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# Digital Camera Identification Based on Original Images

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## 1. Introduction

The development of instruments for copyright protection and pirated copies detection requires new methods of intellectual property protection. Specific of execution of that analysis considerably depends on media type – whether it material or energy and recording device (analog or digital).

### 1.1 Identification task

To analyse the capability of identification due to direct dependence of ID-procedure on media nature it is feasible to select two groups of media: material (physical bodies) and energetical (physical fields: electric currents, sound fields, etc). The common property of any field is wavelike pattern so it can be named wave media type. Electric current both the power carrier and an media. On the material media the information is fixed by changing physical properties according to character alphabet. Information transfer by material media is done by transfer of changed matter. Information fixation by wavelike media is done by environmental changes. Information transfer by wavelike media is performed by energy transfer. According to abovementioned, the analog recording device identification (for example microcassette dictophone) is done by traces leaved on by material media by on-off impulses, transients, inactivity noises, noise of clear media (magnetic tape), high-frequency current for magnetic bias, speed parameters of deck. For analog cameras that type of parameters includes frame margin, film-feeding and optical system specific features. For printers this type of parameters includes features of methods and algorithms of rasterizing and printing methods implementation.

Devices which uses energy media are also identifiable, for example radio transmitting devices are identified by transients of modulated signal.

### 1.2 Digital recording identification features

Easy bit-to-bit copying process of digital information and inapplicability of traditional “original vs copy” division both with non availability of automated procedures of digital sourcing had led to wide distribution of counterfeit production. Identification based on format features, metadata fields, etc is unreliable because of its removal and forgery simplicity. Use of digital watermarks for content protection is not always possible due to computational complexity of embedding procedure.

Widening of digital audio and videorecording devices distribution and an abrupt increase of storage density had led to situation where the most frequently identification case is identifiable records that are external to identifiable device, leading to complete absence of the primary physical state of the primary "source" and file system properties. Than the rest identification way are the identification based on file format features and identification based on features of recording path and postprocessing.

Copyright protection task operates with the same features, but the signal can be presented after multiple format conversions, which preserve consumption quality but changes the physical representation of original signal, so the identifiable and applicable features are ones containing in digital *content* rather than *format* representation.

Currently questions of identification of analog audio, still images and video recording devices are well researched and are based on traces which the recording device leaves on the carrier in process of writing at change of its physical properties. It is widely used at any carrying out of the expertizes which example is, in particular, phototechnical examination. Phototechnical expert appraisal represents judicial expertise on research of facsimiles of various property and the content, photos (including numeral), paper pictures (photo), for definite purposes of criminal, civil or arbitration legal proceedings. Each picture contains information about the circumstances concerning procedure of manufacturing. Phototechnical expert appraisal is produced with a view of identification of objects by their images photos, photographic materials and laboratory accessories on traces on negatives and positives, ascertainment of type and mark of "unknown" photofilms, detections on photos traces of tampering, ascertainment of other circumstances linked to photographing and handling of photographic materials (photos, photographic paper).

Thus, phototechnical expert appraisal tasks are subdivided on:

- Identification - associated with identification of specific object (a picture, a negative, a film);
- Classification - associated with specific object (a photo) belonging to certain group according to existing classification;
- Diagnostic - associated with determination of object properties (a picture, the facsimile), a method of detection its manufacturer, original form recovery.

### 1.2.1 Practical tasks of identification

The immediate practical task of identification of records can be put in various variants. In practice of ascertainment and protection of copyrights, and also detections of a source of media object the most often situations are when record on the initial carrier is exposed to identification - ascertainment or a refutation of the fact of an origin of record from the presented device is required, or the record copied on other carrier (possibly with automatic format conversion, compression of dynamic range or other variants of postprocessing) is exposed to identification. In the latter case initial record obtaining, as a rule is complicated, and frequently impossible. It is required to determine a record ownership to the device presented by means of another records set certainly acquired with it.

### 1.2.2 Digital watermarking as a technique for digital media data identification

The most known decision for maintenance of such protection, in particular the rights to the media information presented in a digital form, is application of digital watermarks (DW). Robust DW represent some information which is built in readout of a signal marked by

them. DW, as a rule, contain some authentic code, the information on the proprietor or the operating information for reproduction and copying tools. Unlike usual watermarks, DW can be not only visible, but also (as a rule) invisible because by the nature DW are distortions of a signal, which is intended for perception by the person in the first place, and, hence, for preservation of consumer qualities of protected audiovisual production should be as less as possible. Invisible DW are analyzed by the special decoder which renders the decision on their presence, and if necessary, extracts the hidden message. The most suitable objects of protection by means of DW are static images, files of audio- and the video data [1-3]. DW applications are not limited to information security applications. The basis areas of DW technology can be united in four groups:

- Copy protection;
- Hidden labeling of documents;
- Proof of authenticity of the information;
- Hidden communication channels.

Definition of the received information authenticity, plays a special role in a modern information exchange. Usually the digital signature is used for authentication. However it is not quite appropriate for authentication of multimedia information. The message with attached digital signature should be stored and transferred absolutely precisely, «bit-to-bit», while multimedia information can slightly be changed both at storage (at the expense of compression and due to insufficient correcting ability of a code), and at transfer (influence of single or package errors in a communication channel). Thus its quality remains admissible for the user, but the digital signature will not work, so the addressee cannot distinguish true, though and a little changed message from the completely false one. Besides, the multimedia data can be transformed from one format to another, thus traditional means of definition of integrity also will not work.

It is possible to tell that DW are capable to protect the content of digital audio/video, instead of its digital representation in the form of sequence of bits. An essential lack of the digital signature is also that it is easy to completely remove it from the message and attach the new signature. Signature removal will allow the infringer to refuse authorship or to mislead the lawful addressee concerning authorship of the message. Modern systems of DW are projected so that to minimise possibility of similar infringements without simultaneous essential deterioration of record. DW should be robust or fragile (depending on application) to deliberate and casual influences. If DW is used for authenticity acknowledgement, inadmissible change of the container should lead to DW destruction (fragile DW). If DW contains an identification code, a firm logo, etc. it should remain at the maximum distortions of the container, of course, not leading to essential distortions of an initial signal. Thus, at use DW the basic problem are the attacks, which aim is infringement of their integrity. It is possible to distinguish the following attacks: the attacks directed on DW removal, the geometrical attacks directed on distortion of the container, cryptographic attacks, attacks against the used embedding method and DW checking procedure [4-6]. Researching new methods of embedding DW, robust against malicious attacks is base problem in researching new methods of protection of the multimedia information presented in a digital form.

Along with clear advantages of a digital watermarks embedding, its application demands inclusion of the additional block of embedding in structure of each recording device. For already existing modern mobile digital recording devices it leads to at least updating of the microprogram and it can be impossible if computing resources of the device are limited.

Besides it, embedding worsens consumer characteristics of received record that is not always tolerable, and, at special importance of originality of digital record, can be inadmissible.

