

# Review of the Fingerprint Liveness Detection (LivDet) Competition Series: 2009 to 2015

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## Abstract

A spoof attack, a subset of presentation attacks, is the use of an artificial replica of a biometric in an attempt to circumvent a biometric sensor. Liveness detection, or presentation attack detection, distinguishes between live and fake biometric traits and is based on the principle that additional information can be garnered above and beyond the data procured by a standard authentication system to determine if a biometric measure is authentic.

The goals for the Liveness Detection (LivDet) competitions are to compare software-based fingerprint liveness detection and artifact detection algorithms (Part 1), as well as fingerprint systems which incorporate liveness detection or artifact detection capabilities (Part 2), using a standardized testing protocol and large quantities of spoof and live tests. The competitions are open to all academic and industrial institutions which have a solution for either software-based or system-based fingerprint liveness detection. The LivDet competitions have been hosted in 2009, 2011, 2013 and 2015 and have shown themselves to provide a crucial look at the current state of the art in liveness detection schemes. There has been a noticeable increase in the number of participants in LivDet competitions as well as a noticeable decrease in error rates across competitions.

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Participants have grown from four to the most recent thirteen submissions for Fingerprint Part 1. Fingerprints Part 2 has held steady at two submissions each competition in 2011 and 2013 and only one for the 2015 edition. The continuous increase of competitors demonstrates a growing interest in the topic.

*Keywords:* Fingerprint, Liveness Detection, Biometric

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## 1. Introduction

Among biometrics, fingerprints are probably the best-known and widespread because of the fingerprint properties: universality, durability and individuality. Unfortunately it has been shown that fingerprint scanners are vulnerable to 5 presentation attacks<sup>1</sup> with an artificial replica of a fingerprint. Therefore, it is important to develop countermeasures to those attacks.

Numerous methods have been proposed to solve the susceptibility of fingerprint devices to attacks by spoof fingers. One primary countermeasure to spoofing attacks is called “liveness detection” or presentation attack detection. 10 Liveness detection is based on the principle that additional information can be garnered above and beyond the data procured and/or processed by a standard verification system, and this additional data can be used to verify if an image is authentic. Liveness detection uses either a hardware-based or software-based system coupled with the authentication program to provide additional security. 15 Hardware-based systems use additional sensors to gain measurements outside of the fingerprint image itself to detect liveness. Software-based systems use image processing algorithms to gather information directly from the collected fingerprint to detect liveness. These systems classify images as either live or fake.

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<sup>1</sup>Traditionally, a majority of papers refer to these types of attacks as “spoofing attacks” but recently the term “presentation attacks” has become the standard [6]. Similarly, presentation attack detection is the standard term for liveness detection. Presentation attack detection is a more general term and can refer to multiple approaches for detecting a presentation attacks beyond liveness detection.

20 Since 2009, in order to assess the main achievements of the state of the art  
in fingerprint liveness detection, University of Cagliari and Clarkson University  
organized the first Fingerprint Liveness Detection Competition.

25 The First International Fingerprint Liveness Detection Competition (LivDet)  
2009 [1], provided an initial assessment of software systems based on the finger-  
print image only. The second, third and fourth Liveness Detection Competitions  
(LivDet 2011 [2], 2013 [3] and 2015 [4]) were created in order to ascertain the  
progressing state of the art in liveness detection, and also included integrated  
system testing.

30 This paper reviews the previous LivDet competitions and how they have  
evolved over the years. Section 2 of this paper describes the background of  
spoofing and liveness detection. Section 3 details the methods used in testing  
for the LivDet competitions as well as descriptions of the datasets that have  
generated from the competition so far. Section 4 discusses the trends across the  
competitions reflecting advances in the state of the art. Section 5 concludes the  
35 paper and discusses the future of the LivDet competitions.

## 2. Background

40 The concept of spoofing has existed for some time now. Research into spoof-  
ing can be seen beginning in 1998 from research conducted by D. Willis and M.  
Lee where six different biometric fingerprint devices were tested against fake  
fingers and it was found that four of the six were susceptible to spoofing attacks  
[8]. This research was approached again in 2000-2002 by multiple institutions  
including; Putte and Kuening as well as Matsumoto et al. [9, 10]. Putte et al.  
examined different types of scanning devices as well as different ways of coun-  
terfeiting fingerprints [9]. The research presented by these researchers looked  
45 at the vulnerability of spoofing. In 2001, Kallo (et al.) looked at a hardware  
solution to Liveness Detection; while in 2002, Schuckers delved into using soft-  
ware approaches for Liveness Detection [11, 12]. Liveness detection, with either  
hardware-based or software-based systems, is used to check if a presented fin-



Figure 1: Negative impression of five fingers using consensual method.

gerprint originates from a live person or an artificial finger. Usually the result  
50 of this analysis is a score used to classify images as either live or fake.

Many solutions have been proposed to solve the vulnerability of spoofing [13, 14]. Bozhao Tan et al. has proposed a solution based on ridge signal and valley noise analysis [13]. This solution examines the perspiration patterns along the ridge and the patterns of noise in the valleys of images [13]. It was proposed  
55 that since live fingers sweat, but spoof fingers do not, the live fingerprint will look “patchy” compared to a spoof [13]. Also it was proposed that due to the properties of a spoof material, spoof fingers will have granules in the valleys that live fingers will not have [13]. Pietro Coli et al. examined static and dynamic features of collected images on a large data set of images [14].

60 There are two general forms of creating artificial fingers, the cooperative method and non-cooperative method. In the cooperative method the subject pushes their finger into a malleable material such as dental impression material, plastic, or wax creating a negative impression of the fingerprint as a mold, see Figure 1. The mold is then filled with a material, such as gelatin, PlayDoh or  
65 silicone. This cast can be used to represent a finger from a live subject, see Figure 2.

The non-cooperative method involves enhancing a latent fingerprint left on a surface, digitizing it through the use of a photograph, and finally printing the negative image on a transparency sheet. This printed image can then be made  
70 into a mold, for example, by etching the image onto a printed circuit board



Figure 2: Latex spoof on finger.

(PCB) which can be used to create the spoof cast as seen on Figure 3.

Most competitions focus on matching, such as the Fingerprint Verification Competition held in 2000, 2002, 2004 and 2006 [15] and the ICB Competition on Iris Recognition (ICIR2013) [16]. However, these competitions did not consider spoofing.

The Liveness Detection Competition series was started in 2009 and created a benchmark for measuring liveness detection algorithms, similar to matching performance. At that time, there had been no other public competitions held that has examined the concept of liveness detection as part of a biometric modality in deterring spoof attacks. In order to understand the motivation of organizing such a competition, we observed that the first trials to face with this topic were often carried out with home-made data sets that were not publicly available, experimental protocols were not unique, and the same reported results were obtained on very small data sets. We pointed out these issues in [7].

Therefore, the basic goal of LivDet has been since its birth to allow researchers testing their own algorithms and systems on publicly available data sets, obtained and collected with the most updated techniques to replicate fingerprints enabled by the experience of Clarkson and Cagliari laboratories, both active on this problem since 2000 and 2003, respectively. At the same time, using a “competition” instead of simply releasing data sets, could be assurance



Figure 3: Etched fingerprints on PCB.

of a free-of-charge, third-party testing using a sequestered test set. (Clarkson and Cagliari has never took part in LivDet as competitors, due to conflict of interest.)

95 LivDet 2009 provided results which demonstrated the state of the art at that time [1] for fingerprint systems. LivDet continued in 2011, 2013 and 2015 [2, 3, 4] and contained two parts: evaluation of software-based systems in Part 1: Algorithms, and evaluation of integrated systems in Part 2: Systems. Fingerprint will be the focus of this paper. However, LivDet 2013 also included a Part 1: Algorithms for the Iris biometric [5] and is continuing in 2015.

100 Since 2009, evaluation of spoof detection for facial systems was performed in the Competition on Counter Measures to 2-D Facial Spoofing Attacks, first held in 2011 and then held a second time in 2013. The purpose of this competition is to address different methods of detection for 2-D facial spoofing [17]. The competition dataset consisted of 400 video sequences, 200 of them real attempts and 200 attack attempts [17]. A subset was released for training and then another subset of the dataset was used for testing purposes.

During these years many works cited the publications related to the first

	2010	2011	2012	2013	2014	2015	Sum
<b>LivDet 2009</b>	4	6	9	2	23	21	65
<b>LivDet 2011</b>			3	7	21	10	41
<b>LivDet 2013</b>					16	10	26

Table 1: Number of LivDet citations on Google Scholar over the years.

three LivDet competitions, 2009 [1], 2011 [2] and 2013 [3]. A quick Google Scholar research produced 65 results for 2009, 41 for 2011 and 26 for 2013.  
 110 Their distribution is shown in more detail in Table 1, ordered by publication year<sup>2</sup>. In Tables 2, 3 and 4 a partial list of these publications is presented.

### 3. Methods and Datasets

The LivDet competitions feature two distinct parts; Part 1: Algorithms and Part 2: Systems with protocols designed to eliminate variability that may be  
 115 present across different algorithms or systems. The protocols for each part will be described in further detail in this section with descriptions of each dataset created through this competition.

#### 3.1. Part 1: Algorithm Datasets

The datasets for Part 1: Algorithms changes with each competition. Each  
 120 competition consists of three to four datasets of live and spoof images from different devices. Eighteen total datasets have been completed and made available thus far in the past four competitions. Fifteen fingerprint liveness datasets and three iris liveness datasets.

LivDet 2009 consisted of data from three optical sensors; Crossmatch, Iden-  
 125 tix, and Biometrika. The fingerprint images were collected using the consensual

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<sup>2</sup>Research was last updated on October 1, 2015

Authors	Algorithm Type	Performance (Average Classification Error)
J. Galbally, et al. [19]	Quality Related Features.	6.6%
E. Marasco, and C. Sansone [21]	Perspiration and Morphology-based Static Features	12.5%
J. Galbally, et al. [22]	Image Quality Assessment	8.2
E. Marasco, and C. Sansone [23]	Multiple Textural Features	12.5%
L. Ghiani, et al. [24]	Comparison of Algorithms	N.A.
D. Gragnaniello, et al. [25]	Wavelet-Markov Local	2.8%
R. Nogueira, et al. [27]	Convolutional Networks	3.9%
Y. Jiang, and L. Xin [28]	Co-occurrence Matrix	6.8%

Table 2: Publications that cite the LivDet 2009 paper.

Authors	Algorithm Type	Performance (Average Classification Error)
L. Ghiani, et al. [24]	Comparison of Algorithms	N.A.
X. Jia, et al. [29]	Multi-Scale Local Binary Pattern	7.5% and 8.9%
D. Gragnaniello, et al. [30]	Local Contrast Phase Descriptor	5.7%
N. Poh, et al. [31]	Likelihood Ratio Computation	N.A.
A. F. Sequeira, and J. S. Cardoso [32]	Modeling the Live Samples Distribution	N.A.
L. Ghiani, et al.	Binarized Statistical Image Features.	7.2%
X. Jia, et al. [36]	Multi-Scale Local Ternary Patterns	9.8%
G.L. Marcialis, et al. [36]	Comparison of Algorithms	N.A.
R. Nogueira, et al. [27]	Convolutional Networks	6.5%
Y. Zhang, et al. [38]	Wavelet Analysis and Local Binary Pattern	12.5%
A. Rattani, et al. [39]	Textural Algorithms	N.A.
P. Johnson, and S. Schuckers [40]	Pore Characteristics	12.0%
X. Jia, et al. [41]	One-Class SVM	N.A.
Y. Jiang, and L. Xin [28]	Co-occurrence Matrix	11.0%

Table 3: Publications that cite the LivDet 2011 paper.

