BRAIN^2 - Machine Learning to Measure Banknote Fitness

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ABSTRACT

A challenge for central banks is to decide whether used banknotes are still suitable for recirculation, or rather should be shredded and replaced by new ones. Obviously longer use of banknotes reduces the printing costs and environmental burden. Given the huge amounts of banknotes in circulation, determining the fitness of banknotes is not only of importance in cost control, but also poses a serious technical challenge in terms of processing speed and accuracy. With the current technology fit notes are often shredded along with unfit ones. In this paper DNB proposes a fitness detection method that may contribute to a reduction of the amount of unnecessary shreds.
We suggest the use of the BRAIN^2 fitness detector. BRAIN^2 is the abbreviation of Banknote Recirculation Analysing & Instructing Neural Network fitness sensor. It is based on a machine learning method using a combination of intensity and contrast differences on colour images of the entire banknote. Studies done by DNB and the University of Amsterdam in 2010 have shown that this approach is successful in post-processing conditions. This study evaluates the performance of the BRAIN^2 algorithm using two on-line systems: the automatic sorting machine CPS 2000 and a double sided portable scanner with sheet feeder.

1. INTRODUCTION

The main reason for sorting banknotes is to count and check for authenticity. Due to the lower priority of fitness sorting in general the performance of existing soil detectors is poor. The result is that a significant amount of (super) fit banknotes is unnecessarily shredded.

To provide input for potential developments on improved fitness sorting first the circulated banknote itself needs to be studied more carefully. At DNB we therefore determined the characteristics of soil. We concluded that the main soiling mechanism of euro banknotes is due to fingerprint deposits. They will cumulate and eventually will form a yellow/brownish layer of aged sebum. In addition it is the (gentle) touch of the human finger causing soil (particularly sebum) adhesion on the elevated parts, the crease- or fold lines, of the banknote revealing a structural yet inhomogeneous appearance [1,2].

Because of the inhomogeneous character of soil it is difficult to describe the level of soiling of banknotes by objective, quantized optical characteristics in order to classify them as fit or unfit. In general we can conclude that soil will be predominantly visible in the blue part of the spectrum due to the typical discoloration of the banknote.

In this paper, we consider both the theory on banknote soiling and a learning based method on the combination of intensity and contrast differences on colour images. Such a method could in principal work as indicated by above outlined soiling studies. Yet up till now, the algorithms used in automatic sorting could not meet the requested requirements to separate unfit from fit well [3].

2. BANKNOTE SOILING

The theory on banknote soiling is described in this paper to provide input for a proper soil detection mechanism. The theory on banknote soiling includes typical structural deterioration characteristics, like soiling, tears and tape to ensure a proper relation to the stage of life. The more accidental deterioration characteristics, like: folded corners, stains, graffiti

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and holes will be put less emphasis on. These phenomena are more or less randomly induced to the banknote in circulation and have a weak relation to the stage of life.

In this paper we describe the deterioration of a banknote by stages. This approach is recommended since the circulation load may differ among countries. As the circulation load differs the deterioration stages remain unchanged yet the life length differs [4].

The following five deterioration stages are identified (see Figure 1 & 2):

0. New Banknote
1. New but crumpled including some mechanical defects
2. Crumpled banknote with soil on elevated parts (fold lines)
3. Pronounced soiling on former fold lines and detached fibres
4. Soil on the entire surface, worn former fold lines are weak spots for tearing

