Latent Fingerprint Detection using a Spectral Texture Feature

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ABSTRACT

Technologies for advancing and supporting criminalistic forensic are an upcoming challenge with rising importance within the domain of multimedia security and forensic. For example the acquisition and automated analysis of latent fingerprints, using high resolution 3D scanners, appears to be a promising area of research. Within the paper we will give a detailed demarcation of biometric and forensic fingerprint analysis. We will introduce the aim of a partly automated process for forensic fingerprint acquisition, detection, and processing. Based on the idea of splitting the overall scan process into a fast, low resolution coarse scan and a high resolution detailed scan, different approaches and algorithms has to be evaluated, whether they are feasible for detecting latent fingerprints. Referring to the subject of biometrics and emerging applications, this work will show an approach of a novel Fourier-based spectral texture feature for detecting latent fingerprints in low resolution grey-scale images. Our work is based on data that is acquired using a chromatic white light sensor (CWL), which provides intensity and topographic information of the scanned surface areas. While using a very limited set of different surfaces so far, our first experiments have shown good results on flat and non structured surfaces. Using the presented feature, it is possible to detect latent fingerprints on these surfaces. Even on slightly structured surfaces, like wood imitation, the application of the spectral density feature yields promising results. However the first evaluation of the spectral density feature has also shown some serious limitations of its use on low resolution images.

Categories and Subject Descriptors

I.4 [**Image Processing and Computer Vision**]: Miscellaneous; I.4.7 [**Feature Measurement**]: Texture

General Terms

Algorithms, Experimentation

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1. INTRODUCTION

In this paper an approach for partly automated acquisition and detection of latent fingerprints, using a chromatic white light sensor, will be presented. For further discussion within this work the used terms will be defined as follows. **Biometrics** covers all techniques for automated identification of individuals based on physical or behavioral characteristics with the objective of authentication and identity verification (see [5]). **Forensics** or forensic science deals with the application of scientific methods for collecting and preserving traces of crime, with the objective of possible use as a court-type evidence (see [9]). **Dactyloscopy** is considered to be a part of criminalistic forensic and it is focused on identifying the causer of a trace, establishing fingerprint collections and securing evidence e.g. fingerprints at a crime scene (see [8]). **Exemplary fingerprints** are directly acquired from a finger and used in biometric context. In contrast **latent fingerprints** are left and discovered at crime scenes under uncontrolled conditions, usually they are not left by purpose. In both scenarios there is a need for **reference fingerprints**, they are acquired in so called enrollment stage, stored in some kind of reference database and used for later matching.

For many years fingerprints have been used widely and very successful for personal identification in our daily life. While biometric access control systems based on fingerprints are common and even used in personal identity cards today, the technical development of the last years has also created new options for digital dactoloscopy. Simultaneously new social and society related developments and a changing security situation connected with a rising level of threat, are demanding new methods and techniques for contactless, fast and preferably area-wide gathering of latent fingerprints. (see [4] for one possible scenario) Figure 1 illustrates the target of a partly automated process and support of the forensic expert.

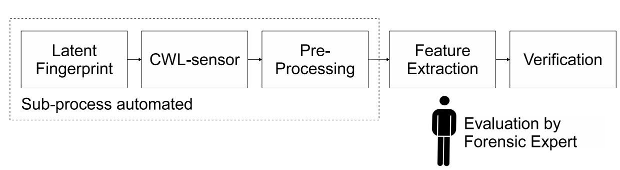

Figure 1: Partly automated Process (Leich et al. [6])

The methods that are used for acquiring latent fingerprints manually in criminal forensic up to now, are very costly in terms of labor and time. Furthermore they have the disadvantage to destroy, or at least heavily alter, the trace itself. After carbonic powder or ninhydrin is used to treat a fingerprint, it is often no longer possible to apply further forensic and / or chemical analysis. For example in most cases it is not possible to apply a DNA analysis anymore, or analyze the left residue for traces of drug consumption. The fingerprint trace itself is destroyed or altered in the moment it gets lifted (see [8]). The use of contactless techniques for gathering latent fingerprints shall support the forensic expert and make it possible to acquire fingerprints in a non-destructive way, even from challenging surfaces (e.g. structured, high reflecting, non-reflecting, etc.) without destroying the integrity of the original trace.