Authors	Algorithm Type	Performance (Average Classification Error)
C. Gottschlich, et al. [42]	Histograms of Invariant Gradients.	6.7%
R. Nogueira, et al. [27]	Convolutional Networks	3.6%
Y. Zhang, et al. [38]	Wavelet Analysis and Local Binary Pattern	2.1%
P. Johnson, and S. Schuckers [40]	Pore Characteristics	N.A.%

Table 4: Publications that cite the LivDet 2013 paper.

approach from three different spoof material types; gelatin, silicone, and play-doh. and numbers of images available can be found in [1]. Figure 4 shows example images from the datasets.

The dataset for LivDet 2011 consisted of images from four different optical devices, Biometrika, Digital Persona, ItalData and Sagem. The spoof materials were gelatin, latex, ecoflex, Play-doh, silicone and wood glue. More information can be found in [2]. Figure 5 shows images used in the database.

The dataset for LivDet 2013 consisted of images from four different devices; Biometrika, Crossmatch, ItalData and Swipe. Spoofs were made from gelatin, body double, latex, play-doh, ecoflex, modasil, and wood glue. LivDet 2013 featured the first use of the non-cooperative method for creating spoof images and was used for Biometrika and ItalData. More information can be found in [3]. Figure 6 gives example images from the databases.

The dataset for LivDet 2015 consists of images from four different optical devices; Green Bit, Biometrika, Digital Persona and Crossmatch. The spoof

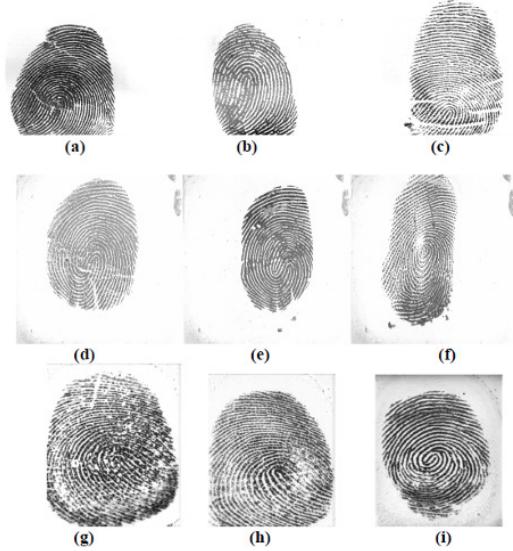


Figure 4: Examples of spoof images of the LivDet 2009 datasets. Crossmatch (top): (a) Play-Doh, (b) gelatin, (c) silicone; Identix (middle): (d) Play-Doh, (e) gelatin, (f) silicone; Biometrika (top): (g) Play-Doh, (h) gelatin, (i) silicone.

materials were Ecoflex, gelatin, latex, wood glue, a liquid Ecoflex and RTV (a two-component silicone rubber) for the Green Bit, the Biometrika and the Digital Persona datasets, and Playdoh, Body Double, Ecoflex, OOMOO (a silicone rubber) and a novel form of gelatin for Crossmatch dataset. More information can be found in [4].

145 *3.2. Part 2: Systems Submissions*  
 Public datasets were not released from systems collections, however data was collected on the submitted systems. Unlike in Part 1: Algorithms where data was pre-generated before the competition, Part 2: Systems data was collected 150 through systematic testing of submitted system. For LivDet 2011 this consisted of 500 live attempts from 50 people (totaling 5 images for each of the R1 and R2 fingers) as well as 750 attempts with spoofs of five materials (play-doh, gelatin, silicone, body double, and latex). For LivDet 2013, 1000 live attempts were conducted as well as 1000 spoof attempts from the materials; Play-Doh,

155 gelatin, Ecoflex, Modasil, and latex. In 2015 the system was tested using the  
156 three known spoof recipes. Two unknown spoof recipes were also tested to  
157 examine the flexibility of the sensor toward novel spoof methods. The known  
158 recipes were Playdoh, Body Double, and Ecoflex. The two unknown recipes used  
159 were OOMOO (a silicone rubber) and a novel form of gelatin. 2011 attempts  
160 were completed with 1010 live attempts from 51 subjects (2 images each of all  
161 10 fingers) and 1001 spoof attempts across the five different materials giving  
162 approximately 200 images per spoof type. 500 spoofs were created from each of  
163 5 fingers of 20 subjects for each of the five spoof materials. Two attempts were  
164 performed with each spoof.

165 The submitted system needs to be able to output a file with the collected  
166 image as well as a liveness score on the range of 0 to 100 with 100 being the  
167 maximum degree of liveness and 50 being the threshold value to determine if  
168 an image is live or spoof. If the system is not able to process a live subject  
169 it is counted as a failure to enroll and counted against the performance of the  
170 system (as part of Ferrlive). However, if the system is unable to process a spoof  
171 finger it is considered as a fake non-response and counted as a positive in terms  
172 of system effectiveness for spoof detection.

### 3.3. Image Quality

173 Fingerprint image quality has a powerful effect on the performance of a  
174 matcher. Many commercial fingerprint systems contain algorithms to ensure  
175 that only higher quality images are accepted to the matcher. This rejects low  
176 quality images where low quality images have been shown to degrade the per-  
177 formance of a matcher [18]. The algorithms and systems submitted for this  
178 competition did not use a quality check to determine what images would pro-  
179 ceed to the liveness detection protocols. Through taking into account the quality  
180 of the images before applying liveness detection a more realistic level of error  
181 can be shown.

Our methodology uses the NIST Fingerprint Image Quality (NFIQ) software  
to examine the quality of all fingerprints used for the competition and examine

<sup>185</sup> the effects of removing lower quality fingerprint images on the liveness detection  
protocols submitted. NFIQ computes a feature vector from a quality image map  
and minutiae quality statistics as an input to a multi-layer perceptron neural  
network classifier [18]. The quality of the fingerprint is determined from the  
neural network output. The quality for each image is assigned on a scale from  
<sup>190</sup> 1 (highest quality) to 5 (lowest quality).

### 3.4. Performance Evaluation

The parameters adopted for the performance evaluation are the following:

- *Ferrlive*: Rate of misclassified live fingerprints.
- *Ferrfake*: Rate of misclassified fake fingerprints.
- *Average Classification Error (ACE)*:  $ACE = (\frac{Ferrlive+Ferrfake}{2})$
- *Equal Error Rate (EER)*: Rate at which Ferrlive and Ferrfake are equal.
- *Accuracy*: Rate of correctly classified live and fake fingerprints at a 0.5 threshold.

### 3.5. Specific challenges

<sup>200</sup> In the last two editions of the competition specific challenges were introduced.  
Two of the 2013 datasets, unlike all the other cases, contain spoofs that  
were collected using latent fingerprints. The 2015 edition had two new com-  
ponents: (1) the testing set included images from two kinds of spoof materials  
which were not present in the training set in order to test the robustness of the  
<sup>205</sup> algorithms with regard to unknown attacks, and (2) one of the data sets was  
collected using a 1000 dpi sensor.

#### 3.5.1. *LivDet 2013 Consensual vs. Semi-Consensual*

In the consensual method the subject pushed his finger into a malleable  
material such as silicon gum creating a negative impression of the fingerprint  
<sup>210</sup> as a mold. The mold was then filled with a material, such as Gelatin. The

“semi-consensual method” consisted of enhancing a latent fingermark pressed on a surface, and digitizing it through the use of a common scanner.<sup>3</sup> Then, through a binarization process and with an appropriate threshold choice, the binarized image of the fingerprint was obtained. The thinning stage allowed the line thickness to be reduced to one pixel obtaining the skeleton of the fingerprint negative. This image was printed on a transparency sheet, in order to have the mold. A gelatin or silicone material was dripped over this image, and, after solidification, separated and used as a fake fingerprint.

The consensual method leads to an almost perfect copy of a live finger, whose mark on a surface is difficult to recognize as a fake unless through an expert dactiloscopist. On the other hand, the spoof created by semi- or unconsensual method is much less similar. In a latent fingerprint, many details are lost and the skeletonization process further deteriorates the spoof quality making it easier to distinguish a live from a fake. However, while it could be hard to convince someone to leave the cast of a finger, it’s potentially much easier to obtain one of his latent fingerprints. The spoof images in the Biometrika and Italdata 2013 datasets were created by printing the negative image on a transparency sheet. As we will see in the next section, the error rates, as would be expected, are lower than those of the other datasets.

### 3.5.2. *LivDet 2015 Hidden Materials and 500 vs 1000 dpi*

As already stated, the testing sets of LivDet 2015 included spoof images of never-seen-before materials. These materials were liquid Ecoflex and RTV for Green Bit, Biometrika and Digital Persona datasets, and OOMOO and Gelatin for Crossmatch dataset. Our aim was to assess the reliability of algorithms. As a matter of fact, in a realistic scenario, the material used to attack a biometric system could be considered unknown as a liveness detector should be able to deal with any kind of spoof material.

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<sup>3</sup>Obviously all subjects were fully aware of this process, and gave the full consent to replicate their fingerprints from their latent marks.

Another peculiarity of the 2015 edition was the presence of the Biometrika HiScan-PRO, a sensor with a resolution of 1000 dpi instead of  $\sim$ 500 dpi resolution for most of the datasets used so far in the competition. It is reasonable to hypothesize that doubling the image resolution, the feature extraction phase should benefit as well as the final performance. The results that we will show in the next section does not confirm this hypothesis.  
240

#### 4. Examination of Results

245 In this Section, we analyze the experimental results for the four LivDet editions. Results show the growth and improvement across the four competitions.

##### 4.1. Trends of Competitors and Results for Fingerprint Part 1: Algorithms

The number of competitors for Fingerprint Part 1: Algorithms have increased during the last years. LivDet 2009 contained a total of 4 algorithm  
250 submissions. LivDet 2011 saw a slight decrease in competitors with only 3 organizations submitting algorithms, however LivDet 2013 and 2015 gave rise to the largest of the competitions with 11 submitted algorithms, nine participants in the former and ten in the latest. Submissions for each LivDet are detailed in Table 5.

255 This increase of participants has shown the grown of interest in the topic, which has been coupled with the general decrease of the error rates.

First of all, the two best algorithms for each competition, in terms of performance, are detailed in Table 6 based on the average error rate across the datasets where “Minimum Average” error rates are the best results and “Second Average” are the second best results.  
260

There is a stark difference between the results seen from LivDet 2009 to LivDet 2015. LivDet 2009 to LivDet 2011 did not see much decrease in error, where LivDet 2013 and LivDet 2015 each decreased in error from the previous competition.

