ASSESSMENT OF ROTATION-INVARIANT TEXTURE CLASSIFICATION THROUGH GABOR FILTERS AND DISCRETE FOURIER TRANSFORM

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Abstract

Gabor features are widely adopted in texture classification, and have proven to give good results in many applications [2]. Unfortunately, in their original formulation, they are not rotation-invariant. This restricts their possible fields of usage.

Various methods have been proposed, in the past, to attain rotation-invariant Gabor features. Among them, the most common are: the *brute force approach*, where all the possible shifts of the feature vector are computed to find the best match between the texture to classify and the training textures [23]; the *circular shift approach*, where the feature vector is re-oriented based on the 'dominant' orientation [16, 1]; and the *total energy approach*, where features pertaining to the same frequency and different orientations are summed up to provide rotation invariance. As detailed in the paper, however, the above mentioned approaches present some theoretical and practical drawbacks that may reduce their effectiveness. In this work we focus on a method to achieve rotation invariant texture classification based on computing the Discrete Fourier Transform (DFT) of Gabor features. Since rotating the original textures produces a circular shift of the Gabor feature vector, the basic idea behind this method is that the circular shift can be converted into a phase shift through the DFT. The phase shift does not affect the magnitude of the transformed coefficients which can be used as rotation-independent representation of textural data. This approach was originally proposed in [12]. Herein we investigate the rationale behind this method and carry out a critical comparison with the other approaches. An extensive experimental campaign was conducted over a database of 120 homogeneous textures of different types. The texture images were considered at nine different rotation angles ($0°$, $5°$, $10°$, $15°$, $30°$, $45°$, $60°$, $75°$ and $90°$). The results show that the approach based on the DFT gives very good results in comparison with the other methods.

Keywords: texture classification, rotation-invariance, Gabor filters, Discrete Fourier Transform

1 Introduction

Texture analysis plays an important role in many activities, such as medical imaging, remote sensing, surface inspection, image retrieval and others. Within texture analysis, classification has recently received great attention, due to its several applications in industry. Texture classification techniques are very attractive for industrial applications, especially in those situations where it is important to group products in lots according to the criterion of "same visual appearance". In many industrial areas there is a growing interest in systems capable of performing such kind of tasks automatically.

In practical applications it is rare that texture images are captured under the same rotation angle or scaling factor. Therefore, for industrial applications to be effective, it is of great importance that texture classification is rotation, translation and scale invariant.

In this paper we are concerned with the rotation-invariant texture classification problem. A simple approach to achieve rotation invariant texture classification starting from Gabor features is described here.

The remainder of the paper is organized as follows: after a review of some related techniques for rotation-invariant texture classification (section 2), the DFT approach is detailed in section 3. Section 4 describes the experimental activity. The results are then presented and critically discussed in section 5. Final considerations are reported in section 6.

2 Related research

The problem of rotation-invariant texture classification has been intensively investigated during the last years. Literature review suggests that rotation invariant texture classification techniques can be grouped into three main families: *pre-processing*, *in-processing* and *post-processing* methods. This classification reflects the fact that rotation invariance can be pursued before feature extraction, during feature extraction and after feature extraction.

Pre-processing approaches come into play before features are extracted from the original images. Such approaches try to estimate the 'characteristic' or 'dominant' direction of a texture. Then the texture is rotated so that its orientation is adjusted to the estimated dominant direction. Various techniques for orientation estimation have been proposed in the past: gradient estimation in the spatial domain [21], signal power analysis in the frequency domain [3], autocovariance function estimation [14] and Radon transform [10, 6]. Such methods present the advantage that they are independent of the feature space, but they are computationally expensive. Furthermore there is an intrinsic difficulty in estimating texture orientation, since some textures may not have a dominant orientation, while other textures may have more than one. As recognized in [10], orientation estimation methods may not work properly with complex textures, since in such cases there could be ambiguity in the estimation of the dominant direction.

