Sensors and Actuators A 198 (2013) 113–118

Contents lists available at SciVerse ScienceDirect

Sensors and Actuators A: Physical

journal homepage: www.elsevier.com/locate/sna

On the recognition of wood slices by means of blur invariants

Jan Flusser*, Tomáš Suk, Barbara Zitová

Institute of Information Theory and Automation, Academy of Sciences of the Czech Republic, Pod vodárenskou věží 4, 182 08 Praha 8, Czech Republic

ARTICLE INFO

Article history:
Received 15 October 2012
Received in revised form 24 April 2013
Accepted 24 April 2013
Available online xxx

Keywords:
Wood slice recognition
Motion blur
Moment invariants
Blur invariants

ABSTRACT

In the recent paper [6] the authors presented an automatic system for visual recognition of wood slices, which are placed on a moving platform. The original method was based on moment invariants. In this comment we explain the mistakes of the method and show how to properly use moment invariants in a wood-slice recognition system. This correction immediately leads to an increase of the recognition rate.

1. Introduction

This paper is a comment on the paper [6] published recently in this journal. In [6], the authors proposed an automatic system for recognition of wood slices depending on their color and texture. The wood specimens are placed on a platform or belt, which is moving linearly with a constant velocity. The down-looking camera is fixed above the platform and connected to the computer.

As the authors correctly realized, in this setup the images are degraded by so-called "blur", under which the fine texture of the specimen disappears and the recognition is more difficult. The primary source of the blur is the relative motion of the specimen and the camera. Potential wrong focus and diffraction also contribute to the blur. The blur can be (at least approximately for a flat scene, constant velocity and short acquisition time, which is the case here) modelled by a 2D convolution

$$g(x, y) = (f * h)(x, y) \tag{1}$$

where $g(x, y)$ is the observed blurred image of the object $f(x, y)$ and $h(x, y)$ is the *point-spread function* (PSF) of the system, which fully characterizes the blur. In practice, $h(x, y)$ is a composition of (usually few) particular PSF's corresponding to the individual blurring factors: $h = h_1 * h_2 * \ldots * h_K$. However, the authors of [6] consider all blur sources other than motion and defocus negligible, which may be true in case of their measurement device.

The parametric form of the motion-blur PSF is known. In case of a linear horizontal motion the PSF has the following form:

$$h(x, y) = \begin{cases} \dfrac{1}{vt}\delta(y) & \Leftrightarrow 0 \le x \le vt \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where v is the motion velocity, t is the exposure time and δ is a Dirac function (see Fig. 1). If the motion vector has another direction, the PSF is just rotated accordingly. If an out-of-focus blur was also present, its particular PSF would be a cylinder whose radius determines the size of the blur, and the composite PSF would be a convolution of these two particular PSF's.

The authors of [6] also correctly pointed out that, in order to beat the blur effect, the recognition should either be performed after the images had been restored or, alternatively, it can be based on image features which are not affected by blur. Since the image restoration is relatively slow (even the simplest non-iterative algorithms require at least three Fourier transforms of the full-size image) and vulnerable to noise, we agree with the authors that the second option is the right choice.

The features which can be used for this purpose are called *blur invariants* and were introduced by Flusser et al. [2,1]. This blur-invariant solution is much faster than the restoration approach (the time superiority of the invariants was in [6] verified experimentally) since the features are calculated directly from the blurred image. Unlike the restored image, they do not provide a complete information but they are sufficient for recognition purposes.

However, in [6] a very important point was ignored: the blur invariance of these features is a direct consequence of the *symmetry* of the PSF. Different invariants exist for PSF's with different symmetries. Invariants for centrosymmetric PSF were published in [1],

* Corresponding author.
E-mail addresses: flusser@utia.cas.cz (J. Flusser), suk@utia.cas.cz (T. Suk), zitova@utia.cas.cz (B. Zitová).