Participants LivDet 2009	Algorithm Name
Dermalog Identification Systems GmbH	Dermalog
Universidad Autonoma de Madrid	ATVS
Anonymous	Anonymous
Anonymous2	Anonymous2
Participants LivDet 2011	Algorithm Name
Dermalog Identification Systems GmbH	Dermalog
University of Naples Federico II	Federico
Chinese Academy of Sciences	CASIA
Participants LivDet 2013	Algorithm Name
Dermalog Identification Systems GmbH	Dermalog
Universidad Autonoma de Madrid	ATVS
HangZhou JLW Technology Co Ltd	HZ-JLW
Federal University of Pernambuco	Itaute
Chinese Academy of Sciences	CAoS
University of Naples Federico II (algorithm 1)	UniNap1
University of Naples Federico II (algorithm 2)	UniNap2
University of Naples Federico II (algorithm 3)	UniNap3
First Anonymous participant	Anonym1
Second Anonymous participant	Anonym2
Third Anonymous participant	Anonym3
Participants LivDet 2015	Algorithm Name
Instituto de Biociencias, Letras e Ciencias Exatas	COPILHA
Institute for Infocomm Research (I2R)	CSI
Institute for Infocomm Research (I2R)	CSI_MM
Dermalog	hbirkholz
Universidade Federal de Pernambuco	hectorn
Anonymous participant	anonym
Hangzhou Jinglianwen Technology Co., Ltd	jinglian
Universidade Federal Rural de Pernambuco	UFPE I
Universidade Federal Rural de Pernambuco	UFPE II
University of Naples Federico II	unina
New York University	nogueira
Zhejiang University of Technology	titanz

Table 5: Participants for Part 1: Algorithms.

2009			
Minimum Avg Ferrlive	Minimum Avg Ferrfake	Second Avg Ferrlive	Second Avg Ferrfake
13.2%	5.4%	20.1%	9.0%
2011			
Minimum Avg Ferrlive	Minimum Avg Ferrfake	Second Avg Ferrlive	Second Avg Ferrfake
11.8%	24.8%	24.5%	24.8%
2013			
Minimum Avg Ferrlive	Minimum Avg Ferrfake	Second Avg Ferrlive	Second Avg Ferrfake
11.96%	1.07%	17.64%	1.10%
2015			
Minimum Avg Ferrlive	Minimum Avg Ferrfake	Second Avg Ferrlive	Second Avg Ferrfake
5.13%	2.79%	6.45%	4.26%

Table 6: Two best error rates for each competition. It can be noticed a positive trend in terms of both Ferrlive and Ferrfake parameters. In particular 2011 and 2015 exhibited very difficult tasks due to the high quality of fingerprint images thus they should be taken into account as a reference of current liveness detector performance against the “worst scenario”, that is, the high quality reproduction of a subject’s fingerprint.

<sup>265</sup> The mean values of the ACE (Average Classification Error) over all the participants calculated for each dataset confirm this trend. Mean and standard deviation are shown in Table 7.

<sup>270</sup> The standard deviation values ranges between 5 and 18% depending on the dataset and competition editions. Mean ACE values confirm the error increase in 2011 due to the high quality of cast and fake materials. The low values in 2013 for the Biometrika and Italdata are due, as stated before, to the use of latent fingerprints in the spoof creation process, creating lower quality spoofs that are easier to detect. In order to confirm that, we compared these values with those obtained for the same sensors in 2011 (see Table 8). Last two rows of <sup>275</sup> Table 8 report average classification error and related standard deviation over above sets. Obviously, further and independent experiments are needed because participants of 2011 and 2013 were different so that different algorithms are likely also. However, results highlight the performance virtually achievable over two scenarios: a sort of “worst case”, namely, the one represented by LivDet <sup>280</sup> 2011, where quality of spoofs is very high, and a sort of “realistic case” (LivDet 2013), where spoofs are created from latent marks as one may expect. The fact that even in this case the average error is 10%, whilst the standard deviation does not differ with regard to LivDet 2011, should not be underestimated. The improvement could be likely due to the different ways of creating the fakes.

2009		
	Mean	Std. Dev.
Identix	8.27	4.65
Crossmaatch	15.59	5.60
Biometrika	32.59	9.64
2011		
	Mean	Std. Dev.
Biometrika	31.30	10.25
ItalData	29.50	9.42
Sagem	16.70	5.33
Digital Persona	23.47	13.70
2013		
	Mean	Std. Dev.
Biometrika	7.32	8.80
Italdata	12.25	18.08
Swipe	16.67	15.30
2015		
	Mean	Std. Dev.
GreenBit	11.47	7.10
Biometrika	15.81	7.12
DigitalPersona	14.89	13.72
Crossmatch	14.65	10.28

Table 7: Mean and standard deviation ACE values for each dataset of the competition.

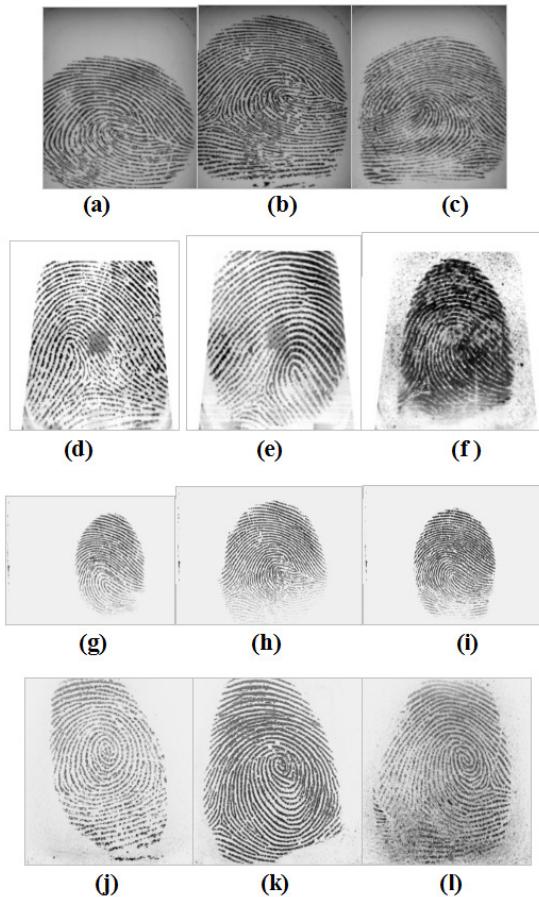


Figure 5: Examples of fake fingerprint images of the LivDet 2011 datasets, from Biometrika  
(a) latex, (b) gelatin, (c) silicone; from Digital Persona: (d) latex, (e) gelatin, (f) silicone;  
from Italdatal: (g) latex (h) gelatin (i) silicone; from Sagem: (j) latex (k) gelatin (l) silicone.

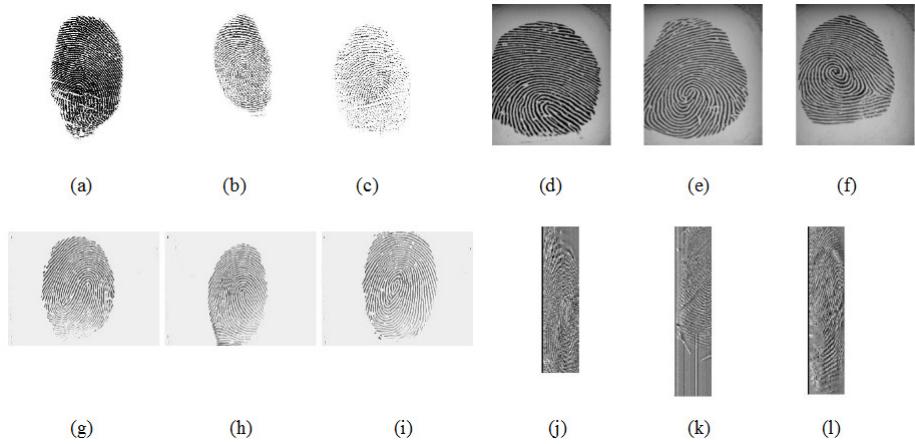


Figure 6: Examples of fake fingerprint images of the LivDet 2013. From Crossmatch (a) body double, (b) latex, (c) wood glue, from Biometrika (d) gelatine, (e) latex, (f) wood glue, from Italdatal (g) gelatine, (h) latex, (i) wood glue, from Swipe (j) body double, (k) latex, (l) wood glue.

	<b>Consensual (LivDet 2011)</b>	<b>Semi-consensual (LivDet 2013)</b>
Biometrika	31.30	7.32
ItalData	29.50	12.25
Mean	30.40	9.78
Standard Deviation	1.27	3.49

Table 8: Comparison between mean ACE values for Biometrika and Italdatal datasets from LivDet 2011 and 2013.

285 The abnormally high values for the LivDet 2013 Crossmatch dataset occurred due to an occurrence in the Live data. The Live images were difficult for the algorithms to recognize. All data was collected in the same time frame and data in training and testing sets were determined randomly among the data collected. A follow-up test was conducted using benchmark algorithms at University of Cagliari and Clarkson University which revealed similar scores on the  
 290 benchmark algorithms as the submitted algorithms with initial results had an EER of 41.28%. The data was further tested with 1000 iterations of train/test dataset generation using a random selection of images for the live training and test sets (with no common subjects between the sets which is a requirement for  
 295 all LivDet competitions). This provided new error rates shown (see Table 9 and Figures 7 and 8)

	Average Error Rate	Standard Deviation
FerrLive	7.57%	2.21%
FerrFake	13.41%	1.95%
Equal Error Rate	9.92%	1.42%

Table 9: Crossmatch 2013 Error Rates across 1000 Tests

Examining these results allows us to draw the conclusion that the original  
 300 selection of subjects was an anomaly that caused improper error rates because each other iteration, even only changing a single subject, dropped FerrLive error rates to 15% and below. Data is being more closely examined in future LivDet competitions in order to counteract this problem with data being processed on a benchmark algorithm before being given to participants. The solution to this for the LivDet 2013 data going forward is to rearrange the training and test sets for future studies using this data. Researchers will need to be clear which split  
 305 of training/test they used in their study. For this reason we removed from the experimental results of those obtained with the Crossmatch 2013 dataset.

LivDet 2015 error rates confirm a decreasing trend with respect to attacks

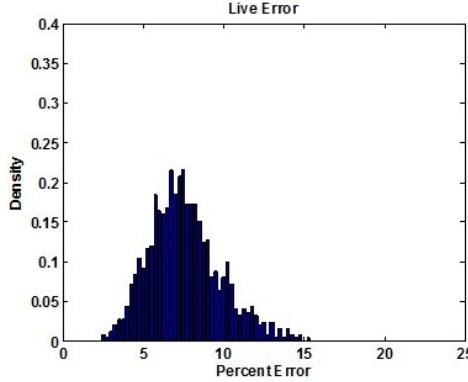


Figure 7: FerrLive Rates across 1000 tests for Crossmatch 2013.

made up of high quality spoofs, with all the mean values between 11% and 16%. These results are summarized in Figure 9.

310      Reported error rates suggest a slow, but steady advancement in the art of liveness and artifact detection. This gives supporting evidence that the technology is evolving and learning to adapt and overcome the presented challenges.

315      Comparing the performance of the LivDet 2015 datasets (as shown in Table 7 and in more details in [4]) two other important remarks can be made: the higher resolution for Biometrika sensor did not necessarily achieve the best classification performance, while the small size of the images for the Digital Persona device generally degrades the accuracy of all algorithms.

320      The DET (Detection Error Tradeoff) curves in Figures 10 (a), 11 (a), 12 (a), 13 (a), show the performance of three of the four best algorithms for LivDet 2015 sorted by ACE (nogueira, unina and anonym). Unfortunately, we could not plot the jinglian's algorithm performance because it output only two possible values, namely 0 or 100. There being no intermediate values it was impossible to obtain different Ferrlive and Ferrfake values varying the threshold value and produce the DET curve. More discussion on fusion results for Figures 10 (b), 11 (b), 12 (b), 13 (b) will be provided in further below.