Other way of authenticity ascertainment is identification on the basis of recording path features, which are presented in a digital record.

### 1.3 Digital images creation in photo cameras

The image on a photosensitive matrix of a photcamera is formed after light passage through a lens and the blurring filter (LF-filter), further postprocessing of digital signal received from a matrix [21]. At the analysis of the given circuit it is possible to select the following main sections of a recording path in digital photographic cameras which can be used for identification on a basis of features induced in resultant images [22]. The lens and bayonet joint form identifiable signs (low-frequency defects of the image, vignetting). Usage of the given signs for the automated and automatic identification is inconvenient in view of complexity of their extraction from context and built-in compensating circuits and algorithms in a majority of the modern cameras.

LF-filter ("blurring filter") is applied to lower moire formed due to space sampling by a photomatrix of image components with frequencies near and above Nyquist frequency. The filter forms average and high-frequency stable signs (the shade of the settled dust, filter spot defects). In view of it placement and, in most cases, impossibility of replacement, the features imported by it, are similar to the signs imported by the matrix. The photosensitive matrix unit with ADC forms stable signs in broad band of frequencies (additive and multiplicative noise of a matrix, defects of sensor elements - pointwise, cluster, column, line). In the majority of digital photcameras for color image forming the Bayer's [7] method is used, thus there is only one photosensitive sensor before which the lattice color filter (color filter array - CFA) is placed. Bayer's grid uses layout of filters of three primary colors allocated shown on a picture 1.3, where  $R$ ,  $G$  and  $B$  accordingly filters of red, green and blue colors. The number of pixels with filters of green color is twice more than number of pixels for red and blue components, that reflects spectral sensitivity features of a human eye. Along with base Bayer pattern there is a set of other variants of a Bayer's matrix, created for the purpose of increasing sensitivity and color rendition accuracy, generally reached at the expense of space resolution of chromaticity.

Algorithms of interpolation form average and high-frequency features (correlative dependences of adjacent pixels, context-dependent interpolation heuristics).

The non-linear processing including noise reduction, color correction, levels correction (brightness, saturation, contrast). Forms low-frequency (gamma correction) and high-frequency (increase of contour sharpness), equalizing.

Compression stage features at the given stage are features of a used format (JPEG or other) such as specific quantization matrixes, a set and placement of the metadada fields.

In the most general case for the analysis of the image received from the real camera, the only accessible image is image in one of storage formats with lossy compression. On occasion (cameras of the upper consumer segment, semiprofessional and professional) also the RAW-version of the image subjected to correction of matrix defects, or compressed by lossless compression methods (TIFF) the image which has transited all steps of processing, except compression with quality loss can be the accessible.

Thus it is possible to formulate the requirements necessary for practically applicable systems of image identification:

1. A basis of camera-by-image identification is the analysis of features leaved to area of pixels of the given image.
2. As an input image format for creation of image identifying the camera, and subsequent identification of belonging the arbitrary checked image to the camera, the most suitable is the raster format without any compression. In view of that similar formats of representation are last formats at logical level for the majority of visual information output devices. It is possible to convert any format of digital images without quality loss.

Thus, for digital photocameras it is possible to select two classes of features which could be used as a basis for identification:

1. Hardware features are reflections of deviations of characteristics of a sensor control steady in time and the subsequent units of handling, including ADC, as separate device in the received digital image. Generally sensor control signs allow to identify a specific copy of the device. In particular for digital cameras those are defects and deviations within tolerances of separate photosensitive elements, defects of elements of the unit of a photosensitive matrix [16, 20].
2. Features of postprocessing algorithms. The digital image received at output of ADC of digital cameras is then further processed. In digital cameras algorithms of the postprocessing that make the greatest impact on the resulted image are algorithms of image recovery from a mosaic (Bayer) structure of a sensor [17], algorithms of increasing contour sharpness and noise reduction. In the majority of the most widespread photocameras of the lower price segment algorithms of postprocessing can not be switched off and the only image formats accessible outside the camera are JPEG or processed TIFF.

In view of that algorithms of postprocessing are the general sometimes for all models of one vendor [16, 23], for detection by sample-unique features it is necessary to take identification on parameters of an analog section, i.e. on the first class of features.

#### 1.4 Methods of matrix data-to-image conversion

Let's consider used algorithmic primitives of interpolation the colors applied to form the color image in digital photographic cameras.

Let light filters of primary colors are allocated in Bayer's grid according to a picture 1.

The algorithms used for recovery of missing color components, are represent "know-how" of vendors and, as a rule, vary depending on model of the camera and type of a photosensitive matrix. However most often they are constructed on the basis of linear and median filtrations primitives, threshold gradients and persistence of color tone.

r(1,1)	g(1,2)	r(1,3)	g(1,4)	r(1,5)	g(1,6)	...
g(2,1)	b(2,2)	g(2,3)	b(2,4)	g(2,5)	b(2,6)	...
r(3,1)	g(3,2)	r(3,3)	g(3,4)	r(3,5)	g(3,6)	...
g(4,1)	b(4,2)	g(4,3)	b(4,4)	g(4,5)	b(4,6)	...
r(5,1)	g(5,2)	r(5,3)	g(5,4)	r(5,5)	g(5,6)	...
g(6,1)	b(6,2)	g(6,3)	b(6,4)	g(6,5)	b(6,6)	...
...	...	...	...	...	...	...

Fig. 1. Color filter array in the Bayer structure

### 1.5 Interpolation based on linear filtering

The elementary primitive of color interpolation is the algorithm of a bilinear filtration which is applied to each channel independently. For channel G ("green") the filter kernel represents:

$$k = \frac{1}{4} \begin{bmatrix} 0 & 1 & 0 \\ 1 & 4 & 1 \\ 0 & 1 & 0 \end{bmatrix},$$

And for channels "red" and "blue" accordingly:

$$k = \frac{1}{4} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}.$$

Other algorithm of the general application is bicubic interpolation, at which kernels for channels of the primary colors are the following:

$$k_G = \frac{1}{256} \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -9 & 0 & -9 & 0 & 0 \\ 0 & -9 & 0 & 81 & 0 & -9 & 0 \\ 1 & 0 & 81 & 256 & 81 & 0 & 1 \\ 0 & -9 & 0 & 81 & 0 & -9 & 0 \\ 0 & 0 & -9 & 0 & -9 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix},$$

$$k_{R,B} = \frac{1}{256} \begin{bmatrix} 1 & 0 & -9 & -16 & -9 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -9 & 0 & 81 & 144 & 81 & 0 & -9 \\ -16 & 0 & 144 & 256 & 81 & 0 & -16 \\ -9 & 0 & 81 & 144 & 81 & 0 & -9 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & -9 & -16 & 9 & 0 & 1 \end{bmatrix}.$$

### 1.6 Interpolation based on color hue constance

Color interpolation can be led also on the basis of assumptions of persistence of color tone in localized areas. Generally, selection of a color tone constant is possible considering property of orderliness of colors within a color circle. Interpolation of a constant of the color tone, offered in [7], is one of the most widespread methods used up to professional cameras. The constant of color tone is defined as a difference between the main color components. At the first stage the algorithm interpolates green channel  $G$ , using the bilinear method considered earlier. For an estimation of an error of "red" pixels bilinear interpolation of a difference  $R^*(\bullet) - G(\bullet)$ , which then incremented by  $G(\bullet)$ . The channel "blue" is recovered similarly.