In-processing approaches try to adopt feature extraction methods which are intrinsically rotation-invariant. Rotation-invariant formulations have been proposed for various feature spaces: co-occurrence matrices [18], *Local Binary Patterns* [13] and wavelets [4, 5]. Rotation-invariant formulations have also been proposed for Gabor filters. In [9] an orientation-independent formulation of Gabor filters is discussed where the directional harmonic component of the filter is replaced by a circular symmetric wave.

Post-processing approaches aim at obtaining rotation invariant feature vectors once they have been calculated. In this work we focus on these techniques, since the solution proposed here falls in this category. Moreover we restrict literature review to approaches that apply to Gabor features.

The main concern in pursuing rotation invariant classification with Gabor features is that they change as the original texture rotates. This is a common characteristic of many other features that can be used in texture classification. However Gabor features exhibit a specific behaviour that can be exploited to achieve rotation-invariant classification. It has been demonstrated that a rotation of the original image corresponds to a circular shift of the components of the Gabor feature vector at the same frequency [23]. Based on this result, it is possible to adopt one of the following strategies:

- to compute a set of Gabor features which does not circular shift as the original images rotate;
- for each texture to classify, try all the possible shifts of the feature vector to find the best match (minimum distance) between the texture to classify and the training textures;
- for each texture to classify, search for a particular trait of the feature vector and use it as the 'origin' of the feature vector, then reorient the feature vector.

The first strategy has been exploited by various authors [8, 19]. We refer to this family of strategies as *total energy* approaches, since they rely on the idea that, even if the energy of Gabor filter response changes from one orientation to another, the total energy of the response at a fixed frequency tends to be quite constant. Based on this concept rotation-invariant features can be estimated either by summing the response of each filter with different orientations at each frequency [8], or by adopting circularly-symmetric (ring-shaped) filters in the frequency domain [19].

The second strategy is often referred to as the *brute force approach*. Since it requires extensive calculation, research activity has been mainly focused on the first and third approach.

Within the last family the so called *circular shift* has emerged as the leading technique to achieve rotation invariant classification from Gabor features. This procedure consists in calculating the total energy of each orientation. The orientation with the highest total energy is called the 'dominant' orientation. Then the feature element which corresponds to the dominant direction is moved as the first element of the feature vector. The other elements are circularly shifted. This process of reordering the feature vector is usually referred to as *normalization*. The circular shift technique has been originally presented in [23], and it has been further investigated in [1] and [16]. This technique can be considered as 'a posteriori' estimation of the dominant orientation of a texture.

For the circular shift approach to work well two assumptions have to be satisfied:

- it is possible to identify the dominant direction of a texture;
- the dominant direction is unique.

The above assumptions may be satisfied in many cases, but in others they may be not. If a texture does not have a dominant direction (anisotropic textures), searching the orientation with the highest total energy may be error prone and noise sensitive. If a texture has more than one dominant direction the circular shift may also fail. Examples of such textures and deeper considerations on this topic can be found in [10].

In the following section we describe an alternative approach for rotation invariant feature normalization based on the Discrete Fourier Transform of the Gabor feature vector. As detailed in the remainder of the paper, the DFT exhibits interesting properties that makes it a good candidate for achieving rotation invariant normalization.

3 DFT approach for rotation invariant texture classification

The basic idea is to obtain a rotation invariant feature vector through the Discrete Fourier Transform. We first recall Gabor features and their properties and then describe the procedure for feature normalization.