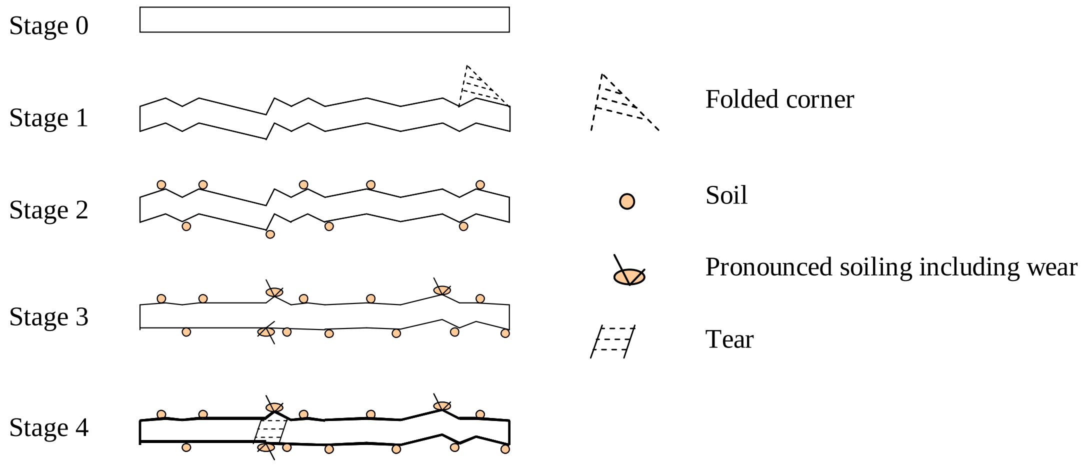

Figure 1 - Schematic cross sections indicating the structural deterioration stages of banknotes.

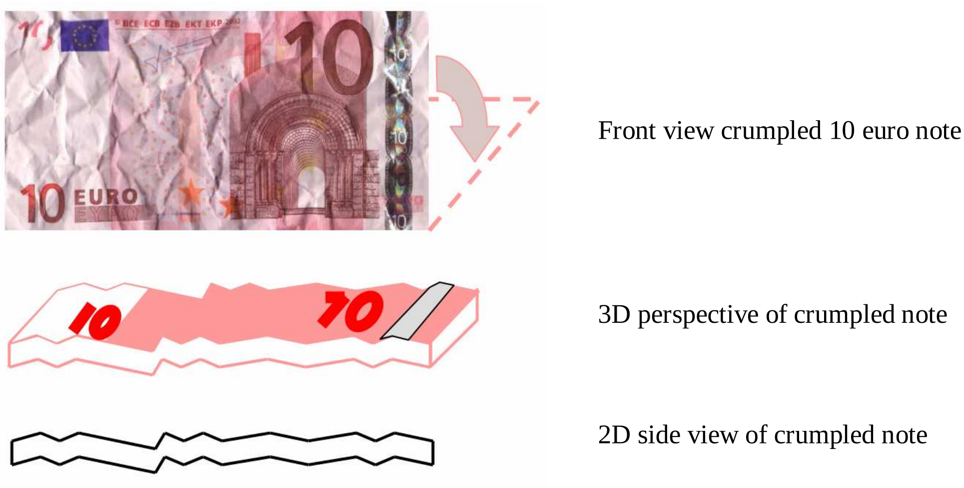

Figure 2 - Explanation on the schematic cross sections in Figure 1, an example of stage 1.

To support the theory images of typical soiled banknotes out of circulation are presented in Appendix A. Due to the fact that creases or folds are less visible in a composed Red-Green-Blue (RGB) image, transparent infrared (IR) images are added. In detail the watermark areas are highlighted as well.

The physical properties and visual appearance of the four typical deterioration stages of a banknote in circulation in the Netherlands are described in the next sub-chapters (for more details see [1]).

2.1 Stage 1

The deterioration stage 1 is characterised by banknotes that are new but crumpled and may include some mechanical defects, like folded corners or tears. The observed physical properties do not show major differences with respect to a new banknote.

2.2 Stage 2

The physical properties of a banknote within stage 2 are becoming somewhat different with respect to stage 0 and 1. The following observations are made:

- Increase in porosity from ~20 ml/min to ~40 ml/min
- Stiffness reduction from 40 mN to ~30 mN
- Micro roughness of recto increases from 1.8 μm to 3.0 μm

These observations can be explained by the relaxation of the cotton fibres within the substrate. Due to banknote handling it is crumpled, folded and touched (massaged). All of these processes do not harm the tough fibres but causes them to reposition in a somewhat more relaxed state [5], resulting in cavities to form which causes a decrease in stiffness and an increase in porosity and micro roughness.