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http://dx.doi.org/10.1016/j.sna.2013.04.035

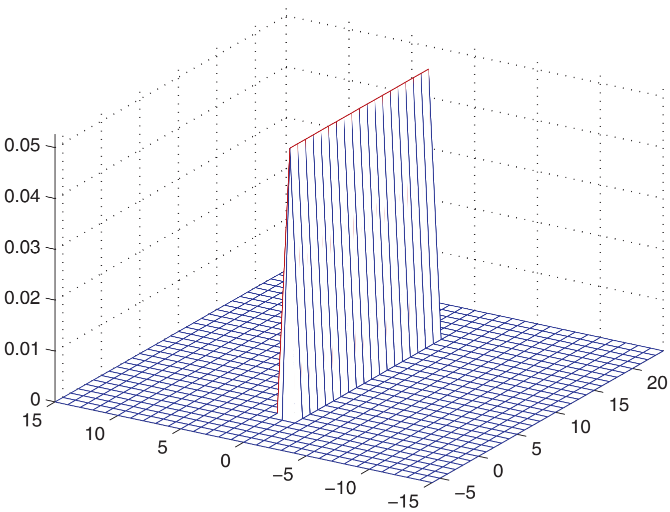

Fig. 1. The PSF of a horizontal motion blur of the length 20 pixels.

for PSF symmetric w.r.t. both axes and diagonals in [2], for PSF with circular symmetry in [5], and for motion blur, Gaussian blur and PSF having N-fold rotation symmetry in [4] (see Fig. 2 for symmetry examples). It is necessary to use only invariants corresponding to the actual shape of the PSF, otherwise the invariance property is violated and the system performance decreases. Unfortunately, in [6] the authors applied invariants designed for axial and diagonal symmetry adopted from [2] to the recognition of images, blurred by the motion blur and combined motion-defocus blur. This is incorrect because neither motion nor motion-defocus blur have such a symmetry and this choice diminishes the recognition rate.

The aim of this paper is to explain how to choose proper invariants for motion and combined motion-defocus blur and, consequently, how to increase the performance of the recognition system. We believe this is helpful for all users who want to use or re-implement the system proposed in [6].

2. The basics of blur invariants

Blur invariants are functions of the image moments. They can be defined for any kind of moments [7] but for simplicity let us stay with *geometric moments* only. Anyway, no other kind of moments was considered in [6]. *Central* geometric moment of image f is defined as

$$\mu_{pq}^{(f)} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x - x_c)^p (y - y_c)^q f(x, y)\,dx\,dy, \tag{3}$$

where x_c, y_c are the coordinates of the image centroid. Central moments are invariant to translation.

Under convolution, the central moments are transformed as

$$\mu_{pq}^{(g)} = \sum_{k=0}^{p}\sum_{j=0}^{q} \binom{p}{k}\binom{q}{j} \mu_{kj}^{(h)} \mu_{p-k,q-j}^{(f)}. \tag{4}$$

For each particular kind of symmetry, certain moments of the PSF are zero. This allows us to properly combine the moments of

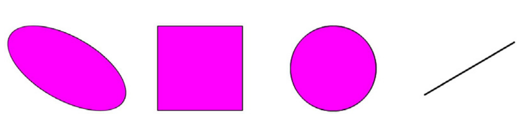

Fig. 2. Examples of the PSF symmetries – central symmetry, symmetry w.r.t. both axes and diagonals, circular symmetry, motion blur. Specific blur invariants exist for each particular case.

the blurred image and in this way to eliminate all the non-zero moments of the PSF and to obtain the desired invariance (see [4] for details).

3. Invariants to motion blur

In [6] it is proposed to use the following invariants of the 4th and 5th order which were borrowed from [2].

- 4th order:

$$B(1,3) = \mu_{13} - \frac{3\mu_{02}\mu_{11}}{\mu_{00}},$$

$$B(3,1) = \mu_{31} - \frac{3\mu_{20}\mu_{11}}{\mu_{00}},$$

$$B(4,0) = \mu_{40} - \mu_{04} - \frac{6\mu_{20}(\mu_{20} - \mu_{02})}{\mu_{00}}.$$