325      Another important indicator of an algorithm validity is the Ferrfake value

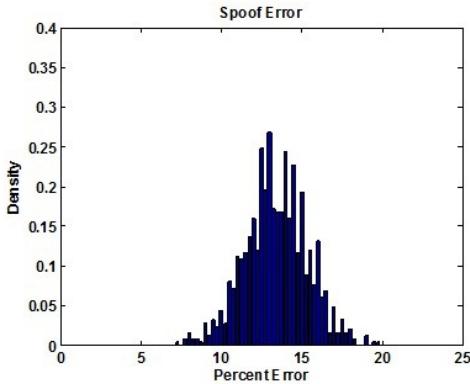


Figure 8: FerrFake Rates across 1000 tests for Crossmatch 2013.

calculated when  $Ferrlive = 1\%$ . This value represent the percentage of spoofs able to hack into the system when the rate of legitimate users that are rejected is no more than 1%. As a matter of fact, by varying the threshold value,  
 330 different Ferrfake and Ferrlive values are obtained and, as the threshold grows from 0 to 100, Ferrfake decrease and Ferrlive increase. Obviously ferrlive value must be kept low to minimize the inconvenience to authorized users but, just as important, the low ferrfake value limits the number of unauthorized users able to enter into the system.

335 Results in Tables 10, 11, 12 and 13 show that even the best performing algorithm (nogueira) is not yet good enough since when  $Ferrlive = 1\%$ , the ferrfake values (testing on all materials) ranges from 2.66% to 19.10%. These are the percentage of unauthorized users that the system is unable to correctly classify. If we consider only the unknown materials, the results are even worse,  
 340 ranging from 3.69% to 25.30%.

345 On the basis of such results, we can say that there is no specific algorithm, among the analyzed ones, able to generalize against never-seen-before spoofing attacks. We observed a performance drop and also found that the amount of the drop is unpredictable as it depends on the material. This should be matter of future discussions.

	<b>all materials</b>	<b>known materials</b>	<b>unknown materials</b>
unina	7.42	2.47	14.49
nogueira	2.66	1.94	3.69
anonym	18.61	10.75	29.82
average	9.56	5.05	16.00
std. dev.	8.19	4.94	13.13

Table 10: Ferrfake values of the best algorithms calculated when  $Ferrlive = 1\%$  for the Crossmatch dataset.

	<b>all materials</b>	<b>known materials</b>	<b>unknown materials</b>
unina	51.30	50.85	52.20
nogueira	19.10	16.00	25.30
anonym	80.83	79.25	84.00
average	50.41	48.70	53.83
std. dev.	30.87	31.68	29.38

Table 11: Ferrfake values of the best algorithms calculated when  $Ferrlive = 1\%$  for the Digital Persona dataset.

	<b>all materials</b>	<b>known materials</b>	<b>unknown materials</b>
unina	41.80	36.10	53.20
nogueira	17.90	15.15	23.40
anonym	75.47	75.25	75.90
average	45.06	42.17	50.83
std. dev.	28.92	30.51	26.33

Table 12: Ferrfake values of the best algorithms calculated when  $Ferrlive = 1\%$  for the Green Bit dataset.

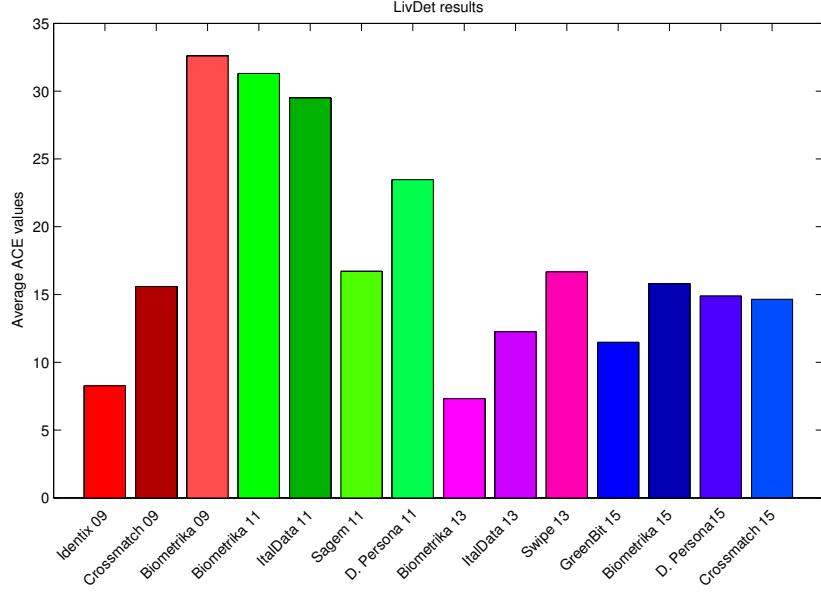


Figure 9: LivDet results over the years: near red colors for 2009, near green for 2011, near magenta for 2013 and near blue for 2015.

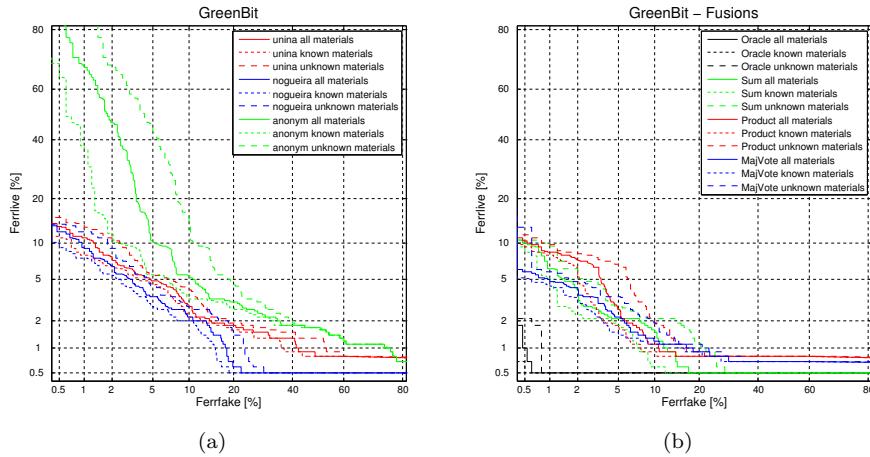


Figure 10: LivDet 2015 Greenbit dataset: DET curves of the nogueira, unina and anonym algorithms (a), DET curves of the fusion of the three classifiers (b).

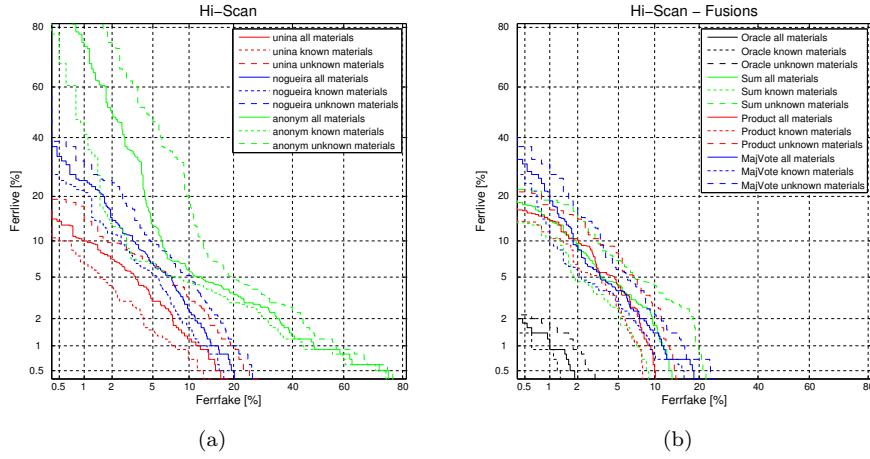


Figure 11: LivDet 2015 Biometrika dataset: DET curves of the nogueira, unina and anonym algorithms (a), DET curves of the fusion of the three classifiers (b).

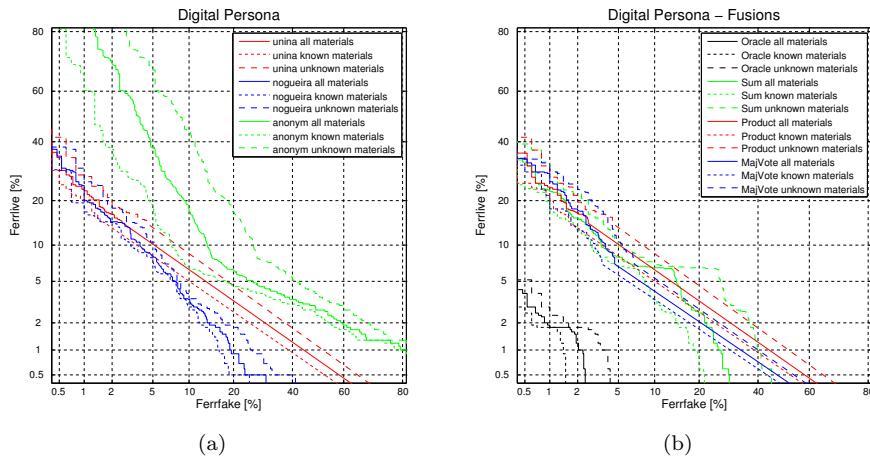


Figure 12: LivDet 2015 Digital Persona dataset: DET curves of the nogueira, unina and anonym algorithms (a), DET curves of the fusion of the three classifiers (b).

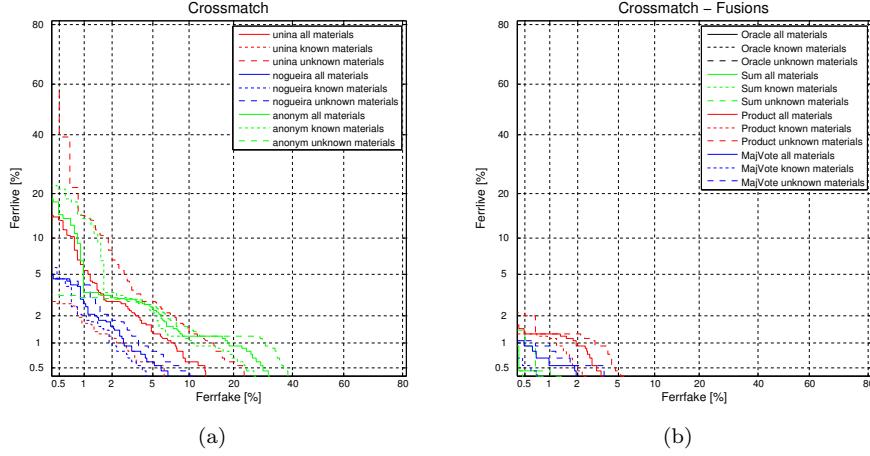


Figure 13: LivDet 2015 Crossmatch dataset: DET curves of the nogueira, unina and anonym algorithms (a), DET curves of the fusion of the three classifiers (b).

	all materials	known materials	unknown materials
unina	11.60	7.50	19.80
nogueira	15.20	12.60	20.40
anonym	48.40	44.05	57.10
average	25.07	21.38	32.43
std. dev.	20.29	19.79	21.36

Table 13: Ferrfake values of the best algorithms calculated when  $Ferrlive = 1\%$  for the Biometrika dataset.