In this stage the (first) soil appears on the elevated parts (crease- or fold lines) of the banknote. The pronounced soiling on the elevated parts may be explained as follows:

- The angle of attack of the human finger is about 45° with respect to the banknote surface
- As the finger hits the surface the affinity between surface and finger contaminants determines the transfer of material towards the banknote
- When the finger encounters (the edges of) an elevated part (defect), finger contaminants are (also) mechanically scraped off (see figure 3)

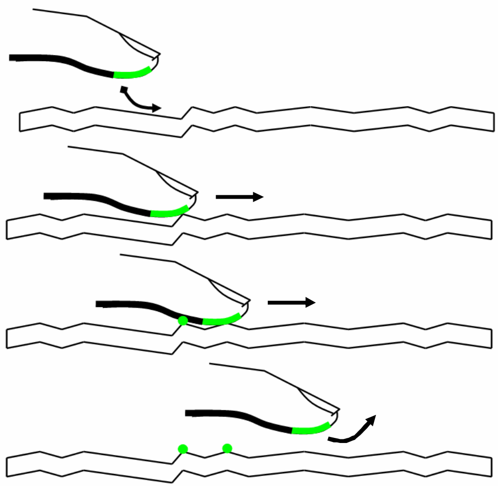

Figure 3 - Schematic representations of the soiling mechanism on elevated parts

Since the process of soiling on the elevated parts is both affinity and mechanically driven this will be the dominant soiling mechanism.

2.3 Stage 3

The physical properties of a banknote within this stage are diverging further from the characteristics of a new banknote. The following observations are made:

- Increase in porosity from ~20 ml/min to ~60 ml/min
- Stiffness reduction from 40 mN to ~25 mN
- Micro roughness of recto increases from 1.8 μm to 3.5 μm
- Thickness increase from 90 μm to 95 μm
- Weight starts to increase

Again all these observations can be explained by the relaxation of the cotton fibres within the substrate due to banknote handling. The weight starts to increase due to add up of soil.

Induced wear by human fingers on (former) fold and crease lines causes fibres to detach. The detached fibres will trap (more) soil towards these regions. Soiling of the lower regions is visible as well. Soiling on the lower regions can take place due to the fact that the banknote flattens with the loss of stiffness.

2.4 Stage 4

The physical properties are characterised of an average worn banknote from circulation for different stages of life. The following observations are made:

- Significant increase in porosity from ~20 ml/min to ~150 ml/min
- Thickness increase of ~10%
- Weight increase of ~2%
- Almost linear stiffness reduction from 40 mN to ~15 mN
- Micro roughness of recto equals that of verso to ~4.0 μm

All observations, with the exception of the weight increase, can be explained by the relaxation of the cotton fibres within the substrate. The small weight increase is due to add up of soil.

The tint of the banknote is in this stage typically yellowish/ brownish. The discolouring of the banknote is caused by two processes: oxidation of the cellulose fibres and naturally ageing of the sebum. Oxidation of the cellulose causes Oxycelluloses to form. This oxidation reaction results in an increase in oxygen containing groups such as carbonyls and carboxylic acids. Oxycelluloses typically causes a yellowing effect on the paper. The layer of sebum does naturally age in the following way:

1. Tri (or di-) glycerids initially decompose to glycerine and fatty acids
2. The double bonds in unsaturated fatty acids are oxidized into carbonic acids
3. These acids trigger other oxidation processes which often result in brown coloured substances

The visual impression of the banknote in this stage is that the entire surface is soiled. Yet the soil in-homogeneity remains, the former fold- and crease lines appear (always) darker.

3. MACHINE LEARNING OF BANKNOTE FITNESS

The analysis presented in the previous section yields significant clues on the information relevant for machine determination of banknote soiling. Various parameters play a role, like the brightness of areas, brightness and colour variations and local colour contrasts indicating the deposits at fold lines. The challenge in soil detection is to have all parameters correct, meaning measuring the proper contrast or intensity areas of the banknote, for the exact (combination of) colours. We consider a learning based method on the combination of intensity and contrast differences on colour images [6]. The evidence from above outlined soiling studies show that such a method could in principal work.