### 1.7 Interpolation based on median filtering

Color interpolation can also be performed by median filtration. Application of the median filter offered in [8] is carried out in two stages. On the first by bilinear interpolation components  $R^*(\bullet)$ ,  $G^*(\bullet)$  and  $B^*(\bullet)$  are calculated, and then the difference between channels with the subsequent median filtration. Let  $M_{rg}(\bullet)$ ,  $M_{gb}(\bullet)$ ,  $M_{rb}(\bullet)$  designate differences after a median filtration. For each pixel sampling of missing colors is estimated as a difference between current value of a component and an appropriate difference after a median filtration.

Recovery of colors can be performed also by the gradient method offered in [9] and for the first time used in photocamera of Kodak DCS 200. The method is based on three-stage process which saves boundaries at interpolation led in a direction, perpendicular their orientation. In the beginning the G-channel along boundaries is interpolated. For example, in case of interpolation of "green" pixel in a position (4,4) horizontal and vertical gradients for "blue" are calculated:

$$H_{4,4} = |(b_{4,2} + b_{4,6}) / 2 - b_{4,4}|,$$

$$V_{4,4} = |b_{2,4} + b_{6,4}| / 2 - b_{4,4}.$$

If horizontal gradient  $H_{4,4}$  greater than vertical gradient  $V_{4,4}$ , it specifies to possible boundary in a horizontal direction and then interpolation of value of "green" pixel is performed only in a vertical direction:

$$G(4,4) = (g_{3,4} + g_{5,4}) / 2.$$

And on the contrary. If horizontal and vertical gradients are equal, values of pixels of the "green" channel calculated by averaging four adjacent pixels:

$$G(4,4) = (g_{3,4} + g_{4,3} + g_{4,5} + g_{5,4}) / 4.$$

Missing  $R(\bullet)$  and  $B(\bullet)$  channels are recovered by interpolation on the basis of constant color tone. For example, the missing blue component of pixels with coordinates (3,4) and (4,4) according to [10] is interpolated by following expressions:

$$B(3,4) = b_{3,3} - G(3,3) + b_{3,5} - G(3,5) / 2 + G(3,4),$$

$$B(4,4) = (b_{3,3} - G(3,3) + b_{3,5} - G(3,5) + b_{5,3} - G(5,3) + b_{5,5} - G(5,5)) / 4 + G(4,4).$$

### 1.8 Interpolation based on variable threshold gradients

The method on the basis of the variable gradients activated on a threshold (Threshold Based Variable Number of Gradient) is based on a variable amount of the gradients which usage is controlled by exceeding of threshold values. In the given primitive possibility to use gradients on all eight directions, namely in two horizontal, two vertical (N, S, E and W accordingly) and four diagonal NW, SW, NE and SE are added.

In each direction on a matrix of pixels the gradient for the selected point on the basis of an array of 5x5 adjacent pixels is calculated. The choice of a configuration of a neighborhood is

done by empirically detected feeble dependence of a difference of the calculated gradient from colors and considered pixels.

For example, vertical, horizontal and diagonal gradients for the "red" pixel allocated in a point (3,3) will be equal accordingly:

$$\begin{aligned} N &= |g_{2,3} - g_{4,3}| + |r_{1,3} - r_{3,3}| + |b_{2,2} - b_{4,2}| / 2 + |b_{2,4} - b_{4,4}| / 2 + |g_{1,2} - g_{3,2}| / 2 + |g_{1,4} - g_{3,4}| / 2 \\ E &= |g_{3,2} - g_{3,4}| + |r_{3,3} - r_{3,5}| + |b_{2,2} - b_{4,2}| / 2 + |b_{4,2} - b_{3,4}| / 2 + |g_{2,3} - g_{2,5}| / 2 + |g_{4,3} - g_{4,5}| / 2 \\ SW &= |b_{2,4} - b_{4,2}| + |r_{5,1} - r_{3,3}| + |g_{2,3} - g_{3,2}| / 2 + |g_{3,4} - g_{4,3}| / 2 + |g_{3,2} - g_{4,1}| / 2 + |g_{4,3} + g_{5,2}| / 2. \end{aligned}$$

On the basis of a set containing 8 gradients, threshold  $T$  is calculated, allowing to define, what directions were used.  $T$  it is defined as  $T = k_1 \cdot \min + k_2 \cdot (\max - \min)$ , where  $\min$  and  $\max$  are the minimum and maximum gradients accordingly, and  $k_1$  and  $k_2$  constants. Author's values are  $k_1=1,5$  and  $k_2=0,5$ . Those directions which gradient is less than a threshold are selected, and for each selected direction mean values for "blue", "red" and "green" are calculated. For example, at coordinates (3,3) mean values for directions N, E, SW are the following:

$$R^N = (r_{1,3} + r_{3,3}) / 2, G^N = g_{2,3}, B^N = (b_{2,2} + b_{2,4}) / 2,$$

$$R^E = (r_{3,3} + r_{3,5}) / 2, G^E = g_{3,4}, B^E = (b_{2,4} + b_{4,4}) / 2,$$

$$R^{SW} = (r_{3,3} + r_{5,1}) / 2, G^{SW} = (g_{3,2} + g_{4,1} + g_{4,3} + g_{5,2}) / 4, B^{SW} = b_{4,2}.$$

Let's designate mean values red, blue and green as  $R_{avg}$ ,  $G_{avg}$ ,  $B_{avg}$  accordingly. Then for the selected pixel mean averaging values for red, dark blue and green in the selected directions will be:  $R_{avg} = (R_s + R_E + R_{SE}) / 3$ ,  $G_{avg} = (G_s + G_E + G_{SE}) / 3$ ,  $B_{avg} = (B_s + B_E + B_{SE})$  (for pixel (3,3) and directions S, E, SE). A final estimation of missing color components levels are:  $G(3,3) = r_{3,3} + (G_{avg} - R_{avg})$  and  $B(3,3) = r_{3,3} + (B_{avg} - R_{avg})$  [11].

## 2. Cameras identification techniques

### 2.1 Camera identification based on artifacts of color interpolation

There are several approaches to the implementation of identification systems for digital cameras based on the above characteristics.

In [12] cameras identification is done based on color interpolation features. The recognition process involves the following steps.