On the other hand, the performance difference among algorithms may be complementary, that is, one algorithm may be able to detect spoofs that another one does not. Accordingly, Figures 14, 15, 16 and 17 show, for each dataset, the 2D and 3D spread plots generated using again three out of the four better algorithms. In the 3D plots each point coordinate corresponds to the three match scores obtained by the three algorithms for each image. In the 2D plots the same results are presented using two algorithms at a time for a total of three 2D plots for each 3D plot. These plots give an idea of the correlation level of the spoof detection ability of the selected algorithms. As a matter of fact, it appears that in many doubtful cases, the uncertainty of a classifier does not correspond to that of the others. For cases which have a high correlation, the points in the graph would be more or less along a diagonal line. However on this plot, the values are well distributed and this indicate a lower correlation between the algorithms and thus may be complementary.

Since there is evidence that the submitted algorithms may be complementary, we performed three fusion techniques at the score level using again three out of the four better algorithms. We used the sum of the *a posteriori* probabilities generated by the three algorithms, the product of the same *a posteriori* probabilities and the majority vote (each fingerprint image is classified as live or fake if the majority of individual algorithms rank it as live or fake). These three fusion techniques have very different characteristics from each other: the product tends to crush on a negative classification (i.e. the pattern rejection) rather than positive (for the zero-product property); the sum instead has an opposite characteristic namely it smooths the differences (such as a low-pass filter); finally, the majority emphasize where classifiers agree. In order to show the pros and cons of these classifiers fusion we also plot the curve of the so called “Oracle response”. The Oracle is an ideal fusion technique that correctly classifies a pattern if that pattern is correctly classified by at least one of the single classifiers. It indicates the maximum accuracy that can be potentially achieved. Obviously, the more the results of the various classifiers are complementary the better are the results of the oracle.

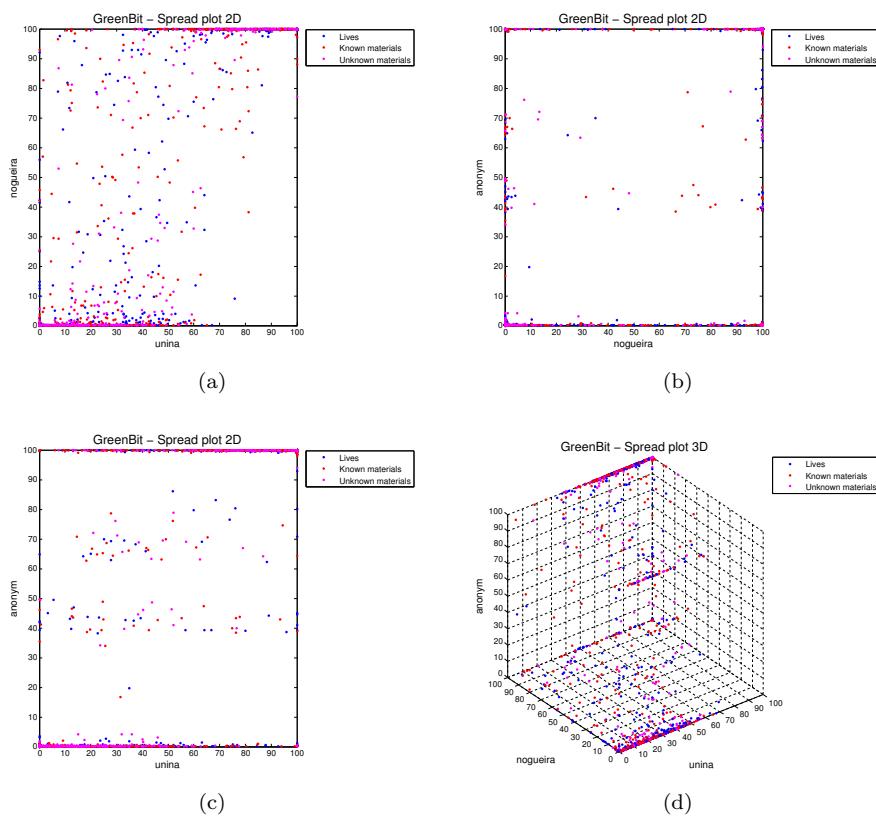


Figure 14: 2D and 3D spread plots for the Greenbit dataset: (a) unina - nogueira, (b) nogueira - anonym, (c) unina - anonym, (d) nogueira - unina - anonym.

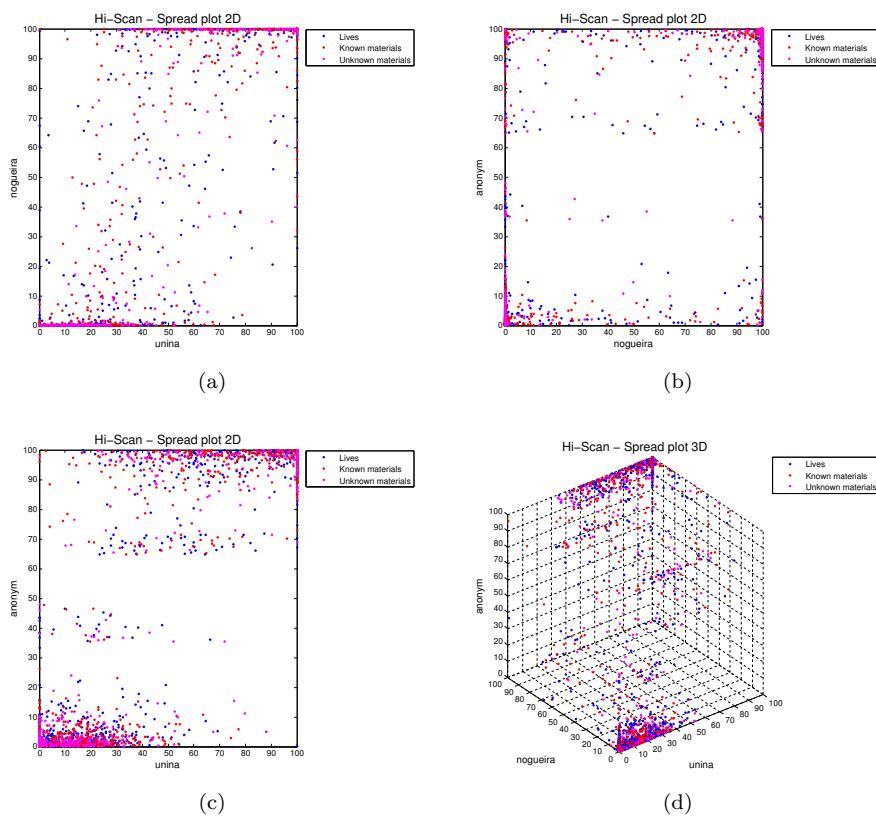


Figure 15: 2D and 3D spread plots for the Biometrika dataset: (a) unina - nogueira, (b) nogueira - anonym, (c) unina - anonym, (d) nogueira - unina - anonym.

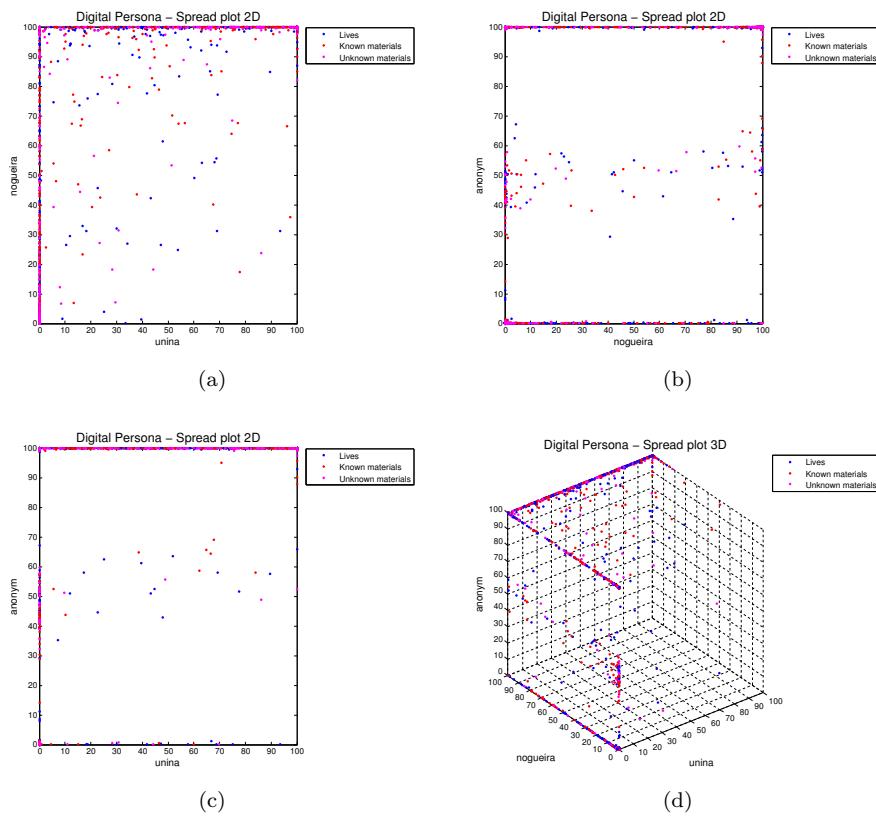


Figure 16: 2D and 3D spread plots for the Digital Persona dataset: (a) unina - nogueira, (b) nogueira - anonym, (c) unina - anonym, (d) nogueira - unina - anonym.

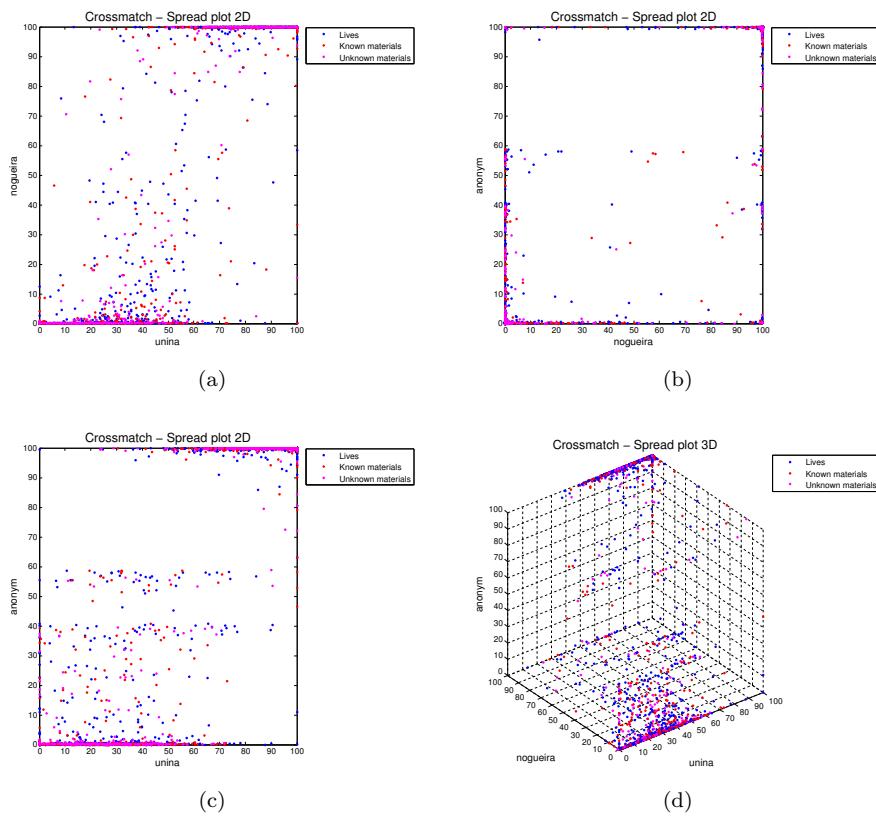


Figure 17: 2D and 3D spread plots for the Crossmatch dataset: (a) unina - nogueira, (b) nogueira - anonym, (c) unina - anonym, (d) nogueira - unina - anonym.