Meanwhile there are different optical methods and technical systems that are capable of a non-destructive and contact-less latent fingerprint acquisition. A very brief overview of the existent techniques is given by Leich et al. in [6]. The data that is used in our paper was acquired by using a chromatic white light sensor (CWL), the scanner is utilizing the effect of chromatic aberration and has been adopted as an off-shelf device from the domain of surface assessment. One advantage of the used technique is, not only the intensity data, but also the topographic information of the surface can be acquired. So a single scan results in two different grey-scale representations of the surface, one intensity image and one topographic image. The processing of topographic information provided by the CWL-sensor, in a different context, is part of Leich et al. [7] and [6].

Due to the fact that using the CWL technique for scanning large surface areas in high resolution is still very time consuming, Hildebrandt et al. [4] presented an approach of splitting the overall scan process into a low resolution coarse scan and a high resolution detail scan. Where the essential task within the coarse scan is to detect and locate latent fingerprints and create regions of interest (ROI) for the later detail scan. The resolution of a coarse scan has been defined between 400 and 100μm, i.e. 62.5 and 250 dpi. Currently numerous different algorithms are evaluated, whether they are feasible or not for detecting latent fingerprints in low resolution scans. Referring to these works we will show an approach of a spectral density feature for detecting and localizing latent fingerprints in intensity images.

This paper is organized as follows. After introduction of important terms and the discrimination of forensics from biometrics, the underlying process of our approach will be shown. Followed by the detailed description of the feature definition and the presentation of our very first experimental results. Conclusions and some proposals for future work can be found in the fith section.

2. BIOMETRIC VS. FORENSIC FINGERPRINT ANALYSIS

In close collaboration with forensic and dactyloscopic experts, the project Digi-Dak is researching potentials for advancing and supporting criminalistic forensic. Within the framework of the project, techniques and procedures are evaluated for partly automating the process of latent fingerprint detection, acquisition and identification, with the objective of supporting the forensic experts and lighten their work. In contrast to biometric identification systems which use exemplary fingerprints, which was widely investigated during the last years and established very successful, the automated acquiring of latent fingerprints in criminalistic forensic is a new area, that needs further scientific research.

Table 1: Influencing factors fingerprint analysis in controlled / uncontrolled environments

Biometrics (controlled environment)	**Forensics** (uncontrolled environment)
exemplary fingerprints	latent fingerprints
exactly one fingerprint	0-n fingerprints
complete fingerprints	partial fingerprints
no overlapping	overlapping fingerprints
singular causer	multiple causers
recent fingerprints	aged fingerprints
non smeared fingerprints	smeared fingerprints
well defined background	arbitrarily surfaces
user interaction	no user interaction
cooperative user	non-cooperative user
small amount of data	high resolution scans
...	...

Automated **biometric systems** have a huge advantage over automated forensic systems. The main reason is, biometric features are acquired under controlled and well known conditions, thus there is almost no influence caused by external factors. For example every time a fingerprint is acquired with the same sensor, the foreground and background conditions are identical, the pressure is more or less constant, the print is not smeared and does not overlap with other fingerprints. Last but not least the position of the fingerprint is well defined and the exact same sensor is used to acquire reference and exemplary fingerprints. Additionally the biometric system is able to interactively guide the user during enrollment and authentication stage and usually the user behaves in a cooperative way. If a scan is of bad quality the user is asked to rerun the enrollment, until a fingerprint of sufficient quality could be acquired. A biometric system supports the user with an optimal enrollment, therefore external influences and errors can be minimized. This scenario can be comprehended as high-grade controlled environment.