Machine categorization of banknotes being fit or unfit is not trivial. First of all, dirtiness of banknotes is hard to define in rules. Current technology establishes usually the amount of reflection of a white part of the banknote often the watermark region. New banknotes tend to reflect more light in such a region, as they are whiter than dirty banknotes. However, paper and printing quality varies, over time and per manufacturer, causing substantial intensity differences over new, unused banknotes. Given the inherently complex manufacturing process of banknotes as a major defence to counterfeiting, further constrains on the printing specifications are hard to implement. Rather than explicitly designing rules to distinguish fit from unfit notes, a machine learning approach is attractive. The machine learning approach is platform independent. Nowadays all new high speed sorters are equipped with RGB image sensors which are suitable for capturing the necessary colour images of circulated banknotes.

A limited set of example fits and example unfits for every type of banknote that should be categorized are used to learn the system. The example fits and example unfits should be selected with care. The set of fit and unfits should be consistent and representative as the system learns from these examples. For consistency reasons the banknote test set is composed by experienced sorter personnel of DNB. Whether or not the test set is representative can be discussed and is a study by itself [7].

The huge bulk of banknotes returned to central banks every day and efficiency improvements driving up the processing speed. Computer vision has dealt with such processing issues and some techniques for fast visual detection or categorization are available nowadays. We implemented a detector BRAIN^2, which is the abbreviation of Banknote Recirculation Analysing& Instructing Neural Network fitness sensor. We combine the idea of measuring reflectance, contrast, and colour content of regions. We design our algorithm to profit from the available knowledge on sebum deposit on banknotes as the major source of soiling by explicitly encoding yellow-blue information. Furthermore, machine learning is applied to automatically select relevant regions for classification. As such, our design yields a fast and accurate banknote categorization method.

3.1 Pre-processing: banknote area detection

In order to apply machine learning algorithms, the banknote paper area has to be detected such that image based machine learning can be used. Hence, the banknote image is segmented from the conveyor belt image, by detecting the sides of the banknote using line fitting. The fitted lines yield the de-skew angle and the image size (see figure 4). The banknote image itself is not de-skewed, the software translates and rotates mathematically the regional features (rectangles, see sub-chapter 3.2). This increases processing speed.

Figure 4 - The camera image with lines fitted next to the banknote area

3.2 Regional features for fitness learning

Certain regions of the image are better suited to detect dirt than other regions. That is why the aim is to determine these regions automatically including their contribution to the fitness categorization. Therefore, each banknote image is subdivided into a pre-defined set of overlapping rectangles of various sizes and aspect ratios, thereby densely sampling the banknote by a large amount of varying rectangular areas. For each rectangle, the average intensity is measured, together with the standard deviation of intensity - the latter yielding a measure of local contrast. Hence, per region, two features are calculated. To counteract variations in overall illumination, due to accumulated dust on the image sensor during operations and variations in overall printing quality, both these numbers are normalized by the average intensity of the whole banknote region.

As we do not only have access to intensity information, but also colour information, the same procedure is repeated for the R, G, and B colour channel, respectively, and for their opponent colour combinations: YB (Yellow-Blue) =R+G-2B, RG=R-2G+B. So, we are left with two numbers (average, standard deviation) per rectangle for six colour channels (including intensity), yielding a total of 12 features per rectangle. Furthermore, for a two-sided setup, the features of the front and back side of the banknote can be assessed, resulting in a large set of features per banknote. From this large set of more or less arbitrary features, a limited number will be selected for fitness classification.