The DET curves in Figures 10 (b), 11 (b), 12 (b), 13 (b), compared with that of the single classifiers, clearly show a result improvement especially when using the sum rule. As a matter of fact, as stated before, sum smooths the differences.  
380 If score values are balanced (that is  $x$  for accept and  $1-x$  for reject) the sum rule emphasizes where classifiers agree as for the majority vote. Moreover, since it averages the results, little doubts of two (wrong) classifiers may be counterbalanced by a strong performance in the (correct) third, leading to better results.  
385 The only case in which the performance declines is that of the Digital Persona dataset. Although the fusion at score-level appear a good solution to improve the performance, current results suggest that individual algorithms must be carefully selected and also appropriate combination methodologies should be studied as well.

#### *4.2. Trends of Competitors and Results for Fingerprint Part 2: Systems*

390 Fingerprint Part 2: Systems has not yet shown growth in the number of competitors, but it has only existed for 3 competitions thus far. There are more limitations to the systems testing portion. It is not surprising that there are not great numbers of entrants given the need for a full fingerprint recognition device to be built with an integrated liveness detection module. There has also  
395 been a general lack of interest in companies shipping full systems for testing and it appears that there is more comfort in submitting an algorithm. Both Livdet 2011 and LivDet 2013 had 2 submissions whilst LivDet 2015 had only one. Information about competitors is shown in Table 14.

400 This portion of the LivDet competitions has distinct recognition for the rapid decrease in error rates. In the span of 2 years, the best results from LivDet 2011 were worse than the worst results of LivDet 2013. Thus, systems tests showed a quicker decrease in error rates as well as the one systems submission in 2013 had lower error rates than any submitted algorithms in LivDet.

405 In 2011, Dermalog performed at a FerrLive of 42.5% and a FerrFake of 0.8%. GreenBit performed at a FerrLive of 38.8% and a FerrFake of 39.47%. Both systems had high FerrLive scores.

Participants LivDet 2011	Algorithm Name
Dermalog Identification Systems GmbH	Dermalog
GreenBit	GreenBit
Participants LivDet 2013	Algorithm Name
Dermalog Identification Systems GmbH	Dermalog
Anonymous	Anonymous1
Participants LivDet 2015	Algorithm Name
Anonymous	Anonymous2

Table 14: Participants for Part 2: Systems.

The 2013 edition produced much better results since Dermalog performed at a FerrLive of 11.8% and a FerrFake of 0.6%. Anonymous1 performed at a FerrLive of 1.4% and a FerrFake of 0.0%. Both systems had low FerrFake rates.  
 410 Anonymous1 received a perfect score of 0.0% error, successfully determining every spoof finger presented as a spoof.

Anonymous2, in 2015, scored a FerrLive of 14.95% and a FerrFake of 6.29% at the (given) threshold of 50 15 showing an improvement over the general results seen in LivDet 2011, however the anonymous system did not perform as well as what was seen in LivDet 2013. There is an 11.09% FerrFake for known recipes and 1% for unknown recipes (15). This result is opposite what has been seen in previous LivDet competitions where known spoof types typically have a better performance than unknown spoof types. The error rate for spoof materials was primarily due to impact on color differences error for the playdoh.  
 415 Testing across 6 different colors of playdoh found that certain colors behaved in different ways. For yellow and white playdoh, the system detected spoofs as fake with high accuracy. For brown and black playdoh, the system would not collect an image. Therefore, it was recorded as a fake non-response and not an error in detection of spoofs. For pink and lime green playdoh, the system incorrectly accepted spoofs as live for almost 100% of images collected. The  
 420  
 425

fact that almost all pink and lime green playdoh images were accepted as live images resulted in a 28% total error rate for playdoh. The system had a 6.9% Fake Non-Response Rate primarily due to brown and black playdoh. This is the first LivDet competition where color of playdoh has been examined in terms of  
430 error rates.

Examining the trends of results over the three competitions has shown that since 2011 there has been a downward trend in error rates for the systems. Ferrlive in 2015 while higher than 2013, is drastically lower than 2011. FerrFake has had similar error rates over the years. While the 2015 competition showed  
435 a 6.29% Ferrfake, the majority of that error stems from playdoh materials, particularly pink and lime colors. If you discount the errors seen in playdoh, the FerrFake is below 2% for the 2015 system. The error rates for winning systems over the years is shown in Figure 18 and Figure 19

## 5. Quality analysis: A Lesson Learned from the LivDet Experience

440 This section explores the impact of spoof quality on algorithm performance.

Over a time span of ten years, the researchers in the respective groups have searched for materials suitable for creating fingerprint spoofs by experimenting with a very large number of materials and related variants. This process is performed independent of the feature extraction algorithms and the classification  
445 methods adopted. In general, it is difficult to create a spoof fingerprint that gives good quality fingerprint images on a consistent basis. The quality analysis here reflects this experience.

With regard to the observation above, Tables 16, 17 report a summary of our research. They include a certain number of materials used as cast and/or  
450 mold. Table 16 summarizes the subjective evaluation made by our stuff over ten years experience, and more than 50000 spoofs realized, of the visual quality of the obtained fake fingerprints when combining the mold material (columns) and the cast material (rows). The visual quality assessment has been made up on the basis of the analysis at the microscope of the spoofs and also the quality of

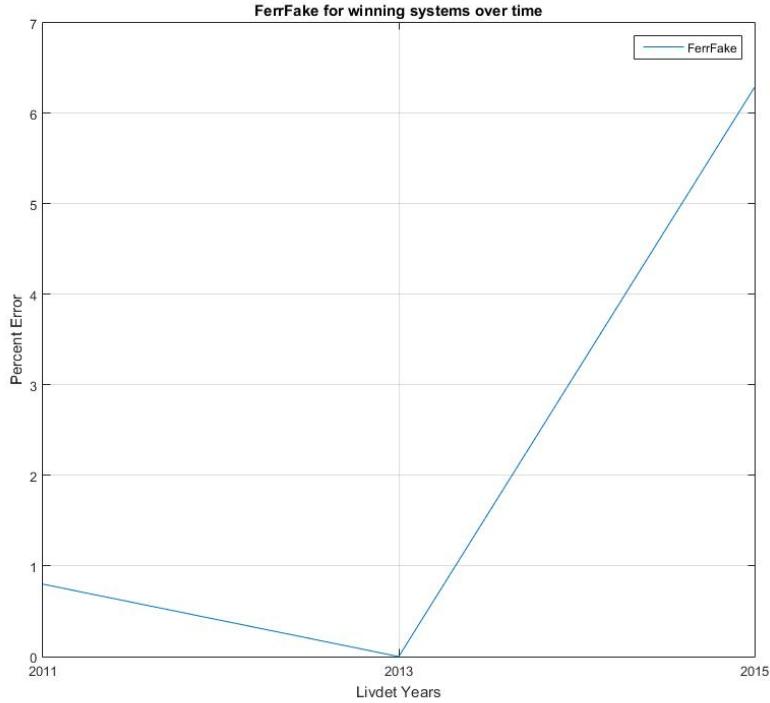


Figure 18: FerrFake for winning systems by year .

455 images acquired by the capture devices. We experienced that certain materials  
 456 are less suitable than others. Several of them are not able to replicate the ridges  
 457 and valleys flow without adding evident artifacts as bubbles and altering the  
 458 ridges edges.

Table 17 shows the subjective evaluation on the easiness of obtaining a good  
 460 spoof from the combination of the same materials of Table 16. This evaluation  
 461 depends on the solidification time of the adopted material, the level of difficulty  
 462 in separating mold and cast without destroying one of them or both, the natural  
 463 dryness or wetness level of the related spoof.

Tables 16, 17 show that, from a practical viewpoint, many materials are  
 465 difficult to manage when fabricating a fake finger. In many cases, the materials

Submitted System	FerrLive	FerrFake
Anonymous	14.95%	6.29%
Submitted System	FerrFake Known	FerrFake Unknown
Anonymous	11.09%	1.00%

Table 15: FerrLive and FerrFake for submitted system in LivDet 2015.

Mold/Material	Foil	RTV	Modasil	Plasticine
Alginat		5	5	
RTV	2	2	4	
Ecoflex	4	1	3	
Gelatine	2	1	3	
Latex	2	1	3	
Modasil	2	2	4	
Transparent Silicone	3			5
White Silicone	2			
Wood glue	2	1	3	
SILIGUM	2			5

Table 16: Quality degree in the spoof fabrication process: 1-Very high, 2-High, 3-Medium, 4-Low, 5-Very Low.

Mold/Material	Foil	RTV	Modasil	Plasticine
Alginat		5	5	
RTV	1	4	3	
Ecoflex	1	4	4	
Gelatine	1	4	3	
Latex	1	4	3	
Modasil	1	4	3	
Transparent Silicone	1			3
White Silicone	1			
Wood glue	1	4	4	
SILIGUM	1			3

Table 17: Easiness degree in the fake fabrication process: 1-Very High, 2-High, 3-Medium, 4-Low, 5-Very Low.

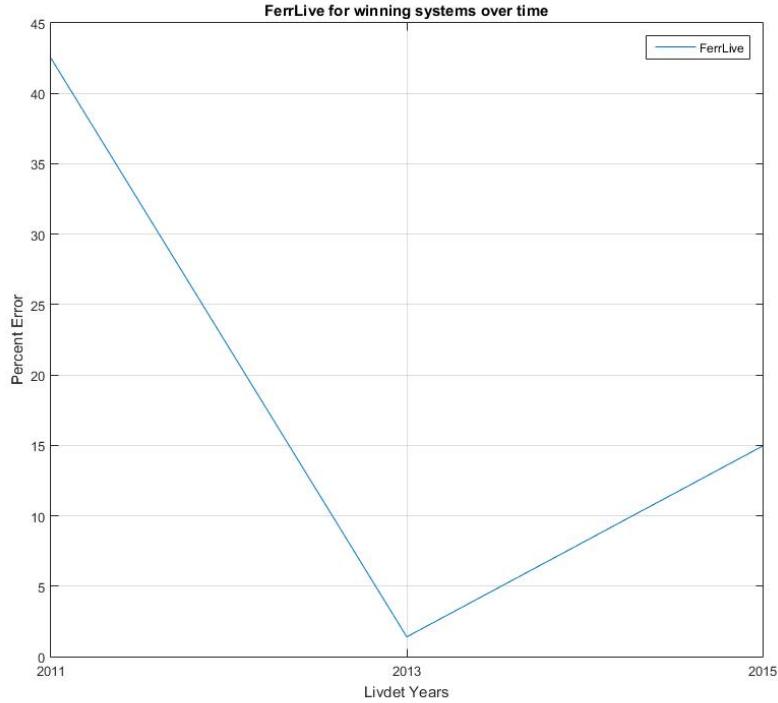


Figure 19: FerrLive for winning systems by year .

with this property also exhibit a low subjective quality level.