- 5th order:

$$B(3,2) = \mu_{32} - \frac{3\mu_{12}\mu_{20} + \mu_{30}\mu_{02}}{\mu_{00}},$$

$$B(2,3) = \mu_{23} - \frac{3\mu_{21}\mu_{02} + \mu_{03}\mu_{20}}{\mu_{00}},$$

$$B(4,1) = \mu_{41} - \frac{6\mu_{21}\mu_{20}}{\mu_{00}},$$

$$B(1,4) = \mu_{14} - \frac{6\mu_{12}\mu_{02}}{\mu_{00}},$$

$$B(0,5) = \mu_{05} - \frac{10\mu_{03}\mu_{02}}{\mu_{00}},$$

$$B(5,0) = \mu_{50} - \frac{10\mu_{30}\mu_{20}}{\mu_{00}}.$$

As we already pointed out, this is incorrect since they are not invariant to motion blur. They require PSF symmetric to both axes and both diagonals (see [2] for the proof), which is not the case of the motion blur (horizontal or vertical motion PSF is not symmetric to diagonals; motion in a general direction is symmetric neither to the axes nor to diagonals). To see this, let us investigate how these invariants are transformed under motion blur. Let us do that here for instance for $B(4,0)$ and for horizontal motion.

$$B(4,0)^{(g)} = \mu_{40}^{(g)} - \mu_{04}^{(g)} - \frac{6\mu_{20}^{(g)}(\mu_{20}^{(g)} - \mu_{02}^{(g)})}{\mu_{00}^{(g)}}.$$

Since we assume $\mu_{00}^{(h)} = 1$ (brightness preserving constraint) we have $\mu_{00}^{(g)} = \mu_{00}^{(f)}$. Using the convolution property (4), the fact that $\mu_{10} = \mu_{01} = 0$ for any image, and calculating the moments of the motion PSF explicitly, we obtain for the other moments

$$\mu_{20}^{(g)} = \mu_{20}^{(f)} + \mu_{20}^{(h)}\mu_{00}^{(f)} = \mu_{20}^{(f)} + \frac{s^2\mu_{00}^{(f)}}{12},$$

$$\mu_{02}^{(g)} = \mu_{02}^{(f)} + \mu_{02}^{(h)}\mu_{00}^{(f)} = \mu_{02}^{(f)},$$

$$\mu_{40}^{(g)} = \mu_{40}^{(f)} + 6\mu_{20}^{(h)}\mu_{20}^{(f)} + \mu_{40}^{(h)}\mu_{00}^{(f)} = \mu_{40}^{(f)} + \frac{s^2\mu_{20}^{(f)}}{2} + \frac{s^4\mu_{00}^{(f)}}{80},$$

$$\mu_{04}^{(g)} = \mu_{04}^{(f)} + 6\mu_{02}^{(h)}\mu_{02}^{(f)} + \mu_{04}^{(h)}\mu_{00}^{(f)} = \mu_{04}^{(f)},$$

where s is the length of the blurring pulse. Now we can substitute into $B(4, 0)^{(g)}$. After some manipulations we get

$$B(4, 0)^{(g)} = B(4, 0)^{(f)} - \frac{s^2(\mu_{20}^{(f)} - \mu_{02}^{(f)})}{2} - \frac{7s^4\mu_{00}^{(f)}}{240},$$

which proves that $B(4, 0)^{(g)}$ depends on the PSF and hence $B(4, 0)$ is not invariant under motion blurring.

Among the nine invariants $B(p, q)$ used in [6], only two of them are actually invariant to motion blur in arbitrary direction: $B(0, 5)$ and $B(5, 0)$. The values of the others are functions of the motion direction and speed, which results in drop of the recognition rate for fast motion. This effect is reported in [6] and evaluated in experiments on simulated data (see Figs. 7–8 in [6]), however without a correct analysis of the reason. It should be noted that in a *simulated* experiment the invariants, if chosen and used properly, must retain their recognition power regardless of the motion parameters.

A correct general construction of a complete system of motion blur invariants of any order can be found in [3]. Here we present explicit forms up to the 7th order for horizontal motion.