3.1 *Gabor features*

A two-dimensional Gabor filter consists of a sinusoidal wave modulated by a gaussian envelope. It performs a localized and oriented frequency analysis of a two-dimensional signal. The formulation in the spatial domain is the following:

$$\psi(x,y) = \frac{F^2}{\pi\gamma\eta} e^{-F^2\left[\left(\frac{x'}{\gamma}\right)^2+\left(\frac{y'}{\eta}\right)^2\right]} e^{i2\pi F x'}; \tag{1}$$

with:

$$\begin{cases} x' = x cos\theta + y sen\theta \\ y' = -x sen\theta + y cos\theta \end{cases} \tag{2}$$

where F is the central frequency of the filter, θ is the angle between the direction of the sinusoidal wave and the x axis of the spatial domain, γ and η the standard deviations of the gaussian envelope respectively in the direction of the wave and orthogonal to it. In the frequency domain the Gabor filter gets the following form:

$$\Psi(u,v) = e^{-\frac{\pi^2}{F^2}\left[\gamma^2\left(u'-F\right)^2+\eta^2 v'^2\right]}; \tag{3}$$

with:

$$\begin{cases} u' = u cos\theta + v sen\theta \\ v' = -u sen\theta + v cos\theta \end{cases} \tag{4}$$

A generic Gabor filter $\psi_{F,\theta}$ with frequency F and orientation θ is applied to an image I through a convolution:

$$W_{F,\theta}(l,m) = \int I(l_1,m_1)\psi^*_{F,\theta}(l-l_1,m-m_1)dl_1 dm_1 \tag{5}$$

where $W_{F,\theta}(l,m)$ is the transformed image at frequency F and orientation θ (* denotes the complex conjugate).

Each transformed image is then characterized by some statistical indicators. Most commonly such indicators are the mean value μ and the standard deviation σ of the magnitude of the transformed coefficients:

$$\mu_{F,\theta} = \frac{\sum_{l=1}^{L}\sum_{m=1}^{M}|W_{F,\theta}(l,m)|}{LM} \tag{6}$$

$$\sigma_{F,\theta} = \sqrt{\frac{\sum_{l=1}^{L}\sum_{m=1}^{M}\left[|W_{F,\theta}(l,m)| - \mu_{F,\theta}\right]^2}{LM}} \tag{7}$$

A Gabor filter bank with P frequencies $F_p = \{F_0, \cdots, F_{P-1}\}$ and Q orientations $\theta_q = \{\theta_0, \cdots, \theta_{Q-1}\}$ gives a feature vector that is usually arranged as follows:

$$\mathbf{V} = \{\mu_{F_0\theta_0}, \sigma_{F_0\theta_0}, ..., \mu_{F_0\theta_{Q-1}}, \sigma_{F_0\theta_{Q-1}}, ..., \\ ..., \mu_{F_{P-1}}, \sigma_{\theta_{Q-1}}\} \tag{8}$$

Gabor filters are widely adopted in texture classification. It can be shown that the Gabor representation is optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency [11]. This characteristic suggests that Gabor filters may be appropriate operators for tasks requiring simultaneous measurement in the two domains [15]. Moreover Gabor filters seem to have important relations with the vision system of mammals. It has been shown that the response of cortical simple cells devoted to the processing of visual signal can be approximated with Gabor functions.

3.2 *Effect of texture rotation on Gabor features*

For sake of clarity and without loss of generality, we can stack the feature vector **V** of equation 8 into a matrix of Gabor features in the following way:

$$[\mathbf{M}] = \begin{pmatrix} \mu_{F_0,\theta_0} & \cdots & \mu_{F_0,\theta_{Q-1}} \\ \mu_{F_1,\theta_0} & \cdots & \mu_{F_1,\theta_{Q-1}} \\ & \cdots & \\ \mu_{F_{P-1},\theta_0} & \cdots & \mu_{F_{P-1},\theta_{Q-1}} \\ \sigma_{F_0,\theta_0} & \cdots & \sigma_{F_0,\theta_{Q-1}} \\ \sigma_{F_1,\theta_0} & \cdots & \sigma_{F_1,\theta_{Q-1}} \\ & \cdots & \\ \sigma_{F_{P-1},\theta_0} & \cdots & \sigma_{F_{P-1},\theta_{Q-1}} \end{pmatrix} \quad (9)$$

