure 11. The differences of the mean curvature at each point is the criterion for constructing the Scale Space. Figure 12 shows detected keypoints of two different scans of the same shoe.

Feature Descriptor

The feature descriptor transforms the area at the detected keypoint into an easy comparable and meaningful description. Usually the approaches combine feature detectors and feature descriptors into one method. Well known methods like MeshSIFT [16] or 3D-SURF [17] use their three-dimensional counterpart of feature descriptors developed for two-dimensional applications. Approaches using Heat Kernel Signatures [19, 20] use these for both – detection and description. In contrast to that another approach called Spin-Images [21] is a feature descriptor only. It is able to describe an object locally or globally.

The concept in [22] was adopted to a scale-invariant version encoding local information. Figure 13 shows a transformation of the area surrounding keypoints into a 2D dense map.
using Spin Images [21]. Here a 3D mesh is transformed into several 2D maps, each related to a keypoint 

\[ S_O : \mathbb{R}^3 \rightarrow \mathbb{R}^2 \]

The 2D dense map is constructed using the equation

\[ (\alpha, \beta) = \left( \sqrt{\|x - p\|^2 - (n \cdot (x - p))^2}, n \cdot (x - p) \right) \]

where \((\alpha, \beta)\) describe the new 2D coordinates. It is a cylindric coordinate system with its point of origin in the regarded point of the mesh. A set of ranked Spin Images describes the object itself, so it can be matched to the abstract brand model.

Figure 14 summarizes the required steps for our shape matching algorithm using real world objects. The shape matching algorithm requires a three dimensional model of the product as input which can be matched to an abstract model of the brand product. The abstract model is a description of features that render the brand unique.

3.3 Odour Features

Much effort has been spent on how odour could be measured. The European Standard EN-13725 [23] defines a method for the objective determination of the odour concentration of a gaseous sample using so called dynamic olfactometry. It is currently the only standardized method for the evaluation of odour impressions.

The dynamic olfactometry is a method where a panel of human assessors evaluates the concentration of odour in a series of standardized presentations of a gas sample. Here the emission rate of odours emanating from point sources, area sources with outward flow and area sources without outward flow are considered. The primary application of this standard is to provide a common basis for evaluation of odorant emissions in the member states of the European Union. Every method claiming the ability to detect arbitrary odour emissions has to benchmark against this standard. An overview of the development and application of electronic noses is given in Gardner and Bartlett [24].

In general it was observed that electronic noses do not react to human inodorous gases and were also unable to detect some gases humans are able to smell naturally. Beginning with the working principle of specific gas.
sensors the concept of electronic noses as a combination of sensor array and diverse pattern recognition algorithms for classification is introduced. In principle the sensor concepts could be divided into three categories. The commercially available electronic nose Artinos basing on the KAMINA (KArlsuher MIkroNase) [25] is a representative of metal conductance sensors. Here the sample gas flowing alongside the sensor surface is changing the concentration and configuration of oxide containing compounds, thus changing the conductance of the metal-oxide, which is then used as a measurement signal. The sensor elements differ by the thickness of silicon dioxide coating. Additionally the temperature is changed over time producing 38 analogue channels containing also transient responses, which are to be analysed. Due to its working principle these sensors deliver the most unspecific data, which is both an advantage and a disadvantage at the same time, since the sensors are suitable for a broad variety of samples, but the signal processing is harder to realise. A metal-oxide conductance sensor using 16 channels was utilized in the project Inherent-ID [4].