- 2nd order

$$M_1 = \mu_{11},$$

$$M_2 = \mu_{02}.$$

- 3rd order

$$M_3 = \mu_{30},$$

$$M_4 = \mu_{21},$$

$$M_5 = \mu_{12},$$

$$M_6 = \mu_{03}.$$

- 4th order

$$M_7 = \mu_{04},$$

$$M_8 = \mu_{13},$$

$$M_9 = \mu_{22} - \frac{\mu_{20}\mu_{02}}{\mu_{00}},$$

$$M_{10} = \mu_{31} - \frac{3\mu_{20}\mu_{11}}{\mu_{00}}.$$

- 5th order:

$$M_{11} = \mu_{14},$$

$$M_{12} = \mu_{05},$$

$$M_{13} = \mu_{32} - \frac{3\mu_{20}\mu_{12}}{\mu_{00}},$$

$$M_{14} = \mu_{23} - \frac{\mu_{20}\mu_{03}}{\mu_{00}},$$

$$M_{15} = \mu_{41} - \frac{6\mu_{20}\mu_{21}}{\mu_{00}},$$

$$M_{16} = \mu_{50} - \frac{10\mu_{20}\mu_{30}}{\mu_{00}}.$$

- 6th order:

$$M_{17} = \mu_{06},$$

$$M_{18} = \mu_{15},$$

$$M_{19} = \mu_{24} - \frac{\mu_{20}\mu_{04}}{\mu_{00}},$$

$$M_{20} = \mu_{33} - \frac{3\mu_{20}\mu_{13}}{\mu_{00}},$$

$$M_{21} = \mu_{42} - \frac{\mu_{40}\mu_{02} + 6\mu_{20}M_9}{\mu_{00}},$$

$$M_{22} = \mu_{51} - \frac{5(\mu_{40}\mu_{11} + 2\mu_{20}M_{10})}{\mu_{00}}.$$

- 7th order:

$$M_{23} = \mu_{07},$$

$$M_{24} = \mu_{16},$$

$$M_{25} = \mu_{25} - \frac{\mu_{20}\mu_{05}}{\mu_{00}},$$

$$M_{26} = \mu_{34} - \frac{3\mu_{20}\mu_{14}}{\mu_{00}},$$

$$M_{27} = \mu_{43} - \frac{\mu_{40}\mu_{03} + 6\mu_{20}M_{14}}{\mu_{00}},$$

$$M_{28} = \mu_{52} - \frac{5(\mu_{40}\mu_{12} + 2\mu_{20}M_{13})}{\mu_{00}},$$

$$M_{29} = \mu_{61} - \frac{15(\mu_{40}\mu_{21} + \mu_{20}M_{15})}{\mu_{00}},$$

$$M_{30} = \mu_{70} - \frac{35\mu_{40}\mu_{30} + 21\mu_{20}M_{16}}{\mu_{00}}.$$

The first-order invariants formally also exist but they are zero by definition. If the motion direction is not horizontal but known, we can just rotate the acquired image properly to make the blur horizontal (note that convolution and rotation commute). If the direction is unknown, then we have to either make the motion blur invariants also invariant to rotation (see [4]) or to use more general invariants to centrosymmetric blur (see the next section). In the case of measurement device used in [6], the motion is apparently always in a known constant direction. In any case, we do not need to know the motion velocity, so it is not necessary to estimate it from the Fourier spectrum.

4. Invariants to composite motion-defocus blur

If out-of-focus blur of an unknown extent is also present in addition to the motion blur, then the composite PSF exhibits a central symmetry with respect to its centroid, i.e. $h(x-x_c, y-y_c) = h(-x+x_c, -y+y_c)$, regardless of the motion direction. Invariants to this kind of blur were introduced in [1] and can be directly adopted. For $p+q$ odd, they are defined in a recursive form

$$C(p,q)^{(f)} = \mu_{pq}^{(f)} - \frac{1}{\mu_{00}^{(f)}} \sum_{n=0}^{p} \sum_{\substack{m=0 \\ 0<n+m<p+q}}^{q} \binom{p}{n}\binom{q}{m} \cdot C(p-n, q-m)^{(f)} \cdot \mu_{nm}^{(f)} \qquad (5)$$

so theoretically one may have as many invariants as needed for a sufficient discriminability. In the discrete domain the meaningful number of invariants is of course limited. As explained in [1], the invariants of even orders do not exist in this case. For the readers' convenience, we present here the low-order invariants in their explicit forms.