Designating  $I(\cdot)$  as one of  $R(\cdot)$ ,  $G(\cdot)$ ,  $B(\cdot)$  channels provided that the pixel in coordinates  $(x, y)$  is correlated linearly with other pixels, it is possible to express value of brightness of a color component as the weighed total of brightness of components of adjacent pixels:

$$I(x, y) = \sum_{i=1}^N \alpha_i I(x + \Delta x_i, y + \Delta y_i), \quad (1)$$

Where  $N$  is a number of correlated pixels,  $\alpha_i$ ,  $\Delta x_i$ ,  $\Delta y_i$  - weight and offset on an axis  $x$  and an axis  $y$  of the pixel correlated from  $i$  th pixel accordingly. The set of such coordinates  $\Delta x_i$ ,  $\Delta y_i$

allocated between  $1 \leq i \leq N$  is considered as a set of the pixels correlated with adjacent pixels. Considering periodic layout of filters (lattice filters - color filter array (CFA) the given correlations will show periodicity. Being based on it in considered article the assumption about identity of scales of pixel sets with different  $x$  and  $y$  that a set of the correlated pixels, and according to their weight for each pixel in  $I(\bullet)$  are identical.

Let's consider the right member of equation (1.1) as *filter*  $F$  applied to  $I(\bullet)$ , designating operation of a filtration  $F(I(\bullet))$  as well as summed averaged square errors from both sides from  $I(\bullet)$ , we receive:

$$MSE(F(I(\bullet))) = \frac{1}{WH} \sum_{x=1}^W \sum_{y=1}^H \left| \sum_{i=1}^N \alpha_i I(x + \Delta x_i, y + \Delta y_i) - I(x, y) \right|^2 \tag{2}$$

Where  $H$  and  $W$  - height and width of an image accordingly. Adding the virtual correlated pixel  $\alpha_{N+1} = -1, \Delta x_{N+1} = \Delta, y_{N+1} = 0$ , the equation (1.2) assumes more arranged air:

$$MSE(F(I(\bullet))) = \frac{1}{WH} \sum_{x=1}^W \sum_{y=1}^H \left| \sum_{i=1}^N \alpha_i I(x + \Delta x_i, y + \Delta y_i) \right|^2 \tag{3}$$

The extension of the equation (1.3) gives the square form rather  $X = \{\alpha_1, \alpha_2, \dots, \alpha_{N+1}\}^T$ :

$$MSE(F(I(\bullet)), I(\bullet)) = X^T A X,$$

Where

$$A(i, j) = \frac{1}{WH} \sum_{x=1}^W \sum_{y=1}^H I(x + \Delta x_i, y + \Delta y_i) \cdot I(x + \Delta x_j, y + \Delta y_j), \quad 1 \leq i, j \leq N + 1.$$

The coefficient of a matrix  $A$  contains the full information for determination of variable vector  $X$ , however, in article obtaining  $X$  optionally and for the further analysis enough matrix affirms that  $A$ .

It was empirically revealed that the correlated pixels mask shown in a figure 2, yields good result ( $N=12$ ).

On a following step the analysis of principal components is done.

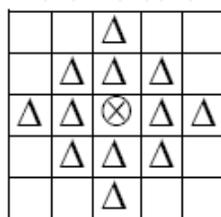


Fig. 2. Correlated pixels mask, where  $\otimes$  – is a center and  $\Delta$  – correlated pixels

Numerical values of elements  $A$  after obtaining are normalized:

$$A^*(i, j) = [A(i, j) - \bar{A}] / \bar{A},$$

$$(1 \leq i, j \leq N + 1),$$

Where

$$\bar{A} = \frac{1}{(N+1)^2} \sum_{1 \leq i, j \leq N+1} A(i, j).$$

Let  $A^*$  it is  $N^2$ -dimensional vector of signs  $\beta$ . Accepting total number of vectors for training of neural network as  $L$   $\{\beta_1, \beta_2, \dots, \beta_L\}$  and their average according:

$$\begin{aligned} \bar{\beta} &= \frac{1}{L} \sum_{i=1}^L \beta_i, \\ \beta_i^* &= \beta_i - \bar{\beta}, \\ i &= 1, 2, \dots, L. \end{aligned}$$

The covariace matrix will be:

$$C = [\beta_1^*, \beta_2^*, \dots, \beta_L^*][\beta_1^*, \beta_2^*, \dots, \beta_L^*]^T / (L-1).$$

Let eigenvalues and eigenvectors  $C$  -  $\{\lambda_1, \lambda_2, \dots, \lambda_L\}$  and  $\{\xi_1, \xi_2, \dots, \xi_L\}$ ,  $\{\zeta_1 \leq \zeta_2 \leq \dots \zeta_{L-1} \leq \zeta_L\}$  accordingly.

Eigenvectors corresponding  $M$  greatest eigenvalues, form a vector of features  $V = [\lambda_1, \lambda_2, \dots, \lambda_M]^T$ . The experiments led by authors, shown that  $M=15$  is enough.  $\beta_i^*$  as a result transforms to  $\Gamma_i = V\beta_i^*$  with dimensionality reduction. Recognition of the image belonging to the specific camera was carried out by trained neural network of direct propagation with 15 input neurons, 50 neurons in the hidden layer (with tangential activation function) and one output neuron (sigmoidal activation function). If we denote a set of color interpolation algorithms  $D$ :  $D^* = D \cup \{\emptyset\}$  where  $\emptyset$  is the empty set corresponding initial  $I(\cdot)$ . Identification by color interpolation consists in defining conversion  $d \in D^*$  which with the greatest probability has been fulfilled over  $I(\cdot)$ , i.e. the purpose is to reference available  $I(\cdot)$  to one of classes  $|D^*|$  of the learning images set nearest to  $I(\cdot)$ , in space of conversion characteristics of debayerization. Thus, to each class of images one neural network should be set in correspondence. To select total number of neural networks the following conditions according to authors is necessary to consider. For the different  $d_i$  it is necessary to use different neural networks ( $d_1, d_2 \in D^*, d_1 \neq d_2$ ) considering essential difference of debayerization operators, applied to the channel of "green" and channels "red"/"blue" should use different neural networks for each color component. By authors of a method the best result were shown when three networks was used, one for each channel. Thus the total of neural networks makes  $|D^*| = |D| + 1$  for each channel and  $3(|D| + 1)$  totally [12]. The given method does not depend on color channels used for identification, on each channel the independent decision which is pseudo-independent, as channels are mutually correlated as shown in [13-14]. Accuracy of identification has been checked by authors on learning and test samplings on 100 images [13]. Accuracy of recognition of 7 algorithms of the interpolation was 100 % (errors of the first and second type are equal to zero). Accuracy of classification by offered methods of real photocaleras made 95-100 % depending on a

photocamera. The method also can be used for check on authenticity of pictures since in those areas at which there are signs of editing the responses of neural network increase by 2-3 times. However, usage of replaced fragments of the image from the same photocamera as a background makes detection impossible [15]. Mehdi Kharrazi, etc. in [16] proposed the method of photocameras identification on the basis of image features. The task of determination of the camera with which help the analyzable picture has been received was thus considered. Proceeding from known sequence of information processing from a photosensitive matrix, it is possible to select two stages, importing the most essential distortions: a stage of debayerization, i.e. full-color image restoration and a postprocessing stage. Totally authors select 34 signs of classification, among them:

- Cross-channel correlation R-G, R-B, B-G (3 scalar features).
- Center of mass for histograms of differences number of pixels with  $i$ ,  $i+1$  and  $i-1$  values (3 scalar features).
- Channelwise power channel wise ratio of color components:

$$E_1 = \frac{|G|^2}{|B|^2}, E_2 = \frac{|G|^2}{|R|^2}, E_3 = \frac{|B|^2}{|R|^2}.$$

- statistics of wavelet transform (subspace decomposition by quadrature mirror filters and averaging each sub-band) (9 features).