In a **forensic context** the the acquisition of latent fingerprints is done in an uncontrolled environment (crime scene), the external influences are not limited as they are in biometric systems. In fact all kind of external influences and disturbing factors may have a significant impact on the acquired data. The fingerprint might be left on arbitrary materials, these might be very "cooperative" non structured surfaces like stainless steel or plain colored furniture surfaces. But these also could be very challenging surfaces that are sucking, oily, rough, heavily structured, corrugated or high / low reflecting, just to name some examples. Table 1 is illustrating some of the possible external influences, forensics has to deal with in opposite to biometrics. Additional to surface characteristics the behavior of the fingerprint causer has a large influence on the acquired data. Biometric systems have the possibility to evaluate the quality of a fingerprint in enrollment, as well as in identification stage and can reject prints of low quality and prompt the user to rerun the scan. Forensic systems do not offer this possibility, the latent fingerprint has to be processed in the way it is found at the crime scene.

3. FINGERPRINT DETECTION

As described before, latent fingerprints can be left in very different conditions and on very unequal surfaces. Therefore it is necessary to develop and evaluate techniques, capable to detect fingerprints under that circumstances and extract the relevant features. While in biometric context it is possible to act on the assumption that a fingerprint is included within the picture and the image data acquired is of very small and normally fixed size, in forensic context there is no knowledge about that. Therefore it is required for further investigation, to decide if a scan contains a fingerprint or not, also referred to as fingerprint detection.

Using the CWL-sensor for scanning large surface areas is currently very time consuming. The effort in time exhibit quadratic growth depending on size and resolution of the area that should be scanned. Time consuming high resolution scans are not justified or feasible, as long as there is no assumption about an included fingerprint. Therefore a surface area has to be reviewed to decide whether there is need for a detailed scan or not. In [4] a possible solution for that problem is presented. It is suggested to split the overall scanning process into a fast and time-saving, low resolution coarse scan for detecting possible regions of interest (ROI). Within the next step a high resolution detailed scan can be executed on the identified regions to extract fingerprint features for identification.

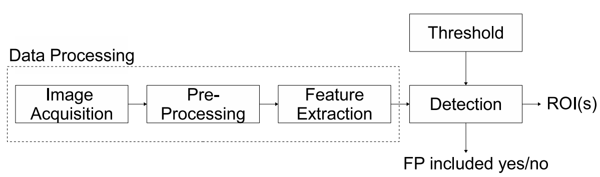

Figure 2: Data processing and detection in coarse scan

Splitting the scanning process into coarse and detail scan can minimize the efforts in time and resources. Therefore a reliable detector is required, which has the ability to detect interesting regions inside the coarse scan, also reffered to as region of interest. Figure 2 illustrates the underlying process of the coarse scan. From the previous explanation two core problems can be identified:

1. detection of fingerprints areas in coarse scan data
2. determination of 0...n regions of interest

The following consideration of the spectral texture features is aligned to detecting and localizing fingerprints in coarse scans. Therefore it will focus only on these parts of the previously presented process. Other factors of influence, like aging, multiple causers, quality of the fingerprints or overlapping are not yet considered within the following very first examination. Furthermore the spectral density feature is just one of the features, that are evaluated at the moment with the objective of building a robust classification system for detecting latent fingerprints.

3.1 Definition of Spectral Density Groups

The features are combinations of statistical values of grouped spectral density. The spectral density is retrieved from a discrete equidistant two-dimensional signal x (see Fig. 3 a). The signal has a size of N by N, where N is a power of two.

$$x_{m,n} \in \mathbb{R};\ m,n = 0 \ldots N-1;\ N \in \{2^p \mid p \in \mathbb{N}\}$$

The spectral density is retrieved by calculating the two-dimensional discrete Fourier transform (DFT) X of the signal (see [1, 2], Fig. 3 b). Because N is a power of two, the fast Fourier transformation (FFT) algorithm can be used (see [3]).

$$X_{k,l} = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} \omega_N^{2kmln} x_{m,n};\ \omega_N = e^{-\frac{2\pi i}{N}};\ k,l = 0 \ldots N-1$$

The groups are build by angle and length of the waves represented in the spectrum. In order to relate the values of the spectrum $X_{k,l}$ with their wave length and wave angle, the indexes k and l are transformed to center the Fourier spectrum (see Fig. 3 c).