Now let's indicate with $\mathbf{x} = \{x_0, \cdots, x_{Q-1}\}$ the generic row of the matrix $[\mathbf{M}]$. It is known [16, 23, 1] that a rotation of the input texture produces a circular shift of the vector $\mathbf{x}$: if the input image rotates by π/Q radians, the generic $\mathbf{x}$ vector theoretically changes to $\tilde{\mathbf{x}} = \{x_{Q-1}, x_0, x_1, \cdots, x_{Q-2}\}$. For such reason Gabor features are not rotation invariant. Measuring the distance between textures in the feature space is likely to produce incorrect classification. Similar texture images with relative rotation will be classified erroneusly.

3.3 *Rotation invariant Gabor features*

In order to obtain rotation-invariant features, we compute the Discrete Fourier Transform of the original feature vector $\mathbf{x}$:

$$X_k = \sum_{q=0}^{Q-1} x_q e^{-\frac{2\pi i}{N}kq}; k = \{0, \cdots, Q-1\} \quad (10)$$

The output of the DFT is a vector $\mathbf{X}$ of complex numbers. Applying a circular shift to the input vector $\mathbf{x}$ by l points corresponds to multiplying the Discrete Fourier Transform $\mathbf{X}$ by the linear phase factor $e^{-i\frac{2\pi k}{N}l}$ [17]. The modulus of the transformed coefficients X_k, is not affected by such multiplication, and thus the vector $|\mathbf{X}| = \{|X_0|, \cdots, |X_{Q-1}|\}$ is independent of any circular shift of the input vector $\mathbf{x}$. Moreover, being $\mathbf{x}$ a vector of real values, the vector $\mathbf{X}$ is hermitian symmetric:

$$X_k = X^*_{k-q}; k = \{0, \cdots, Q-1\} \quad (11)$$

As a consequence the DFT output is half redundant, and we get the complete information by looking at the first $\lfloor Q/2 \rfloor + 1$ elements of the transformed vector.

The rotation invariant version $[\mathbf{M}_I]$ of the matrix $[\mathbf{M}]$ is obtained by computing the DFT of each row of the matrix $[\mathbf{M}]$, and retaining only the first $\lfloor Q/2 \rfloor + 1$ elements:

$$[\mathbf{M}_I] = \begin{pmatrix} X_{0,\mu F_0} & \cdots & X_{Q',\mu F_0} \\ X_{0,\mu F_1} & \cdots & X_{Q',\mu F_1} \\ X_{0,\mu F_{P-1}} & \cdots & X_{Q',\mu F_{P-1}} \\ & \cdots & \\ X_{0,\sigma F_0} & \cdots & X_{Q',\sigma F_0} \\ X_{0,\sigma F_1} & \cdots & X_{Q',\sigma F_1} \\ & \cdots & \\ X_{0,\sigma F_{P-1}} & \cdots & X_{Q',\sigma F_{P-1}} \end{pmatrix} \quad (12)$$

where $X_{i,\mu F_p}$ represents the magnitude of the $j-th$ spectral component of the mean value of the Gabor response at frequency p; $X_{i,\sigma F_p}$ the same spectral component of the standard deviation of the Gabor response at the same frequency. $Q' = \lfloor Q/2 \rfloor$.

The effects of switching from the original Gabor feature space to the transformed space can be appreciated in figures 2 and 3. As an example we considered here the directional texture shown in figure 1. We can see that different orientation of the texture produces a circular shift in the original Gabor feature vector (fig. 2) . The circular shift disappears in the transformed feature space (fig. 3).

Figure 1: Original texture at $0°$ (left) and at $60°$ (right).