Along with enumerated features metrics of image quality proposed in [16] has been used. All used metrics can be divided into following groups:

- pixelwise difference metrics (MSE, AMSE).
- correlation metrics (for example normalized mutual correlation).
- spectral difference metrics.

To classify vectors the SVM-based classifier has been used. At learning stage 120 of 300 images were used, with 180 at test stage. An average accuracy of camera identification in "1 out of 2" were 98,73% with 88,02% when images were regular photos.

In [17] an identification method based on proprietary interpolation algorithms used in camera. The basis of algorithm is pixel correlation estimation listed in [18] with two estimations: estimation of pixel value by adjacent pixels' values and demosaic kernel used for raw data processing. As precise configuration of area used for interpolation is unknown, several different configurations were used, with additional assumption about different interpolation algorithms used in gradient and texturized areas. Camera identification experiments were done on a basis of two cameras: Sony DSC-P51 и Nikon E-2100. It has been acknowledged that filter kernel increase leads to accuracy increase (for kernels 3x3, 4x4, 5x5, accuracies were from 89.3 to 95.7%).

## 2.2 Camera identification based on matrix defects

Camera identification based on postprocessing algorithms features possess several disadvantages, the most fundamental is impossibility of practical use for one-model camera identification, even in "1 of 2" case.

In [19] camera identification method based on defective ("hot" and "dead" pixels) are presented but its effectiveness is limited for cameras without build-in pixel defects correction and "dark frame" subtraction.

Camera identification based on dark frame correction along with obvious advantage of identification of concrete camera sample inherent critical disadvantage namely requirement of dark frames to identify cameras, which makes this method nearly completely useless in practical sense.

In [20] the camera identification method based on non-uniformity of pixel matrix namely different photosensitivity of pixels.

There are many sources of defects and noises which are generated at different image processing stages. Even if sensors form several images of absolutely static scene, the resulted digital representations may possess insignificant alterations of intensity between "same pixel" of image. It appears partly from shot noise [14,15] which is random, and partially because of structure non-uniformity, which is deterministic and slowly changed across even very large sets of image for similar conditions.

Structural non-uniformity presented in every image and can be used for camera identification. Due to similarity of non-uniformity's nature and random noise it is frequently named structural noise.

By averaging multiple images context impact is reduced and structural noises are separated structural matrix noise can be viewed as two components – fixed pattern noise (FPN) and photo-response non-uniform noise (PRNU). Fixed pattern noise is induced by dark currents and defined primarily by pixels non-uniformity in absence of light on sensitive sensor area. Due to additive nature of FPN, modern digital cameras suppress it automatically by subtracting the dark frame from every image [14]. FPN depends on matrix temperature and time of exposure. Natural images primary structural noise component is PRNU. It is caused by pixels non-uniformity (PNU), primarily non-uniform photosensitivity due to non-homogeneity of silicon wafers and random fluctuations in sensor manufacturing process. Source and character of noise induced by pixels non-uniformities make correlation of noise extracted from two even identical matrixes small. Also temperature and humidity don't render influence to PNU-noise. Light refraction on dust particles and optical system also induced its contribution to PRNU-noise, but these effects are not stable (dust can migrate over the matrix surface, vignette type changes with focal length or lens change) hence, can't be used for reliable identification.

The model of image obtaining process is the following. Let absolute photon number on pixel's area with coordinates  $(i, j)$  corresponds  $x_{ij}$ , where  $i = 1..m, j = 1..n, m \times n$  – photosensitive matrix resolution. If we designate shooting noise as  $\eta_{ij}$ , additive noise due to reading and other noises as  $\varepsilon_{ij}$ , dark currents as  $c_{ij}$ . Then sensor's output  $y_{ij}$  is:

$$y_{ij} = f_{ij}(x_{ij} + \eta_{ij}) + c_{ij} + \varepsilon_{ij}. \quad (*)$$

Here  $f_{ij}$  is almost 1 and is multiplicative PRNU-noise.

Final image pixels  $p_{ij}$  are completely formed after multiple-stage processing of  $y_{ij}$  including, interpolation over adjacent pixels, color correction and image filtering. Many of that operations are non-linear like gamma correction white balance estimation, adaptive Bayer structure interpolation based on strategies for missing color recoveries. So:

$$p_{ij} = P(y_{ij}, N(y_{ij}), i, j),$$

where  $P$  is a non-linear function of pixel's value, its coordinates and its neighborhood  $N(y_{ij})$ .

Structure noise can be suppressed by subtracting additive noise  $c_{ij}$ , then dividing pixels value by normalized frame's values:

$$x'_{ij} = (y_{ij} - c_{ij}) / f_{ij}',$$

where  $x'_{ij}$  is a corrected pixels value,  $f_{ij}'$  is an approximation of  $f_{ij}$  by averaging multiple flat-exposure frames  $f_{ij}^{(k)}$ ,  $k = 1..K$  :

$$f_{ij}' = \frac{\sum_k f_{ij}^{(k)}}{\sum_{i,j,k} f_{ij}^{(k)}} m \cdot n.$$

This operation cannot be done on  $p_{ij}$ , only over raw data from photosensitive matrix  $y_{ij}$  prior successive image processing.

Properties of pixel non-uniformity noise

To get better understanding influence of structural noise onto resulted images and determine its characteristics in the following experiments were done:

Using ambient light 118 images were made on Canon camera with automatic exposure and focused on infinity. White balance was set to create neutral gray images.

All obtained images possessed pronounced brightness gradient (vignetting). To eliminate that low-frequency distortion the HF-filter with cutoff frequency at  $(150/1136)\pi$ . Then images were averaged thus random noise was suppressed and structural noise summed. Spectrum of the signal resembles white spectrum with decrease of HF-components area, which is explainable as consequences of color interpolation over pixel neighborhood. PNU-noises are not presented in saturated and completely dark areas where FPN prevails. Owing to noise-like of the PNU-components of matrix noise, it is natural to use correlation method for its detection [16].