A similar sensor setup is used in [26], the difference being that the sensor elements are coated with different polymers, which induce a change in conductance to specific gas components. It was shown that with four different sensor types held at four different temperatures, so a total of 16 channels and following linear discriminant analysis ovarian cancer could be detected from tissue samples. There are still some issues with falsely rejected samples, but the results were quite impressive with respect to the use of ad-hoc methods. Another sensor concept utilising polymer coatings are the quartz microbalance sensor arrays as described in [27]. These sensors detect the change of frequency when a gas is flowing over the sensor surface. In principle these arrays are very sensitive but also very susceptible to disturbances. Most of recently published results in odour detection are based on linear discriminant analysis and derivatives thereof. These methods are efficient in classification of complex sensor data, but with a manageable number of classes. And these methods need a significant amount of data present and are therefore not suitable for the here elaborated problem of one to many matching, as needed for the application in counterfeit detection. An additional obstacle is the sensitivity to ambient conditions which result in wide variance of measurement data from the same class of samples. Effort is made in the extraction of relevant features for the purpose of reducing the dimensionality and the suppression of ambient influences which was done by independent component analysis. An attempt of designing a general odour model was made in [28], but was not successful due to the sensors used and the fact that nonlinear behaviour was excluded in advance. So the usage of specific models is more promising.
Desired Signal Extraction

As it was described in the previous chapter there are many ambient influences to odour sensing. For example humidity and temperature are different in Germany and Malaysia. Additionally a mathematical expression for the composition of odour is not linear, so odourous influences cannot be filtered out easily. Given these facts and that the used Artinos Sensor returns most unspecific data it is a challenge to filter environmental influences.

Figure 16: Independent Components of the measurements of a test object (left) and the environment (right) taken with an 16-channel multi gas sensor array, arb. unit

To meet the challenge of extracting desired signals in a robust fashion and filter the environmental noise we use a similar approach to blind source separation, where two different measurements are conducted. The first one is a pattern from the environment without test object. The second is a pattern from the desired sample in the beforementioned environment. The first signal can then be used to extract the plain odour of the object itself from the second signal. The components can be identified and thus the ambient influence can be filtered. Since the electronic nose measurement data delivers a nonlinear mixture of the environmental and sample odour there is no obvious connection between these two patterns.

One approach to divide the signals into their components is the Independent Component Analysis (ICA). Here the separation is done by statistical means. At most the ICA can return as many independent components as the number of sensors used for capturing the input data, whilst reducing the complexity. In general the ICA has two major problems. The first problem is that the independent components are permuted. The sequence of two algorithmic cycles might not be the same even with the same data. The second problem is the loss of variance information in the independent components, since it cannot be restored.

Figure 16 shows the independent components of a textile sample pattern on the left and the environmental reference pattern on the right side. The independent components were extracted by an extended Bell & Sejnowski Algorithm [29] with adjusted break condition. Here the covariance criterion [30] was used.

\[ E\{g(u)u^T\} = I \]

If this equation is true the \( g_i(y_i) \) and \( y_j \) are uncorrelated for \( i \neq j \). Therefore this can be seen as a nonlinear variant of principal component analysis.

The next step after the ICA is to check the integrity of the independent components. There are a some independent components which seem to be noise. An autocorrelation analysis identifies a possible noise contribution. These independent components can be omitted. Af-
Figure 17: The Independent Components with reasonable high similarity measure are indicated by arrows. Noise contribution was omitted. arb. unit

Figure 18: Core information of a textile sample, arb. unit

Figure 19: Concept of feature fusion

4 WORKFLOW

With the features described above there is a strong basis for automated classification of patterns. The key point for a robust and reliable counterfeit detection is the combination of these features and additional user information with the aim to derive a decision whether the probe is likely to be a counterfeit. An advantage of the proposed algorithms for feature extraction is the possibility to utilize statistical frameworks since the features are represented by probability density distributions.

In general there are various approaches possible. Starting with a direct fusion of the features as proposed in [31] and shown in Figure 19, or a more sophisticated approach which is taking the process of probing into account. Such a workflow is depicted in Figure 20.

Here the decision process is not necessarily based on the utilization of all features, since some of them are dispensable or could be misleading. Think of the probing of shirt, obviously the 3D geometry cannot give a relevant contribution to the decision process and the
3D scanning can therefore be omitted. The classification itself is done with an adjusted Bayesian approach where special account was given to the detection of novel and therefore unknown patterns. This was done with estimation of the Level of Significance distribution, which gives a decision information and an additional value of the plausibility of this decision, cf. [32].