- 3rd order

$$C(3,0) = \mu_{30},$$

$$C(2,1) = \mu_{21},$$

$$C(1,2) = \mu_{12},$$

$$C(0,3) = \mu_{03}.$$

- 5th order

$$C(5,0) = \mu_{50} - \frac{10\mu_{30}\mu_{20}}{\mu_{00}},$$

$$C(4,1) = \mu_{41} - \frac{2}{\mu_{00}}(3\mu_{21}\mu_{20} + 2\mu_{30}\mu_{11}),$$

$$C(3,2) = \mu_{32} - \frac{1}{\mu_{00}}(3\mu_{12}\mu_{20} + \mu_{30}\mu_{02} + 6\mu_{21}\mu_{11}),$$

$$C(2,3) = \mu_{23} - \frac{1}{\mu_{00}}(3\mu_{21}\mu_{02} + \mu_{03}\mu_{20} + 6\mu_{12}\mu_{11}),$$

$$C(1,4) = \mu_{14} - \frac{2}{\mu_{00}}(3\mu_{12}\mu_{02} + 2\mu_{03}\mu_{11}),$$

$$C(0,5) = \mu_{05} - \frac{10\mu_{03}\mu_{02}}{\mu_{00}}.$$

- 7th order

$$C(7,0) = \mu_{70} - \frac{7}{\mu_{00}}(3\mu_{50}\mu_{20} + 5\mu_{30}\mu_{40}) + \frac{210\mu_{30}\mu_{20}^2}{\mu_{00}^2},$$

$$C(6,1) = \mu_{61} - \frac{1}{\mu_{00}}(6\mu_{50}\mu_{11} + 15\mu_{41}\mu_{20} + 15\mu_{40}\mu_{21} + 20\mu_{31}\mu_{30}) + \frac{30}{\mu_{00}^2}(3\mu_{21}\mu_{20}^2 + 4\mu_{30}\mu_{20}\mu_{11}),$$

$$C(5,2) = \mu_{52} - \frac{1}{\mu_{00}}(\mu_{50}\mu_{02} + 10\mu_{30}\mu_{22} + 10\mu_{32}\mu_{20} + 20\mu_{31}\mu_{21} + 10\mu_{41}\mu_{11} + 5\mu_{40}\mu_{12}) + \frac{10}{\mu_{00}^2}(3\mu_{12}\mu_{20}^2 + 2\mu_{30}\mu_{20}\mu_{02} + 4\mu_{30}\mu_{11}^2 + 12\mu_{21}\mu_{20}\mu_{11}),$$

$$C(4,3) = \mu_{43} - \frac{1}{\mu_{00}}(\mu_{40}\mu_{03} + 18\mu_{21}\mu_{22} + 12\mu_{31}\mu_{12} + 4\mu_{30}\mu_{13} + 3\mu_{41}\mu_{02} + 12\mu_{32}\mu_{11} + 6\mu_{23}\mu_{20}) + \frac{6}{\mu_{00}^2}(\mu_{03}\mu_{20}^2 + 4\mu_{30}\mu_{11}\mu_{02} + 12\mu_{21}\mu_{11}^2 + 12\mu_{12}\mu_{20}\mu_{11} + 6\mu_{21}\mu_{02}\mu_{20}),$$

$$C(3,4) = \mu_{34} - \frac{1}{\mu_{00}}(\mu_{04}\mu_{30} + 18\mu_{12}\mu_{22} + 12\mu_{13}\mu_{21} + 4\mu_{03}\mu_{31} + 3\mu_{14}\mu_{20} + 12\mu_{23}\mu_{11} + 6\mu_{32}\mu_{02}) + \frac{6}{\mu_{00}^2}(\mu_{30}\mu_{02}^2 + 4\mu_{03}\mu_{11}\mu_{20} + 12\mu_{12}\mu_{11}^2 + 12\mu_{21}\mu_{02}\mu_{11} + 6\mu_{12}\mu_{20}\mu_{02}),$$

$$C(2,5) = \mu_{25} - \frac{1}{\mu_{00}}(\mu_{05}\mu_{20} + 10\mu_{03}\mu_{22} + 10\mu_{23}\mu_{02} + 20\mu_{13}\mu_{12} + 10\mu_{14}\mu_{11} + 5\mu_{04}\mu_{21}) + \frac{10}{\mu_{00}^2}(3\mu_{21}\mu_{02}^2 + 2\mu_{03}\mu_{02}\mu_{20} + 4\mu_{03}\mu_{11}^2 + 12\mu_{12}\mu_{02}\mu_{11}),$$