### 2.3 Identification based on non-uniformity of pixels sensitivity

In the absence of access in consumer-grade cameras to sensors output  $y_{ij}$ , usually it is impossible to extract PNU from gray-frame. However it is possible to approximate noise by averaging multiple images  $p(k)$   $k= 1, \dots, Np$ . Process speed-up is performed by filtering and averaging of residual noise  $n(k)$ :

$$n^{(k)} = p^{(k)} - F(p^{(k)}).$$

Other advantage of operation with residual noise that low-frequency component of PRNU is automatically suppressed. It is obvious that, the more the number of images ( $N > 50$ ), the less influence of the single source image will take place. Originally, the filter based on wavelet transform was used. So advantages of this method are:

- No access to internals of camera is required;
- Applicable to all cameras built on the basis of photosensitive matrixes.

## 2.4 Detection based on correlation coefficient

To detect image  $p$  belonging to specific camera  $C$  it is possible to calculate correlation  $\rho_C$  between residual and structural noise  $n=p-F(p)$  for the camera:

$$\rho_C = \text{corr}(n, P_C) = \frac{(n - \bar{n})(P_C - \bar{P}_C)}{\|n - \bar{n}\| \|P_C - \bar{P}_C\|}.$$

Now it is possible to define distribution  $\rho_C(q)$  for different images  $q$  made by the camera  $C$  and distribution  $\rho_C(q')$  for images  $q'$  made not by the camera  $C$ . Based on Neumann-Pirson approach and minimizing error rate the reached accuracy of classification made from 78 % to 95 % on 320 images from 9 digital cameras.

## 2.5 Identification technique of digital recording devices based on correlation of digital images

For development of a technique of identification of photocameras under images it is necessary to consider architecture of prospective system of identification. The system includes units:

- Input format converter;
- Detector of container modifying;
- Feature vector former;
- Feature vector saving;
- Feature vector search and extraction;
- Device identification.

An input format for identification system should be lossless format like full-color BMP to which all images and video streams are convertible. Typical output formats of modern cameras are JPEG and TIFF. In the feature vector former, digital image is converted to the feature vector represents an image for identification an storage purposes.

In the unit of device identification the estimation of likeness of two or more vectors is estimated allowing to accept or reject device similarity hypothesis.

### 2.5.1 Feature vector forming for digital cameras identification

Feature vector former is based on photosensitive matrix identification techniques, namely PRNU-features. As there will always be both signal and noise (PRNU-components and image context and (or) other noises) it is preferable to use filters to increase signal-noise ratio. To select HF-components, which represent PRNU can be done by Wiener filtering:

$$\begin{aligned} \mu &= \frac{1}{NM} \sum_{n_1, n_2 \in \eta} a(n_1, n_2) \\ \sigma^2 &= \frac{1}{NM} \sum_{n_1, n_2 \in \eta} a^2(n_1, n_2) - \mu^2 \\ b(n_1, n_2) &= \mu + \frac{\sigma^2 - v^2}{\sigma^2} (a(n_1, n_2) - \mu), \end{aligned}$$

where  $N$  and  $M$  are number of pixels of neighborhood by  $y$  and  $x$  axis respectively.

$a(n_1, n_2)$  – is a value of pixel with  $(n_1, n_2)$  coordinates.

Thus averaged values for specific matrix is:

$$W_{approx} = \frac{\sum (I - F(I))}{N},$$

where  $F(I)$  is a filter operation.

The best results were achieved by  $5 \times 5$  mask. It has been shown that Wiener filter provides better separation, comparing with wavelet transform filter in [21]. The offered identification technique has been researched for identification possibility of 13 cameras [22-27], each with 100 images. Images from every camera were divided into 2 sets - training set used for camera fingerprinting and the test set, used for identity check [21]. The central crop of an image with 1024x1024 pixels size was used for identification purposes.

To process an image  $I$  for fingerprint creation or identification the color-to-grayscale conversion has been applied. Fingerprint is an averaged sum of all HF-components, forming  $W_{approx}$  value. To check identity of an image  $I_q$ , the correlation coefficient is evaluated:

$$p = cc(F(I_q), W_{approx}),$$

where  $p$  – is a correlation coefficient, and  $cc$  – cross correlation.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	<b>0.0908</b>	0.0010	0.0042	0.0004	0.0037	0.0026	0.0028	0.0020	0.0040	0.0033	0.0031	0.0032	0.0035
2	0.0006	<b>0.1494</b>	-0.0001	0.0015	0.0005	0.0006	-0.0001	0.0000	0.0005	0.0003	0.0004	0.0001	0.0007
3	0.0028	-0.0001	<b>0.1364</b>	0.0003	0.0018	0.0004	0.0017	0.0020	0.0030	0.0023	0.0017	0.0024	0.0016
4	-0.0001	0.0009	-0.0004	<b>0.1889</b>	0.0002	-0.0007	-0.0004	-0.0009	-0.0000	-0.0003	-0.0007	-0.0001	-0.0005
5	0.0054	0.0019	0.0035	0.0000	<b>0.0727</b>	0.0025	0.0042	0.0024	0.0044	0.0022	0.0033	0.0029	0.0038
6	0.0022	0.0004	0.0004	0.0000	0.0015	<b>0.1423</b>	0.0006	0.0001	0.0016	0.0009	0.0013	0.0007	0.0036
7	0.0010	-0.0007	0.0005	-0.0001	0.0010	0.0001	<b>0.2645</b>	-0.0012	0.0010	0.0008	0.0012	0.0017	0.0014
8	0.0003	0.0008	0.0009	-0.0001	0.0004	-0.0001	-0.0005	<b>0.7079</b>	0.0000	0.0012	-0.0001	0.0009	-0.0005
9	0.0049	0.0004	0.0046	0.0001	0.0031	0.0018	0.0027	0.0029	<b>0.1038</b>	0.0017	0.0033	0.0036	0.0019
10	0.0027	0.0013	0.0031	0.0002	0.0023	0.0015	0.0017	0.0032	0.0025	<b>0.1005</b>	0.0090	0.0030	0.0014
11	0.0011	0.0007	0.0020	-0.0010	0.0013	0.0004	0.0012	-0.0002	0.0006	0.0013	<b>0.3776</b>	0.0006	0.0007
12	0.0025	0.0002	0.0023	-0.0006	0.0018	0.0004	0.0023	0.0016	0.0028	0.0016	0.0020	<b>0.1294</b>	0.0016
13	0.0015	0.0001	0.0010	-0.0006	0.0017	0.0022	0.0009	-0.0006	0.0008	0.0009	0.0009	0.0003	<b>0.2747</b>

Table 1. An averaged correlation coefficients for 13 cameras.

On intersection of columns and lines with identical indexes there are correlation coefficients of images and a fingerprint, received by the same camera. Thus, at matrix coincidence, correlation value is 0.1 - 0.7 and for incoincident cameras is 0.001 - 0.054.