$$k' = ((k + {}^1\!/_2 N) \bmod N) - {}^1\!/_2\,(N-1)\,;\ k' \in \mathbb{R}$$

$$l' = ((l + {}^1\!/_2 N) \bmod N) - {}^1\!/_2\,(N-1)\,;\ l' \in \mathbb{R}$$

A polar mapping leads to angle $\alpha_{k,l}$ and radius $r_{k,l}$.

$$\alpha_{k,l} = \tan^{-1} \frac{k'}{l'}$$

$$r_{k,l} = \sqrt{k'^2 + l'^2}$$

The wave length $\lambda_{k,l}$ is derived from the radius $r_{k,l}$. The physical size of the samples d is used to translate the wave length from the index space of the spectrum to spatial units.

$$d :\ \text{sample size of } x$$

$$\lambda_{k,l} = d\,({}^1\!/_2 N - r_{k,l})$$

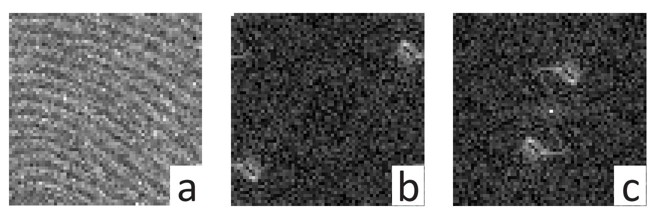

Figure 3: a) Fingerprint image x. b) Absolute Fourier spectrum X. c) Shifted spectrum.

The spectral density is calculated by the absolute value of the spectrum X and is grouped by wave length $\lambda_{k,l}$ (see Fig. 4 a) and by wave angle $\alpha_{k,l}$ (see Fig. 4 b). The ring R_w is the set of all spectral values with a wave length about 2^w, and the sector S_{w,a_A} is the sub set of spectral values in R_w with the wave angle $a = 0 \ldots A-1$ with $A \in \mathbb{N}$ as the number of angle groups in the interval $\alpha_{k,l} \in [0, \pi[$. The interval does not need to reach 2π because the Fourier spectrum of a real signal is rotational symmetric and therefore only one half of the spectrum is significant.

$$R_w = \left\{ |X_{k,l}| : \left\lfloor \frac{\log \lambda_{k,l}}{\log 2} \right\rfloor = w \right\};\ w \in \mathbb{N}$$

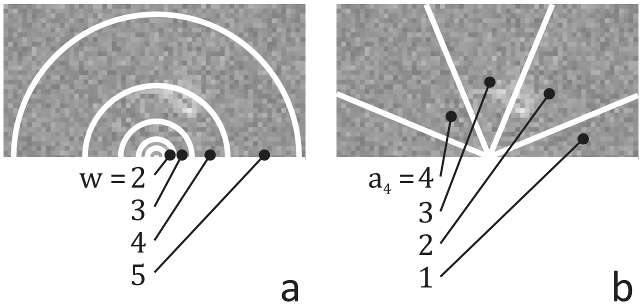

Figure 4: a) Spectral density grouping by wave length. b) Spectral density grouping by wave angle ($A = 4$).

$$S_{w,a_A} = \left\{ |X_{k,l}| : |X_{k,l}| \in R_w \wedge \left[A \frac{\alpha_{k,l}}{\pi} \right] = a \right\}$$

Figure 5 visualizes the ring R_w which contains all spectral density values, in the wave length group w and the sector S_{w,a_A} which contains all spectral density values in the wave length group w and the angle group a out of 4 angle groups.

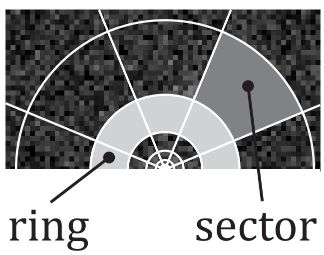

Figure 5: Ring R_w and sector S_{w,a_4}

3.2 Definition of Statistical Features

Based on the well-known concept of spectral density, we suggest two levels of statistical values on the spectral density groups:

1. Statistical values over a sector S_{w,a_A}, which is a group of spectral density values, gathered by angle and wave length
2. Statistical values over a ring R_w, which is a group of spectral density values, gathered by wave length only