Therefore, thanks to this lesson, the LivDet competition challenge participants with images coming from the spoofs obtained with the best and most “potentially dangerous” materials. The materials choice is made on the basis of the best trade off between the criteria pointed out in Tables 16, 17 and the objective quality values output by quality assessment algorithms such as NFIQ.

What reported has been confirmed along the four LivDet editions. In particular the FerrFake and FerrLive rates for each differing quality levels support the idea that the images quality level is correlated with the error rate decrease. The error rates for each range of quality levels for Dermalog in LivDet 2011 Fingerprint Part 1: Algorithms is shown in figure 20, as an example. The graphs

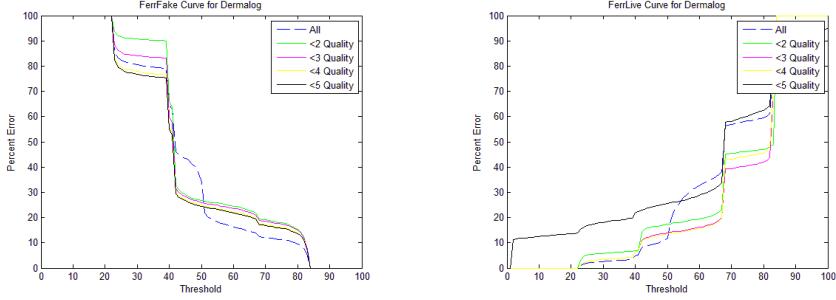


Figure 20: Error rates by quality level.

showcase from images of only quality level 1 up to all quality levels being shown. As lower quality spoof images were added, ferrfake generally decreased. For all images which included the worst quality images, the error rates were less consistent likely due to the variability in low quality spoofs.

The percentage of images at each quality level for two representative datasets for LivDet 2011, 2013, and 2015, respectively, are given in Figures 21, 22, and 23. The Crossmatch dataset had high percentages of the data being in the top two quality levels in both LivDet 2011 and 2013. The swipe dataset had many images that were read as being of lower quality which could be seen in the data itself because of the difficulty in collecting spoof data on the swipe device.

## 6. Conclusions

Since its first edition in 2009, the Fingerprint Liveness Detection Competition was aimed to allow research centres and companies a fair and independent assessment of their anti-spoofing algorithms and systems.

We have seen over time an increasing interest for this event, and the general recognition for the enormous amount of data made publicly available. The number of citations that LivDet competitions have collected is one of the tangible signs of such interest (about 100 citations according to Google Scholar) and further demonstrates the benefits that the scientific community has received from

LivDet events.

The competition results show that liveness detection algorithms and systems strongly improved their performance: from about 70% classification accuracy achieved in LivDet 2011, to 90% classification accuracy in LivDet 2015. This 500 result, obtained under very difficult conditions like the ones of the consensual methodology of fingerprints replication, is comparable with that obtained in LivDet 2013 (first two data sets), where the algorithms performance was tested under the easier task of fingerprints replication from latent marks. Moreover, the two challenges characterizing the last edition, namely, the presence of 1000 dpi capture device and the evaluation against “unknown” spoofing materials, further contributed to show the great improvement that researchers achieved on these issues: submitted algorithms performed very well on both 500 and 1000 dpi capture devices, and some of them also exhibited a good robustness degree against never-seen-before attacks. Results reported on fusion also shows that 510 the liveness detection could further benefit from the combination of multiple features and approaches. A specific section on algorithms and systems fusion might be explicitly added to a future LivDet edition.

There is a dark side of the Moon, of course. It is evident that, despite the remarkable results reported in this paper, there is a clear need of further 515 improvements. Current performance for most submissions are not yet good enough for embedding a liveness detection algorithm into fingerprint verification system where the error rate is still too high for many real applications. In the authors’ opinion, discovering and explaining benefits and limitations of the currently used features is still an issue whose solution should be encouraged, 520 because only the full understanding of the physical process which leads to the finger’s replica and what features extraction process exactly does will shed light on the characteristics most useful for classification. We are aware that this is a challenging task, and many years could pass before seeing concrete results. However, we believe this could be the next challenge for a future edition of 525 LivDet, the Fingerprint Liveness Detection Competition.

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## References

[1] G.L. Marcialis, et al., First International Fingerprint Liveness Detection 535 Competition LivDet 2009.

[2] D. Yambay, et al., LivDet 2011 - Fingerprint Liveness Detection Competition 2011, 5th IAPR/IEEE Int. Conf. on Biometrics (ICB 2012), New Delhi (India), March, 29th, April, 1st, 2012.

[3] G.L. Marcialis, et al., LivDet 2013 Fingerprint Liveness Detection Competition 540 2013, 6th IAPR/IEEE Int. Conf. on Biometrics (ICB2013), Madrid (Spain), June, 4th, June, 7, 2013.

[4] G.L. Marcialis, et al., LivDet 2015 Fingerprint Liveness Detection Competition 2015, 7th IEEE Int. Conf. on Biometrics: Theory, Applications and Systems (BTAS 2015), in press.

545 [5] D. Yambay, et al., LivDet-iris 2013-Iris Liveness Detection Competition 2013. IEEE International Joint Conference on Biometrics (IJCB 2014), 2014.

[6] C. Sousedik, and C. Busch, Presentation attack detection methods for fingerprint recognition systems: a survey, IET Biometrics, 2014.

[7] P. Coli, G.L. Marcialis, and F. Roli, Vitality detection from fingerprint images: a critical survey, IEEE/IAPR 2nd International Conference on Biometrics ICB 2007, August, 27-29, 2007, Seoul (Korea), S.-W. Lee and S. Li Eds., 550 Springer LNCS 4642, pp.722-731.

[8] D. Willis, M. Lee, Six Biometric Devices Point The Finger At Security. Biometrics Under Our Thumb, Network Computing, June 1998.

555 [9] van der Putte, T. and Keuning, J.: Biometrical Fingerprint Recognition: Dont Get Your Fingers Burned, SMART CARD RESERCH AND ADVANCED APPLICATIONS, IFIP TC8/WG8.8 Fourth Working Conference on Smart Card Research and Advanced Applications, pp. 289-303 (2001).

560 [10] T. Matsumoto, H. Matsumoto, K. Yamada, and S. Hoshino, Impact of artificial gummy fingers on fingerprint systems, In Proceedings of SPIE, 4677, Optical Security and Counterfeit Deterrence Techniques IV, Yokohama, Japan.

565 [11] Peter Kallo, Imre Kiss, Andras Podmaniczky, all of Budapest, Janos Talosi, Negykanizsa, All of (HU). Detector for Recognizing the Living Character of a Finger in a Fingerprint Recognizing Apparatus Patent US 6,175641, Jan. 16, 2001.

[12] Schuckers SAC. Spoofing and Anti-Spoofing Measures. Information Security Technical Report, Vol 7. No. 4, pages 56-62, 2002.

570 [13] Bozhao Tan, Stephanie Schuckers, Spoofing protection for fingerprint scanner by fusing ridge signal and valley noise, Pattern Recognition, Volume 43, Issue 8, August 2010, Pages 2845-2857, ISSN 0031-3203, DOI: 10.1016/j.patcog.2010.01.023.

575 [14] P. Coli, G.L. Marcialis, and F. Roli, Fingerprint silicon replicas: static and dynamic features for vitality detection using an optical capture device, International Journal of Image and Graphics, World Scientific, 8 (4) 495-512, 2008.

[15] Cappelli, Raffaele, et al. "Fingerprint verification competition 2006." Biometric Technology Today 15.7 (2007): 7-9.

580 [16] Alonso-Fernandez, Fernando, and Josef Bigun. "Halmstad University submission to the First ICB Competition on Iris Recognition (ICIR2013)." (2013).

[17] Chakka, Murali Mohan, et al. "Competition on counter measures to 2-d facial spoofing attacks." *Biometrics (IJCB)*, 2011 International Joint Conference on. IEEE, 2011.

[18] C. Watson, M. Garris, E. Tabassi, C. Wilson, R. McCabe, S. Janet, K. 585 Ko. *Users Guide to NIST Biometric Image Software*. National Institute of Standards and Technology.

[19] J. Galbally, et al., A high performance fingerprint liveness detection method based on quality related features, *Future Gener. Comput. Syst.* 28, 1 (January 2012), 311-321. DOI=10.1016/j.future.2010.11.024

[20] B. Biggio, et al., Security evaluation of biometric authentication systems under real spoofing attacks, in *Biometrics, IET*, vol.1, no.1, pp.11-24, March 590 2012

[21] E. Marasco, and C. Sansone, Combining perspiration- and morphology-based static features for fingerprint liveness detection, *Pattern Recognition Letters*, Volume 33, Issue 9, 1 July 2012, Pages 1148-1156, ISSN 0167-8655 595

[22] J. Galbally, et al., Image Quality Assessment for Fake Biometric Detection: Application to Iris, Fingerprint, and Face Recognition, in *Image Processing, IEEE Transactions on*, vol.23, no.2, pp.710-724, Feb. 2014, doi: 10.1109/TIP.2013.2292332

[23] E. Marasco, and C. Sansone, An anti-spoofing technique using multiple 600 textural features in fingerprint scanners, in *Biometric Measurements and Systems for Security and Medical Applications (BIOMS)*, 2010 IEEE Workshop on, vol., no., pp.8-14, 9-9 Sept. 2010, doi: 10.1109/BIOMS.2010.5610440

[24] L. Ghiani, et al., Experimental results on fingerprint liveness detection, In 605 Proceedings of the 7th international conference on Articulated Motion and Deformable Objects (AMDO 2012), Springer-Verlag, Berlin, Heidelberg, 210-218

[25] D. Gragnaniello, et al., Wavelet-Markov local descriptor for detecting fake fingerprints, *Electronics Letters*, 2014, 50, (6), p. 439-441, DOI: 10.1049/el.2013.4044, IET Digital Library

[26] P. B. Patil, and H. Shabahat, An Anti-Spoofing Technique Using Multiple Textural Features in Fingerprint Scanner, *International Journal of Electrical, Electronics and Computer Engineering*

[27] R. Nogueira, et al., Evaluating software-based fingerprint liveness detection using Convolutional Networks and Local Binary Patterns, in *Biometric Measurements and Systems for Security and Medical Applications (BIOMS) Proceedings*, 2014 IEEE Workshop on , vol., no., pp.22-29, 17-17 Oct. 2014 doi: 10.1109/BIOMS.2014.6951531

[28] Y. Jiang, and L. Xin, Spoof Fingerprint Detection based on Co-occurrence Matrix, *International Journal of Signal Processing, Image Processing and Pattern Recognition* (2015).

[29] X. Jia, et al., Multi-scale local binary pattern with filters for spoof finger- print detection, *Information Sciences*, Volume 268, 1 June 2014, Pages 91-102, ISSN 0020-0255, <http://dx.doi.org/10.1016/j.ins.2013.06.041>.

[30] D. Gragnaniello, et al., Local contrast phase descriptor for fingerprint live- ness detection, *Pattern Recognition*, Volume 48, Issue 4, April 2015, Pages 1050-1058, ISSN 0031-3203, <http://dx.doi.org/10.1016/j.patcog.2014.05.021>.

[31] N. Poh, et al., Anti-forensic resistant likelihood ratio computation: A case study using fingerprint biometrics, in *Signal Processing Conference (EU- SIPCO)*, 2014 Proceedings of the 22nd European , vol., no., pp.1377-1381, 1-5 Sept. 2014

[32] A. F. Sequeira, and J. S. Cardoso, Fingerprint Liveness Detection in the Presence of Capable Intruders, *Sensors*. 2015, 15(6):14615-14638.