3.3 Learning the relevant features

A simple yet effective method is applied to select features, see [6] for details. A relevant set of these features is automatically obtained by providing a training set of images. The set must contain examples of fit banknotes, and a separate set of examples of unfit banknotes of a single denomination. First, from all available features, the single feature best discriminating between the example fits and the example unfits is chosen. Here, discrimination is obtained by considering a threshold value for each feature: if the value of a feature is above the threshold, the example is considered fit, otherwise unfit. This threshold is chosen such that the best classification result is obtained for that single feature. However, even with that best option, this classifier will make errors – given its simplicity compared to the difficult problem of fitness sorting. And even when selecting the one feature with its corresponding threshold yielding the smallest classification error, this might only be marginally above the probability level. The key insight is that many of such “weak” classifiers become a strong classifier when combined together, known as “AdaBoost”. After having obtained the single best feature (with threshold) for discriminating fits from unfits, the importance of each example is re-weighted. Correct classified examples are weighted less relative to incorrect classified ones, and the procedure is repeated to find a second-best feature, which now emphasizes on the previously incorrectly classified examples. Again, re-weighting takes place, and a third classifier is found. The procedure is repeated until a sufficient number of feature classifiers, typically 40, are combined. An example of selected region for 10 euro banknotes is shown in figure 5. The selection of regions and proposed colour combinations are dependent on the test set and capturing device.

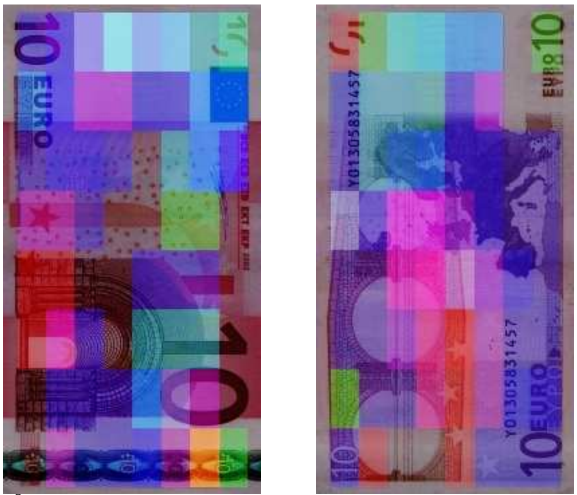

Figure 5 - Selected regions by BRAIN^2. The regions are overlaid over the respective colour channel to which the region corresponds. So, blue regions are taken from the blue channel, yellow regions from both red and green, and white regions from all three channels etc. The intensity of the region overlay indicates the region’s contribution to the overall fitness classifier.

4. RESULTS

An advantage of, after training a feature selector, is that only the selected features need to be calculated for the classification into fit or unfit. These can be implemented on a high speed sorting machine. In order to assess the performance of our BRAIN^2 approach, we learned and applied the classifier on a set of euro banknotes. The algorithm was evaluated for three different experiments:

1. Post-processing on laptop
2. Prototype single-sided imaging system on a DeLaRue CPS 2000
3. Double sided portable scanner with sheet feeder

4.1 Post-processing on laptop

We collected images at the Oesterreichische Banknoten- und Sicherheitsdruck GmbH (OeBS) using their single note inspection system ABCS-2, see table 1. We will refer to this dataset as the OeBS dataset.

	Training		Validation	
Denomination	Fit	Unfit	Fit	Unfit
Euro 5	150	150	1348	950
Euro 10	150	150	1456	1000
Euro 20	150	150	450	633
Euro 50	150	150	1397	595

Table 1 - Amount of banknotes in the OeBS data set used for evaluation.

The performance was measured using colour images and grey images. The grey images were derived from the colour images. The use of colour is demonstrated to significantly outperform grey value features, especially for the euro 20 and euro 50 denominations (see table 2).

	Color	Grey
Euro 5	5.5%	11.1%
Euro 10	5.1%	11.2%
Euro 20	2.7%	29.1%
Euro 50	2.6%	27.3%

Table 2 - Sorting results for the OeBS data set. False unfit rate at 5% accepted false fits

4.2 Prototype single-sided imaging system on a DeLaRue CPS 2000

The second evaluation uses a high speed sorting machine DeLaRue CPS 2000 implemented with a prototype single-sided imaging system.

DNB runs eight CPS 2000 high speed sorting machines. One CPS 2000 machine is devoted for testing of sensors in general. The machine has additional space available especially for testing purposes. New sensor developments and testing by banknote equipment manufactures can relatively easily be accommodated. DNB's skilled technicians do make this all possible. The same for the reconfiguration of the belt path on the CPS 2000; a belt free section was created to be able to capture the entire banknote image (see figure 6).