## 2.6 Image rotation detection based on Radon transform

Photosensitive matrix of a modern digital camera naturally possesses non-uniformity of its elements, both photosensitive and signal amplifiers. As the charge is transferred by columns, the well-known phenomena called banding occurs, resulting high-frequency noise. After image reconstruction process [3] and subjective quality improvements completing, the resulted image is compressed, usually according to JPEG standard, which introduces blocking effect, and contributes regular pattern to rows and columns as well.

This phenomena can be used to detect angle of rotation. To detect an angle of image rotation the Radon transform of its fragment could be performed with successive analysis of Radon projections with Fourier transform. Radon transform can be defined as follows: Let function  $f(x, y)$ , is defined in  $D$ . We will consider some straight line  $L$  on a plane  $xy$ , crossing area  $D$ . Then, integrating function  $f(x, y)$  along line  $L$ , we receive a projection or linear integral of function  $f$ . Integration along all possible lines  $L$  on a plane allows to define Radon transform:

$$f^* = Rf = \int_L f(x, y) ds,$$

where  $ds$  - an increment of length along  $L$ .

For minimization of edge effects impact of analyzed area on high-frequency part of an image it is advisable to apply Radon transform over circular fragment with smoothed borders. Selection of a fragment from the image and smoothing of its borders were done [4] by normalized two-dimensional Gaussian window

$$h(t) = \frac{\exp\left(\frac{-t^2}{2\delta^2}\right)}{\sqrt{2\pi} \cdot \delta}$$

$$\delta = \frac{\sqrt{\ln(2)}}{2\pi BT}$$

shown in figure 3.

Refinement to an angle which  $90^\circ$  degrees multiple is possible to make due to uncompensated banding traces, which are consequences of non-uniformity of image brightness component obtained from CCD or CMOS matrixes [2] and traces of compression artifacts. A consequence of the given phenomenon will be unequal level of maxima of a Fourier spectrum obtained from result of Radon transform that allows to select only 2 or (in some cases) 4 angles. Examples of columns spectrograms for a matrix of Radon transformed image fragment 1024x1024 pixel size are represented in figure 4.

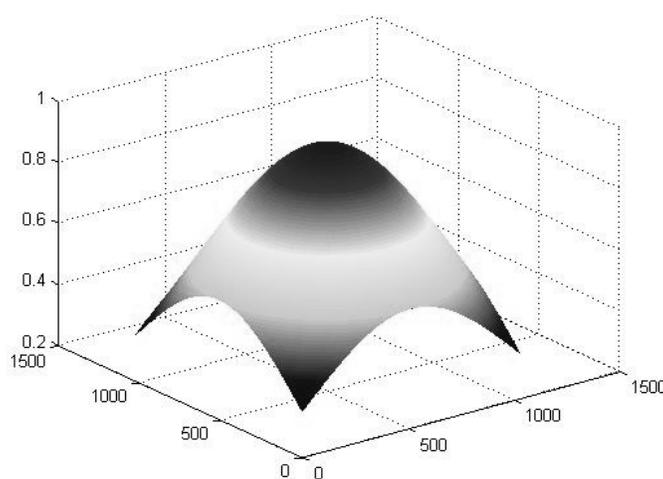


Fig. 3. Two-dimensional normalized Gaussian window used to select an image fragment

In drawing there are maxima at values of rotating angle with added  $90^\circ$  multiples.. At transition from a corner  $89^\circ$  to a corner  $90^\circ$  occurrence of maxima in a peak spectrum is observed. Similar change of character of a peak spectrum gives a possibility to establish value of a image rotation degree.

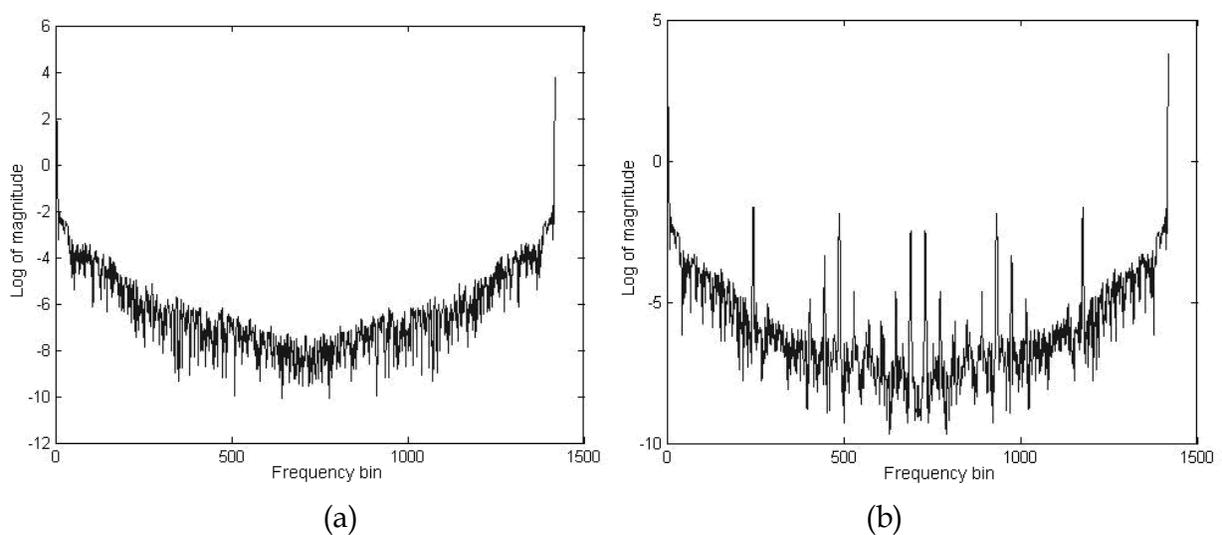


Fig. 4. Spectrums of the projections corresponding to angles  $89^\circ$  and  $90^\circ$  (a-b) for  $1024 \times 1024$  pixels image fragment

Result (an average of a spectrum for the Radon-transformed image for projection angles from  $0^\circ$  to  $360^\circ$  with  $10^\circ$  step) is presented in figure 5 and a dissection of it – an average of Radon projection spectrograms for image fragment  $1024 \times 1024$  pixels in figure 5. Local maximums at  $10^\circ$ ,  $100^\circ$ ,  $190^\circ$ ,  $280^\circ$  in figure 6 correspond diagonally-placed maximums in figure 6. To determine the influence of image size change (resize operation), defined as the relation of the linear sizes of the initial image to resulted one on possibility of rotation detection by Radon transform, different scales of original image has also been investigated.