Given min and max, we choose the following statistical functions for the features, where $B \subset \mathbb{R}$ is a set of real values:

$$\text{span}(B) = \max(B) - \min(B)$$

$$\text{mean}(B) = \frac{1}{|B|} \sum B$$

$$\text{std}(B) = \frac{1}{|B| - 1} \sum B';\ B' = \left\{ b^2 | b \in B \right\}$$

A statistical function $f \in \{\min, \max, \text{span}, \text{mean}, \text{std}\}$ has the signature $f : \mathbb{R}^\star \to \mathbb{R}$. The generic statistical function for the first level $g_{w,A,f}$ returns a set of statistical values build with f over all sectors $S_{w,a,_A}$ in the ring R_w for a given A.

$$g_{w,A,f} = \{ f(S_{w,a_A}) \,| a = 0 \ldots A - 1 \}$$

For the second level there are two generic statistical functions: $h_{w,f}$, based on a complete wave length group R_w and t_{w,A,f_1,f_2} based on the results of the generic first level function g_{w,A,f_1}.

$$h_{w,f} = f(R_w)$$

$$t_{w,A,f_1,f_2} = f_2(g_{w,A,f_1})$$

The angle group count A is a trade-of between angle sensitivity and wave length sensitivity for large wave lengths. Because on the one hand with a raising A more wave angles can be distincted. But on the other hand a sector S_{w,a_A} can only deliver meaningful statistical values if its cardinality is sufficient and the number of samples near the center of the discrete spectrum is falling with a raising A. Whereby the discrete spectrum is representing the spectral density in the wave band w. Useful values for A are found with 4, 6 and with a sufficient large signal size 8.

The wave band w describes the spatial frequency used by a statistical feature. For example a signal x with $d = 150\,\mu$m, a $w = 8$ selects all spectral density values $|X_{k,l}|$ representing wave lengths $2^w \mu\text{m} \le \lambda_{k,l} < 2^{w+1} \mu$m which is $256\,\mu\text{m} \le \lambda_{k,l} < 512\,\mu$m.

Because the orientation of potentially existing papillary line patterns in the signal is unknown, the functions used for the feature, must be independent of the wave angle. While only second level functions are independent of the wave angle, only those can be used to build a feature. The first level functions are used implicitly by the generic second level function t_{w,A,f_1,f_2}.

In this first approach using statistical features from the spectral density, we use the following hypothesis to detect the characteristics of papillary lines:
A ring with a wave band typical for papillary lines shows a significant directionality. The neighbor rings with a wave band lower and higher do not show significant directionality. The wave band of papillary lines depend on certain unknown parameters like distance from the fingerprint core, natural tendency of line strength or forces, compressing the skin while touching a surface, and is therefore varying in a relatively wide range.

The directionality of a ring can be expressed by the hypotenuse of the two functions $\text{ringStd}(w) = h_{w,\text{std}}$ and $\text{sectMeanStd}(w, A) = t_{w,A,\text{mean},\text{std}}$. Even though there are other options expressing the directionality, the hypotenuse of these two function is considered to be sufficient for expressing the directionality in this first approach.

$$\text{dir}(w, A) = \sqrt{\text{ringStd}(w)^2 + \text{sectMeanStd}(w, A)^2}$$

To express the relation between a ring with a wave band typical for papillary lines and its neighbors, the following dominance function is used.

$$\text{dom}(w, A) = \text{dir}(w, A) - 1/2\, (\text{dir}(w - 1, A) + \text{dir}(w + 1, A))$$

The variety of papillary line strengths is handled by building the maximum of the dominance over a number of typical wave bands.

$$\text{domMax}(w_1, w_2, A) = \max_{i=w_1}^{w_2} \text{dom}(i, A)$$

4. FIRST EXPERIMENTS

Papillary lines can have a line width from $150\,\mu$m up to $800\,\mu$m. This is regarding lateral transformation of the line pattern due to deformation of the finger skin while contacting the surface. To be sensitive for papillary lines, the wave bands $w = 7 \dots 9$ with the wave length intervals $]128, 256]\,\mu$m, $]256, 512]\,\mu$m and $]512, 1024]\,\mu$m are used in this first experiment. Further only $A = 4$ angle groups are tested. As a result of these restrictions, the feature domMax $(7, 9, 4)$ is selected for the first experiment.