Creating a soil detector using the method described in chapter 3 we basically need six items:

- High speed sorting platform
- High speed gray scale camera
- Illumination (Red, Green and Blue LED arrays)
- Control electronics
- IO card
- PC with machine learning software

The high speed RGB camera is a commercially acquired line scan camera (EM2, AVIIVA) mounted with a telecentric lens (Pentax C5028A-M035 5 Mega). Illumination is oblique from both sides (left and right of the lens, single side of the banknote) using RGB led arrays (Red LAL7x125-R/m5; Green Red LAL7x125-G/m5; Blue LAL7x125-B/M5/65k; Vision & Control). The electronics to control the illumination and an adaptation in the RGB led arrays is specially developed and assembled by DNB technicians. The interfacing with the DLR CPS sorting machine is realised without assistance of the sorting machine manufacturer. The interface supports timing and fitness decision signals which make real-time fitness sorting possible.

	Training		Validation	
Denomination	Fit	Unfit	Fit	Unfit
Euro 10	60	60	500	500

Table 3 - DNB data set used for evaluation.

The inspection software runs on a Dell T3500 PC with a Intel® Xeon® W3565 (Quad Core, 3.20 GHz, 8MB Cache, 4.80 GT/s Intel® QPI) with a bus speed of 1333MHz. This PC is equipped with a commercial available DAQ card (DAQ2501, ADLINK) with several I/O lines like DA, AD and TLL lines. Furthermore, the PC is equipped with a frame grabber (X64-CL Express, Teledyne DALSA) interfacing with the line-scan camera.

In operational mode the CPS 2000 system processes 2,000 banknotes per minute. The interface between the CPS 2000 and the new algorithm operated at this speed. For this setup a training and validation set of euro 10 banknotes was used as specified in table 3. This dataset is referred to as the DNB euro 10 dataset. To instruct the single-sided prototype the front side of the euro 10 banknotes is used. A result of 2% false fits is achieved at a false unfit rate of 5%.

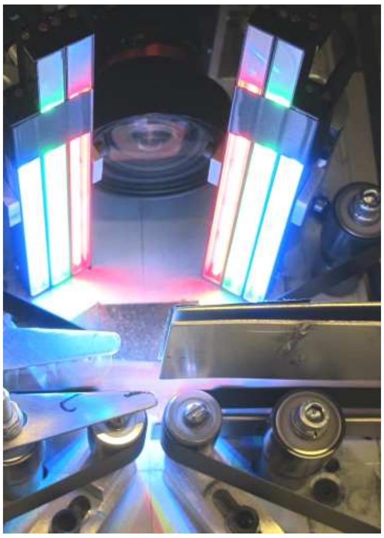

Figure 6 - Prototype single-sided imaging system on a DeLaRue CPS 2000 with modified belt free transport.

4.3 Double sided portable scanner with sheet feeder

For the third evaluation the BRAIN^2 software was connected to an of the shelf double sided portable scanner with sheet feeder (P-150, Canon). The software runs on a laptop, a Lenovo T420s with i7 processor (Figure 7), nowadays any laptop will do.

In this setup the DNB euro 10 dataset (table 3) was re-used. The images were collected by the scanner rather than by the CPS 2000 sorting machine. The scanner was set to correct the skewed images, using automatic page size detection. As we consider this setup relevant as lab-tool, rather than a sorting machine, we consider the equal error rate. The equal error rate is the performance for which the false fit rate equals the false unfit rate. An equal-error rate of 1.5% was achieved for this setup for the euro 10.

Figure 7 - Double sided portable scanner with sheet feeder connected to laptop

5. DISCUSSION

This paper evaluates a machine learning algorithm for banknote fitness sorting in three different experiments:

1. Post-processing on laptop
2. Prototype single-sided imaging system on a DeLaRue CPS 2000
3. Double sided portable scanner with sheet feeder

All three experiments show excellent performance for the proposed machine learning method. This reveals the potential of the method: it is platform independent. It can be used on: high speed sorters, slow desktop scanners and in post-processing conditions. As the last item is concerned, it is a powerful tool to advice on areas of interest including thresholds to discriminate best between fit and unfit notes.