5 CONCLUSION

It was shown that the Inherent-ID Project adopts a novel approach to protecting high-value products from counterfeiting. The approach is based on the stationary and mobile capture of key product features indissolubly linked with the product which enable its production process to be traced. This not only renders the application of security tags obsolete but also gives enhanced protection against counterfeiting as the inherent characteristics that the high-quality production process impregnate in the genuine product are combined with one another to serve as proof of product identity. They form the basis on which electronic certificates of authenticity can be issued without the need for complicated explicit security markings. Methods for the capture and control of identity characteristics are being elaborated in the Inherent-ID project for system integration using intelligent cameras and an electronic nose. The identity characteristics captured by this range of sensors serve both for the product identification and product authentication. At the same time this also offers opportunities for improving documentation of product flows in the supply chain. Full documentation serves as a complement to the inherent characteristics of the authentic product and offers valuable information of verification of the genuine article, thus serving to safeguard against counterfeits.

6 PERSPECTIVE

The approach of the project Inherent ID can be adopted to a possible future scenario for counterfeit detection. As shown in Figure 21 the approach could be ported to work with con-
sumer electronics like smartphones, since 3D cameras are already available there. The textural features and the shape features of an object could be detected with the built-in cameras. The classification itself can then be done with an approach using Service Oriented Architectures (SOA), where the features are transferred from the smartphone over the internet to a server. This is necessary because even recent smartphones with multicore cpu’s are too slow to compute the proposed algorithms in a timely fashion. This enables not only customs officials to detect counterfeits, any customer would be able to do that using the detection app. This could lead to a whole new market driven combat against product piracy.

7 ACKNOWLEDGEMENTS

The authors would like to acknowledge the funding of the research project Inherent-ID by the senate of the state Berlin and the European Regional Development Fund. The project is embedded in the Fraunhofer Cluster of Innovation Secure Identity Berlin Brandenburg. Furthermore we would like to acknowledge the work done by our students Evelyn Jungnickel and Norman Franke in the project.

8 THE AUTHORS

The authors are working within the Automation Group at Production Technology Center (PTC) Berlin, Germany. The PTC comprises the department of Industrial Automation Technology at Technische Universität Berlin and the Fraunhofer Institute for Production Systems and Design Technology. The main tasks of the Automation Group are fundamental research and lecturing in a broad band of topics regarding industrial automation such as process automation and robotics, process monitoring and simulation, image processing and pattern recognition.

9 REFERENCES

[1] European Comission,

[2] OECD,


[6] Y. Xu, H. Ji, C. Fermüller,
J Comput Vision 83, pp. 85-100, 2009

[7] M. Varma, A. Zisserman,
, ECCV Volume 3, pp. 255-271, 2002

[8] M. Varma, A. Zisserman,
, CPVR Volume 2, pp. 691-698, 2003

[9] B. Jähne,
, ISBN 3-540-24035-7, 2005

[10] Besl P, and McKay N.
IEEE Transactions on Pattern Analysis and Machine Intelligence, 14(2):239-256, 1992

    Shape Modeling International, 2004

    Proc. EUROGRAPHICS Workshop on 3D Object Retrieval (3DOR), 2010

[14] Sipiran I and Bustos B.


[16] Maes C., Fabry T., Keustermans J., Smeets D., Suetens P., Vandermeulen D.

    Proc ECCV. 2010.

[18] Litman R, Bronstein A, Bronstein M.

[19] Sun J, Ovsjanikov M, Guibas L.


[21] A. Johnson, M. Hebert,
    IEEE PAMI 21, pp. 433-449, 1999

[22] Darom T, Keller Y.

[23] EN 13725,
    DIN EN 13725:2003

[24] J. W. Gardner, P. N. Bartlett,

[25] D. Haeringer, J. Goschnick,
    Sensors and actuators B-Chemical Vol. 132, Nr. 2, 2008

[26] J. Chilo, G. Horvath, T. Lindblad, R. Olsson,
    Lecture Notes in Computer Science Volume 5633, 2009

    2nd IWA International Workshop & Conference on Odour & VOC’s, Singapore, 2003

[28] F. Bitter,

[29] Bell, A.J., Sejnowski, T.J.
    Neural Computation, 7, 6, pp. 1129-1159, 1994


[31] H. B. Mitchell
    Springer publishing, 2007

[32] S. Kühn,