In this first experiment a test set of 15 images from CWL scans of three different surfaces were made. Each prepared with 12 real fingerprints and 3 faked prints created by painting a spot with a text marker. The surfaces are:

- **CD jewel case** (CD) as a representative for transparent and glossy surfaces

- **White furniture** (WF) as a representative for slightly structured plastic surfaces

- **Wood imitation** (WI) as representative for structured and colored surfaces

The sample size of the scans is $d = 100\,\mu$m. To build an image, describing regions including potential finger prints, the intensity images are processed with a sliding window. The window size in pixels is 64 – the smallest power of two containing a physical length of 5 mm. The 5 mm are chosen to have enough spectral density values for long wave lengths in the center of the shifted spectrum for statistical features (see section 3.2).

$$\frac{5\,\text{mm}}{100\,\mu\text{m}} = 50,\ \left\lceil \frac{\log 50}{\log 2} \right\rceil = 6,\ 2^6 = 64$$

The content of the window is used as signal x. The step size for the sliding window is 16 px, this creates an overlap of 75%. The selected feature domMax $(7, 9, 4)$ is used as brightness for the result image. After using a global threshold and a combination of open and close filter for suppressing small regions, the ROIs with potential fingerprints can easily be determined. Figure 6 shows the result for an image of the test set with a real fingerprint on a CD jewel case and figure 7 the result for wood imitation. The result for an image with a faked print on wood imitation is shown in figure 8.

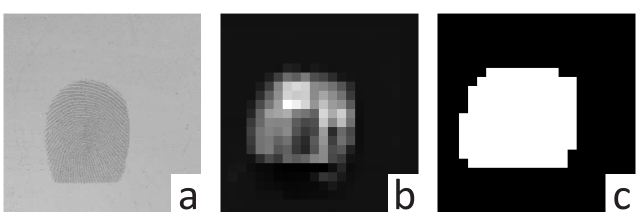

Figure 6: a) original image with fingerprint on CD jewel case, b) result of domMax(7,9,4), c) result after post processing

The performance is evaluated by counting the found regions in the result images. The results for all images in the test set is shown in table 2. For each material evaluated we used 12 scans with a real fingerprint included and additionally three scans including fingerprint-like fakes. For each scan the determined regions were counted and compared to manually annotated regions. The result is split up

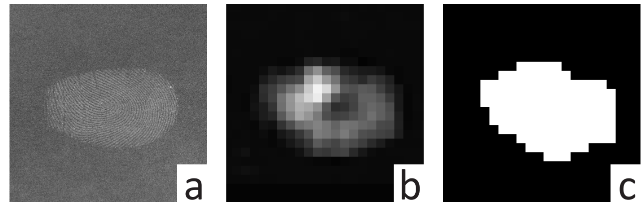

Figure 7: a) original image with fingerprint on wood imitation, b) result of domMax(7,9,4), c) result after post processing

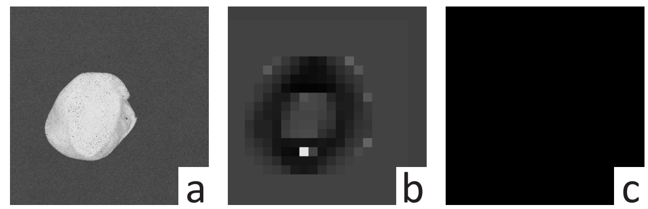

Figure 8: a) original image with faked print, b) result of domMax(7,9,4), c) result after post processing

in true positive and false positive matches, e.g. the results for CD jewel case show: out of 12 real fingerprints 11 were successfully detected (true positive) no region without a fingerprint was falsely detected (false positive). Regarding the fingerprint fakes all three fakes were falsely detected as real fingerprints (false positive). There is no possibility for true positives in scans that only contain faked fingerprints.