Whereas soil detectors in general focus on the watermark region, the reported results demonstrate that the entire banknote surface should be used for a proper analysis;

- Printed areas: with increasing deterioration the ink contrast decreases since the bright background will become yellowish/ brownish due to soiling.
- Ink wear: especially the Intagalio areas are susceptive to ink wear. With increasing wear the ink will appear less solid.
- (Double) fold and crease lines: they reveal mechanical damage and soiling.
- Foil stripe and patches: with increasing deterioration these features become dull.

The proposed method indicates differences in regions of interest and colour usage between the denominations. It seems that there is not one “fitness standard” for all denominations and sorting systems. This is clearly visible in the discrimination between fit and unfit for euro 5, 10, 20 and 50. The information needed to separate well between fit and unfit is more complex for euro 20 and euro 50 (see Figure 8). The use of colour information increases significantly the performance of the euro 20 and euro 50 as observed in post-processing conditions.

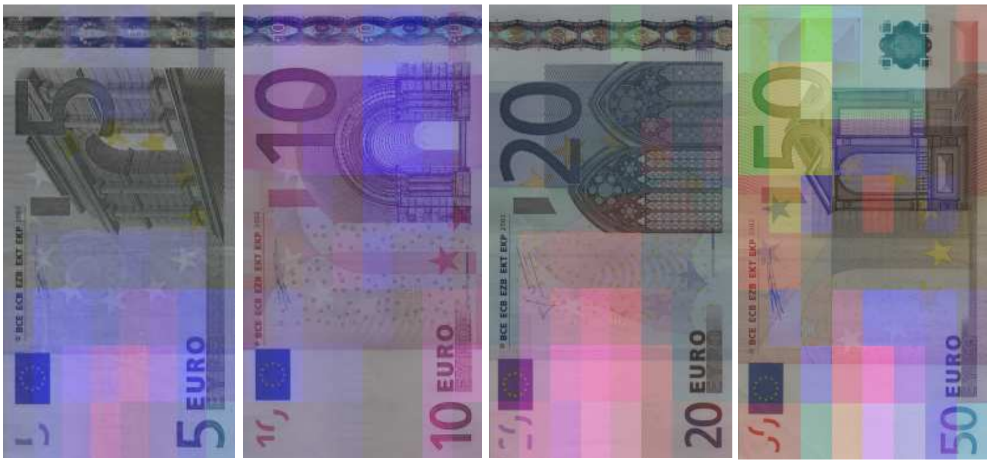

Figure 8 – Selected regions by BRAIN^2 on DeLaRue CPS 2000. The regions are overlaid over the respective colour channel to which the region corresponds. It seems that there is not one “fitness standard” for the 5, 10, 20 and 50 denominations. To discriminate well between fit and unfit for euro 5 and 10 BRAIN^2 uses to a large extend the blue channel, whereas for the euro 20 and 50 BRAIN^2 mainly uses a combination of all colour channels. Thereby BRAIN^2 retrieves most information out of the watermark area for euro 5 and 20. For euro 10 and 50 BRAIN^2 puts also emphasis on the printed area.

BRAIN^2 is generic: it is able to learn fitness from a broad range of input images of banknotes, given some minimum requirements on quality in colour reproduction and resolution. The knowledge needed for sorting banknotes is captured in the provided training set and is automatically extracted by the software. Furthermore facing and denomination can be determined using the same learning procedure. As such, any machine vision systems supplier will be able to install the necessary hardware for fitness sorting.

6. ACKNOWLEDGEMENT

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The authors are proud to mention the following people, without them this BRAIN^2 project would not have been possible. Special thanks to the people of the DNB technical bureau and Hans Broeders. Ton Rondeel performed all adjustments on the CPS transporting system. Hans Broeders for his help composing the necessary banknote test sets including their classification.