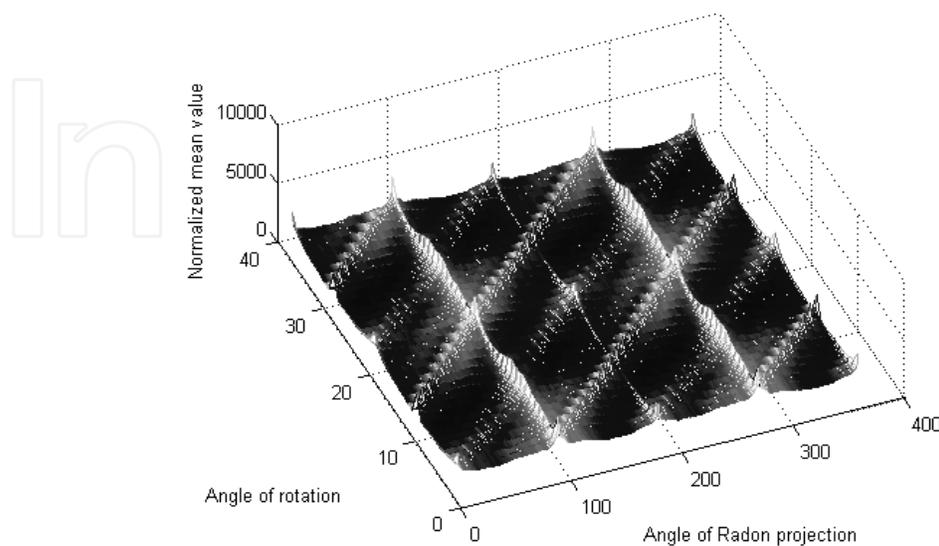


Fig. 5. An average of a spectrum of capacity of transformation of Radon (corners from  $0^\circ$  to  $360^\circ$ ) at corners of turn from  $0^\circ$  to  $360^\circ$  with step  $10^\circ$

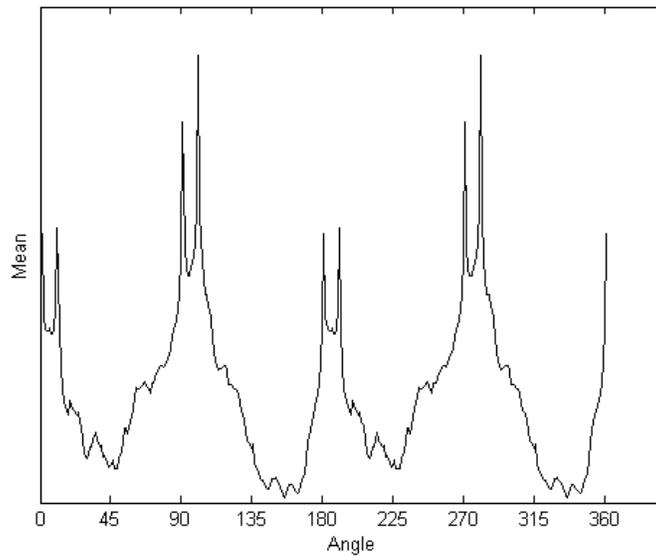


Fig. 6. An average of the spectrogram of projections of Radon of a fragment of the image dimension 1024x1024 pixel for corners from 0 to 360°

In figure 7 the two-dimensional dependence diagram of a magnitude average calculated on a set of image Radon transforms is shown where peak of normalized averaged spectrum located at 10° of Radon transform for angles from [5°..15°], applied to the image with an initial rotation angle of 10° and image scaling factor varied from 1 to 0,1 by 0,1 step. Even at 0.2 scale coefficient the maximum, which corresponds to correct rotation angle, is visible, so rotation operation can be undone. In figure 6 values of spectrogram average of Radon transform (rotation angles from (0°..20°)) for 80 images obtained from one camera and rotated by 10° (a) with histograms (b) are shown.

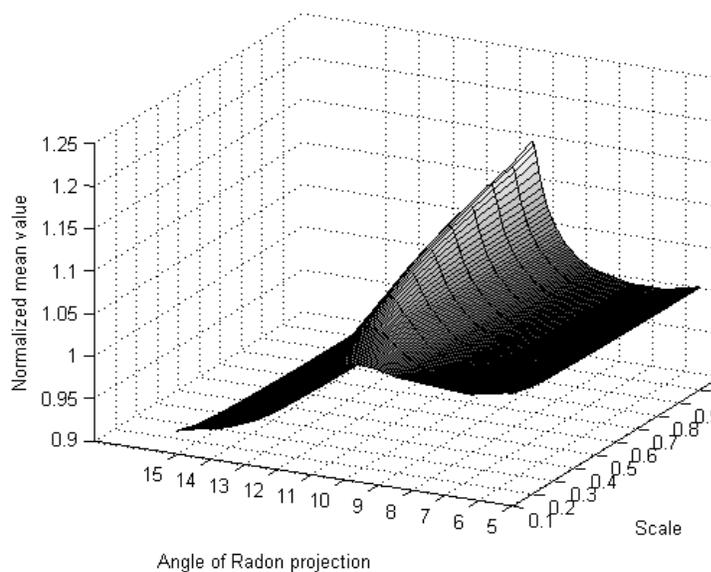


Fig. 7. Dependence of a normalized mean value of averaged spectrum on scaling factor and angle of a Radon projection

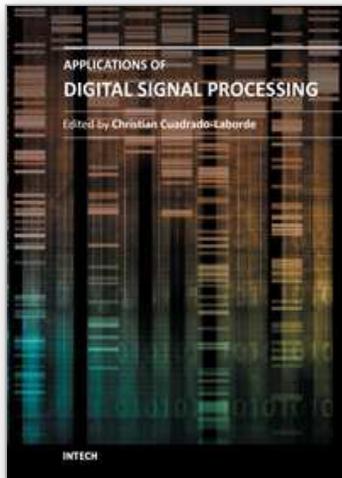
### 3. Conclusion

The methods of digital cameras identification allow defining the fact of origin of digital images from the specific camera. In comparison with artificial digital watermarks embedded by either the special software, or device modification, identification based on innate difference of every single camera allows to identify cameras by the analysis of statistical regularities in digital media. Explicit advantages of the given identification methods are their applicability to images of consumer cameras without necessity of internals access or camera firmware modification. Methods of cameras identification on the basis of processing differences allow to identify cameras vendors. Methods of identification based on non-uniformities of record path allow to identify separate copies of one model of camera. Essential hindrance for correct identification of cameras is scaling and rotation of the images which are exposed to identification process. To ascertain the fact of rotation and its reversing the Radon transform with the subsequent projections processing by Fourier transform can be used.

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## **Applications of Digital Signal Processing**

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In this book the reader will find a collection of chapters authored/co-authored by a large number of experts around the world, covering the broad field of digital signal processing. This book intends to provide highlights of the current research in the digital signal processing area, showing the recent advances in this field. This work is mainly destined to researchers in the digital signal processing and related areas but it is also accessible to anyone with a scientific background desiring to have an up-to-date overview of this domain. Each chapter is self-contained and can be read independently of the others. These nineteenth chapters present methodological advances and recent applications of digital signal processing in various domains as communications, filtering, medicine, astronomy, and image processing.

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