[33] G. Fumera, et al., Multimodal Antispoofing in Biometric Recognition Systems, in *Handbook of Biometric Antispoofing*, S. Marcel, M. Nixon, and S. Li (Eds.), Springer, pp. 145-164, DOI: 10.1007/978-1-4471-6524-8\_9, 2014

[34] N. Poh, et al., Toward an attack-sensitive tamper-resistant biometric recognition with a symmetric matcher: A fingerprint case study, in *Computational Intelligence in Biometrics and Identity Management (CIBIM)*, 2014 IEEE Symposium on, vol., no., pp.175-180, 9-12 Dec. 2014, doi: 10.1109/CIBIM.2014.7015460

[35] L. Ghiani, et al., Fingerprint Liveness Detection using Binarized Statistical Image Features, in *Biometrics: Theory, Applications and Systems (BTAS)*, 2013 IEEE Sixth International Conference on, vol., no., pp.1-6, Sept. 29 2013-Oct. 2 2013, doi: 10.1109/BTAS.2013.6712708

[36] X. Jia, et al., Multi-scale block local ternary patterns for fingerprints vitality detection, in *Biometrics (ICB)*, 2013 International Conference on, vol., no., pp.1-6, 4-7 June 2013, doi: 10.1109/ICB.2013.6612964

[37] G.L. Marcialis, et al., Large Scale Experiments on Fingerprint Liveness Detection, Joint IAPR Int. Work. on Structural and Statistical Pattern Recognition (SPR & SSPR 2012), Hiroshima (Japan), November, 7-9, 2012, Springer LNCS 7625, pp. 501-509, 2012

[38] Y. Zhang, et al., Fake Fingerprint Detection Based on Wavelet Analysis and Local Binary Pattern, *Biometric Recognition (CCBR 2014)*, 8833: 191-198 2014

[39] A. Rattani, et al., Open Set Fingerprint Spoof Detection Across Novel Fabrication Materials, in *Information Forensics and Security, IEEE Transactions on*, vol.10, no.11, pp.2447-2460, Nov. 2015, doi: 10.1109/TIFS.2015.2464772

[40] P. Johnson, and S. Schuckers, Fingerprint pore characteristics for liveness detection, *Proceedings of the International Conference of the Biometrics Spe*

cial Interest Group (BIOSIG), Darmstadt, Germany, 1012 September 2014;  
pp. 18.

[41] X. Jia, et al., One-Class SVM with Negative Examples for Fingerprint  
Liveness Detection, *Biometric Recognition*. Springer International Publishing,  
2014. 216-224.

[42] C. Gottschlich, et al., Fingerprint liveness detection based on histograms of  
invariant gradients, *Biometrics (IJCB)*, 2014 IEEE International Joint Conference on. IEEE, 2014.

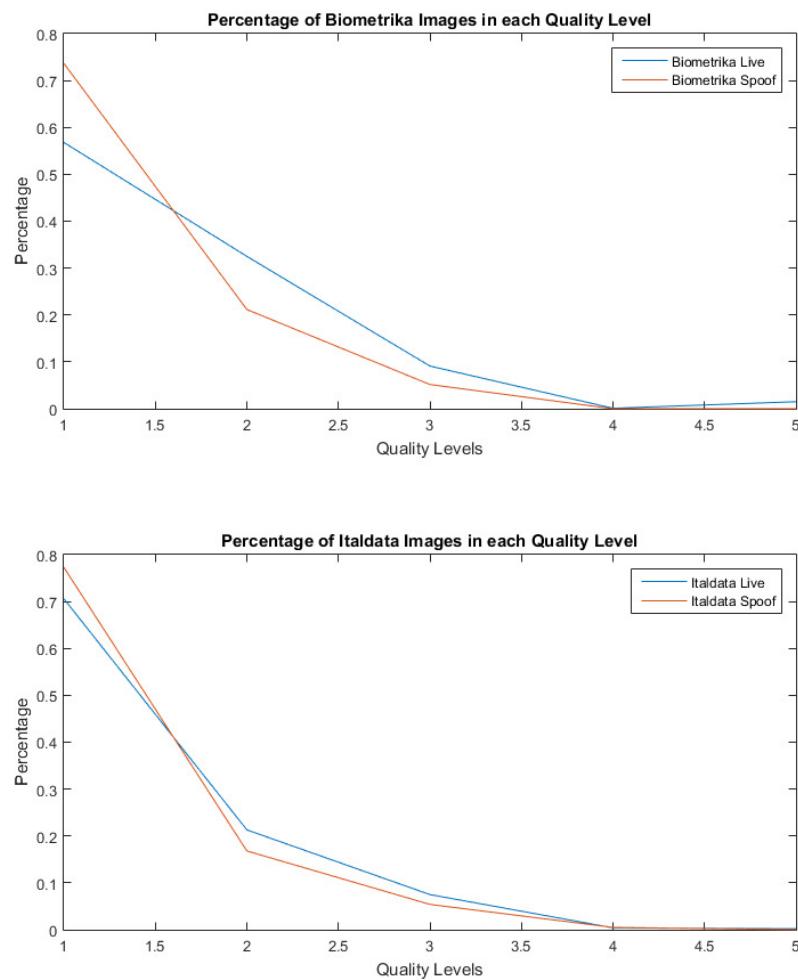


Figure 21: Percentages of Images per Quality Level for LivDet 2011.

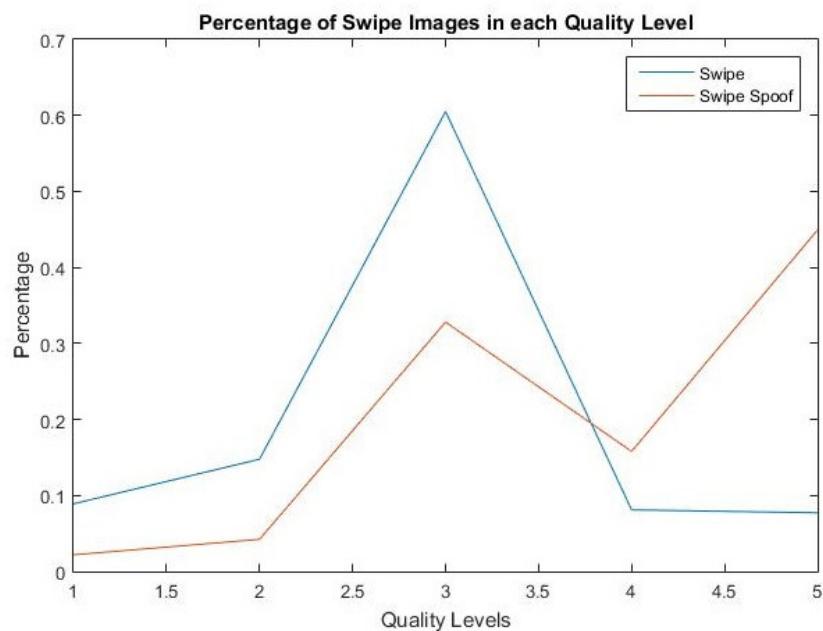
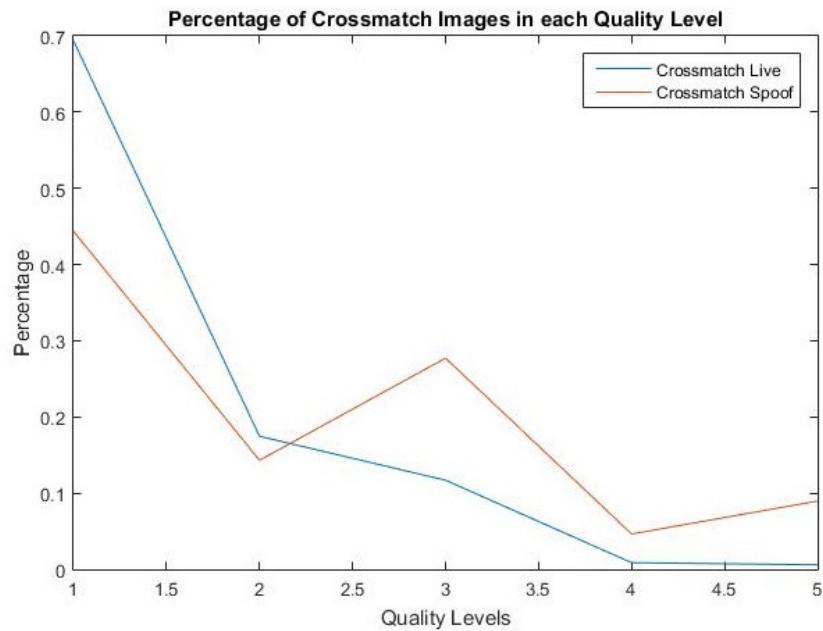


Figure 22: Percentages of images per Quality Level for LivDet 2013.

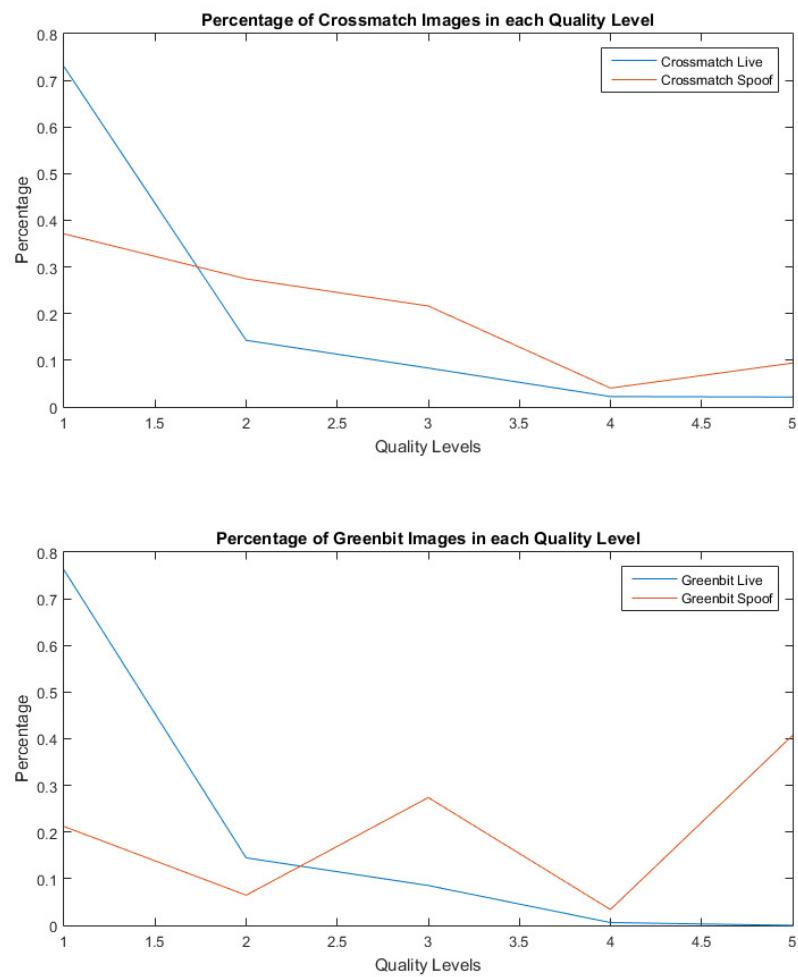


Figure 23: Percentages of images per Quality Level for LivDet 2015.