$$C(1,6) = \mu_{16} - \frac{1}{\mu_{00}}(6\mu_{05}\mu_{11} + 15\mu_{14}\mu_{02} + 15\mu_{04}\mu_{12} + 20\mu_{13}\mu_{03}) + \frac{30^2}{\mu_{\ 00}}(3\mu_{12}\mu_{02}^2 + 4\mu_{03}\mu_{02}\mu_{11}),$$

$$C(0,7) = \mu_{07} - \frac{7}{\mu_{00}}(3\mu_{05}\mu_{02} + 5\mu_{03}\mu_{04}) + \frac{210\mu_{03}\mu_{02}^2}{\mu_{00}^2}.$$

5. An illustrative experiment

To demonstrate the differences among the three discussed systems of the invariants, we performed the following simple experiment. An image of a leaf was blurred by a horizontal motion

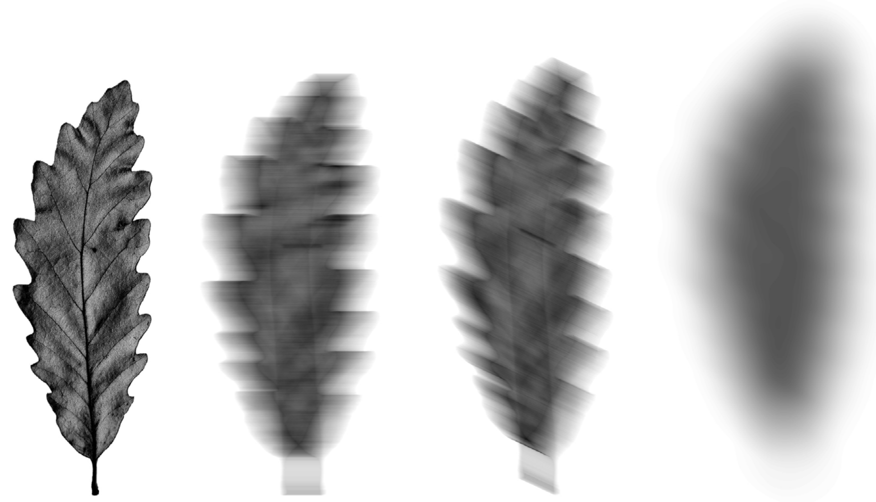

Fig. 3. The leaf of *Quercus cerris*: (a) the original, (b) horizontal motion blur, (c) 25° motion blur, and (d) compound 25° motion + defocus blur.

Table 1
The values of the invariants.

Invariant	Fig. 3a	Fig. 3b	Fig. 3c	Fig. 3d
$B(4,0)$ $[10^{16}]$	−2.0036	−1.9013	−1.9377	−1.9377
$B(3,1)$ $[10^{13}]$	8.9440	8.9440	8.8385	8.8385
M_7 $[10^{16}]$	2.9264	2.9264	2.9475	3.3085
M_8 $[10^{15}]$	−1.2859	−1.2859	−1.0640	−1.1183
$C(2,1)$ $[10^{11}]$	−4.4914	−4.4914	−4.4915	−4.4915
$C(5,0)$ $[10^{16}]$	3.1141	3.1141	3.1141	3.1141

blur, by a motion blur of the direction 25°, and by a composite motion-defocus blur (see Fig. 3). To eliminate all other potential sources of errors, we used a computer-generated blurs and we suppressed the boundary effect by image zero-padding. For these four images we calculated two *B*-type, *M*-type and *C*-type blur invariants of the 4th and 5th order. Their values are shown in Table 1. One can see from Table 1 how important is to understand the theoretical properties of the invariants and to choose those which match with the given task. $B(4, 0)$ requires axially symmetric blur which is not the case in (b)–(d) and hence it does not offer the invariance to present blurs (note that the relative error of $B(4, 0)$ value is more than 5 %). $B(3, 1)$ is by chance equal to M_{10}, so it is invariant to horizontal motion blur but is not invariant in (c) and (d) cases. The same is true for M_7 and M_8; note that the relative error of M_8 in the (c) case is more than 17 %. On the other hand, both *C*-type invariants provide a perfect stability.