Table 2: Results of found ROIs

material	prints		true positive	false positive
CD	real	12	11	0
	fake	3	0	3
WF	real	12	12	1
	fake	3	0	3
WI	real	12	9	1
	fake	3	0	1

Limitations

The statistical features on the spectral density depend on the availability of sufficient values per group. To gain enough values for wave lengths up to 1mm, the block to be transformed with Fourier transformation can not be smaller then a certain minimal size. Consequently the resolution of the resulting image after applying a statistical feature with a sliding window is very limited. While the directionality of lines in a block, derived by a statistical feature with respect to the angle groups, works well in regions with straight lines, it does not work well with curved lines, typical for the core of a fingerprint. Further, the resolution of the original image needs to fulfill the Nyquist theorem for the thinnest papillary lines to avoid interference patterns in the image. If a surface scan contains texture patterns with significant spectral density in the typical wave bands of papillary lines, the statistical features are not expected to be capable of distinguishing between the texture and a fingerprint.

5. CONCLUSION AND FUTURE WORK

The main aim was to develop a feature for detecting latent fingerprints in image data acquired by using a CWL-sensor. Therefore fingerprints were applied to the surfaces and scanned with the CWL-sensor. The obtained intensity images were processed with a sliding window for blockwise calculation of the feature. By using a global threshold, the regions of interest were derived. For this first approach we focused on the three material surfaces introduced in the experiment section, but expect to expand the application of the feature to other and more challenging materials.

First experiments with the parametrization described in the experiment section have shown good results on planar surfaces. Even on slightly structured surfaces like furniture wood imitation (see Figure 6) the results are promising. In contrast to the surfaces that were processed so far, we are expecting challenges when using materials with surface characteristics containing dominant frequencies in the same wave band as papillary line patterns.

In future work we plan to build a sufficient database with test images of a series of different surfaces, including and not including fingerprints of different quality. To explore the potential of the statistical features on the spectral density, we will compare different combinations of the statistical values (level 1 and level 2). Further we plan to evaluate the sensitivity of the features. Therefore the results obtained by processing surface images with real latent fingerprints will be compared to results obtained by processing surface images with fingerprint alike smudges. Moreover the fusion of intensity images from the CWL-sensor with topography images may lead to better results on surfaces with difficult reflection characteristics.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] R. N. Bracewell. *The Fourier Transform and its Application*. Electrical and Elctronic Engineering. McGraw-Hill, New York, second edition edition, 1986.

[2] W. L. Briggs and V. E. Henson. *The DFT: An Owner's Manual for Discrete Fourier Transform*. Society for Industrial Mathematics, Philadelphia, 1987.

[3] E. O. Brigham. *Fast Fourier Transform and Its Applications*. Prentice Hall, New Jersey, 1988.

[4] M. Hildebrandt, J. Dittmann, M. Pocs, M. Ulrich, R. Merkel, and T. Fries. Privacy preserving challenges - new design aspects for latent fingerprint detection systems with contact-less sensors for future preventive applications in airport luggage handling. In *Springer Lecture notes in computer science Vol. 6583*, 2011.

[5] ISO/IEC. Information technology - biometrics tutorial. Technical Report ISO/IEC TR 24741:2007(E), ISO/IEC, 2007.

[6] M. Leich, S. Kiltz, J. Dittmann, and C. Vielhauer. Non-destructive forensic latent fingerprint acquisition with chromatic white light sensors. In *Proceedings of SPIE 7880*, 2011.

[7] M. Leich, S. Kiltz, C. Kraetzer, J. Dittmann, and C. Vielhauer. Preliminary study of statistical pattern recognition-based coin counterfeit detection by means of high resolution 3d scanners: Three-dimensional imaging, interaction, and measurement. In *Proceedings of SPIE Vol. 7864*, 2011.

[8] U. Steinert. Daktyloskopie (german). http://www.gletschertraum.de/Lehrmaterialien/KT/23_Skriptum_Daktyloskopie.pdf, 2008.

[9] U. Steinert. Grundlagen der kriminaltechnik (german). http://www.gletschertraum.de/Lehrmaterialien/KT/22_Skriptum_Grundlagen.pdf, 2008.