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APPENDIX A IMAGES OF EURO 5 BANKNOTES

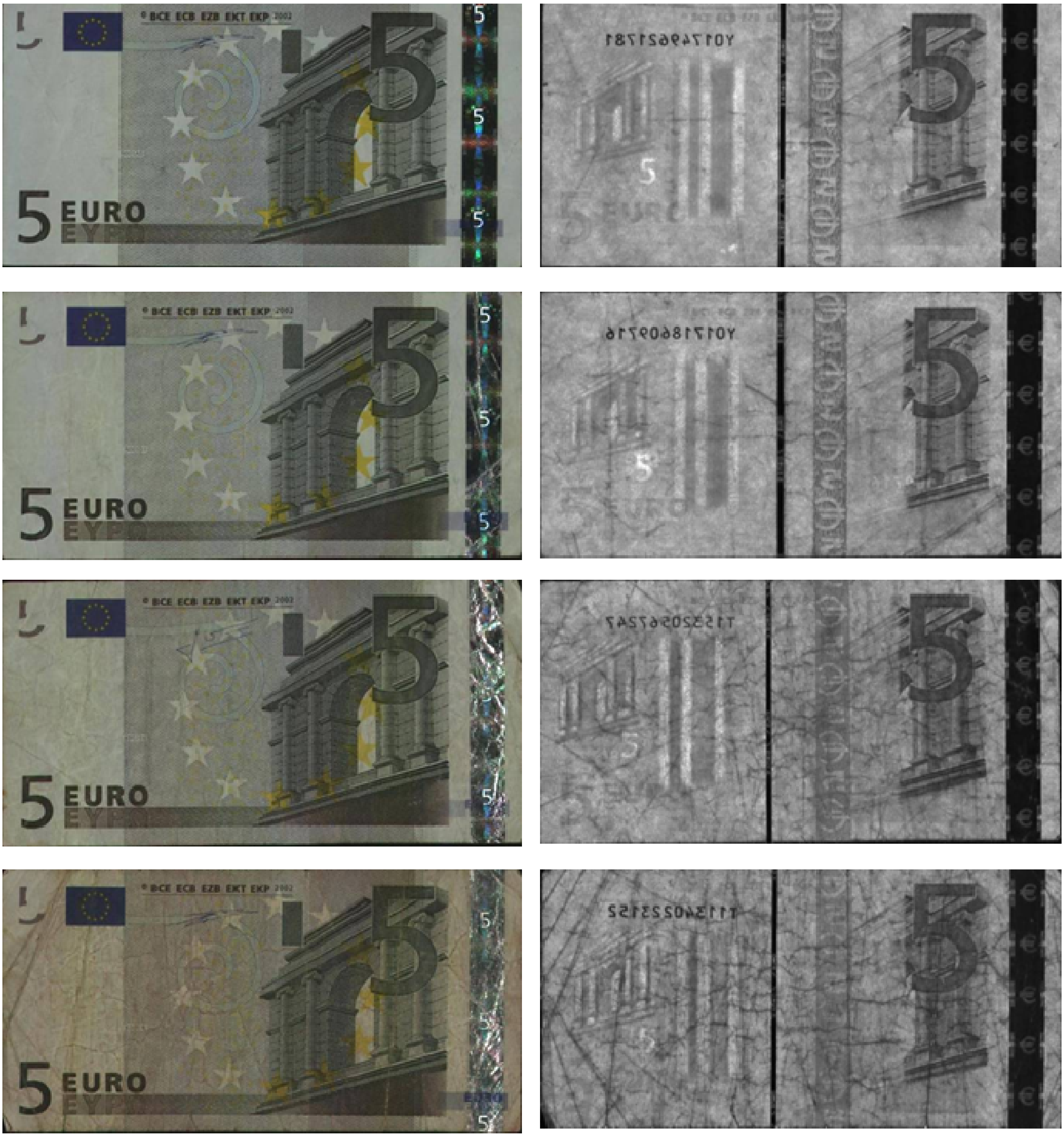

Figure 8 - Deterioration stages one up to four, left images are in RGB, right images IR in transmission*

* Images are taken by the single note inspection system of OeBS, the ABCS-2 system.

Figure 9 - Deterioration stages one up to four, watermark images in RGB