6. Conclusion

This paper is a response to the recent paper [6]. The idea of using moment blur invariants in wood slice recognition is a reasonable one but the choice of the invariants and their usage in [6] is inappropriate. Here we have explained the cause of the drop of the recognition power in the experiments and have shown which invariants should be used in the wood recognition systems of this kind.

The concluding recommendation for the users is as follows. For pure linear motion blur in a known direction use the *M*-type invariants (adjusted to the direction) while for any centro-symmetric blur use the *C*-type invariants, which will cover linear motion blur in arbitrary (unknown) direction and composite motion-defocus blur, among others.

Acknowledgement

This work has been supported by the grant No. P103/11/1552 of the Czech Science Foundation.

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Biographies

Jan Flusser received the M.Sc. degree in mathematical engineering from the Czech Technical University, Prague, Czech Republic in 1985, the Ph.D. degree in computer science from the Czechoslovak Academy of Sciences in 1990, and the D.Sc. degree in technical cybernetics in 2001. Since 1985 he has been with the Institute of Information Theory and Automation, Academy of Sciences of the Czech Republic, Prague. In 1995–2007, he was holding the position of a head of Department of Image Processing. Currently (since 2007) he is a Director of the Institute. He is a full professor of Computer Science at the Czech Technical University and at the Charles University, Prague, Czech Republic, where he gives undergraduate and graduate courses on Digital Image Processing, Pattern Recognition, and Moment Invariants and Wavelets. Jan Flusser's research interest covers moments and moment invariants, image registration, image fusion, multichannel blind deconvolution, and super-resolution imaging. He has authored and coauthored more than 150 research publications in these areas, including the monograph "Moments and Moment Invariants in Pattern Recognition" (Wiley, 2009), tutorials and invited/keynote talks at major international conferences. In 2007 Jan Flusser received the Award of the Chairman of the Czech Science Foundation for the best research project and won the Prize of the Academy of Sciences of the Czech Republic for the contribution to image fusion theory. In 2010, he was awarded by the prestigious SCOPUS 1000 Award presented by Elsevier.

Tomáš Suk received the M.Sc. degree in electrical engineering from the Czech Technical University, Faculty of Electrical Engineering, Prague, 1987. The CSc. degree (corresponds to Ph.D.) in Computer Science from the Czechoslovak Academy of Sciences, Prague, 1992. From 1991 he is researcher with the Institute of Information Theory and Automation, Academy of Sciences of the Czech Republic, Prague, member of Dept. of Image Processing. He has authored 14 journal papers and 31 conference papers. He is a co-author of the book "Moments and Moment Invariants in Pattern Recognition" (Wiley, 2009). Tomáš Suk's research interests includes digital image processing, pattern recognition, image filtering, invariant features, moment and point invariants, geometric transformations of images, and applications in remote sensing, astronomy, medicine, botany and computer vision. In 2002 Tomáš Suk received the Otto Wichterle premium of the Academy of Sciences of the Czech Republic for young scientists.

Barbara Zitová received the M.Sc. degree in Computer Science from the Charles University, Prague, Czech Republic in 1995 and the PhD degree in software systems from the Charles University, Prague, Czech Republic in 2000. Since 1995, she has been with the Institute of Information Theory and Automation, Academy of Sciences of the Czech Republic, Prague. Since 2008 she is the head of Department of Image Processing. She gives undergraduate and graduate courses on Digital Image Processing and Wavelets in Image Processing at the Czech Technical University and at the Charles University, Prague, Czech Republic. Barbara Zitova's research interests include geometric invariants, image enhancement, image registration and image fusion, and image processing in cultural heritage applications. She has authored/coauthored more than 50 research publications in these areas, including the monograph "Moments and Moment Invariants in Pattern Recognition" (Wiley, 2009) and tutorials at major conferences. In 2003 Barbara Zitová received the Josef Hlavka Student Prize, in 2006 the Otto Wichterle premium of the Academy of Sciences of the Czech Republic for young scientists, and in 2010 she was awarded by the prestigious SCOPUS 1000 Award presented by Elsevier.