4 Experimental activity

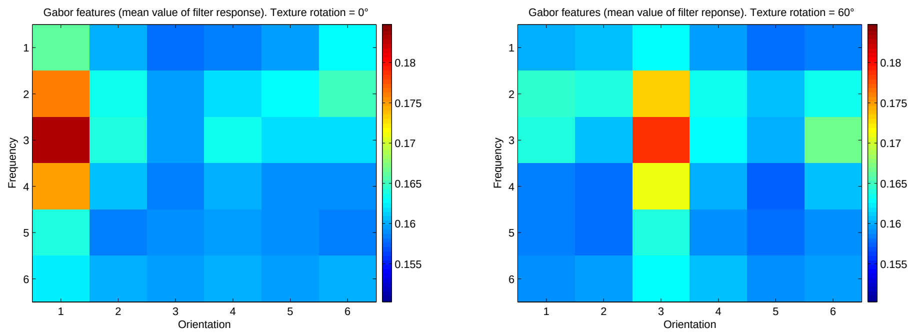

Figure 2: Gabor features of the texture of fig. 1 (mean value of the Gabor filter response). The (i, j) square is the response at frequency i and orientation j. A shift along the i direction shows up as the texture orientation changes from $0°$ to $60°$.

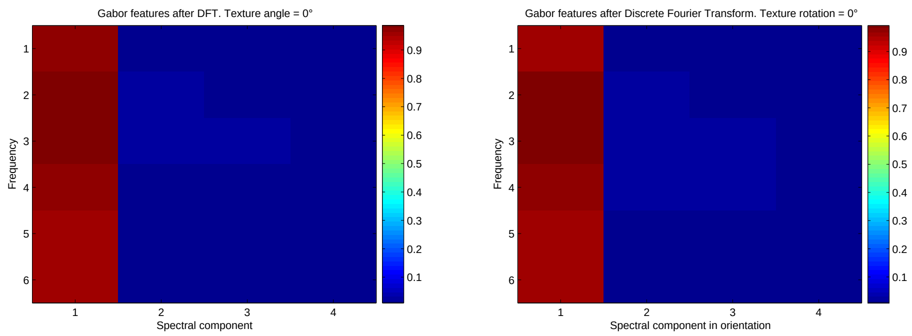

Figure 3: Gabor features of the texture shown in fig. 1 (mean value of the filter response) after DFT transform. The (i, j) square is the $j-$th spectral component of the response at frequency i. We can appreciate that the shift along the i direction disappeared.

In order to test the effectiveness of the above described technique, we carried out an experimental campaign as detailed here below.

4.1 *Experimental dataset*

A database of 120 texture images (fig. 4) has been set-up using the OuTex library [20]. The textures used here have been selected from the group *horizon 100dpi*. We decided to use textures from the OuTex database since it provides hardware-rotated textures, and thus it permits to avoid texture rotation by software. Rotation by software, infact, can introduce artifacts in the rotated images that may alter classification results. In particular it is possible to download textures rotated by the following angles: 0°, 5°, 10°, 15°, 30°, 45°, 60°, 75° and 90°. It is worth noticing that the texture database adopted here is challenging, since it contains many similar textures.

The size of the original images is 746 x 538 pixels. Each original image was subdivided into 12 non-overlapping sub-images, yelding a database of 1440 texture samples. In the process of composing the data set we took care in selecting texture images as uniform as possible. This to avoid mistaken classifications after image subdivision.

4.2 *Feature extraction*

Six different Gabor feature spaces, resulting from three different Gabor filter banks with four frequencies and six, eight and ten orientations, and with six frequencies and six, eight and ten orientations were used. Based on the results of a previous work [7] we set the values of the smoothing parameters η and γ (equations 1 and 3) equal to 0.5. A frequency progression value of $\sqrt{2}$ (half-octave spacing) has been used. The central frequency of the filter at the highest frequency is computed as a consequence, as shown in [7]. The feature vector is composed of the mean values and standard deviations of the magnitude of each transformed image, as in equations 6, 7 and 8.

Figure 4: The 120 textures from the OuTex database used in the experimental activity. *Barleyrice*{001, 002}; *Canvas*{003, 004, 006, 008, 009, 011}; *Cardboard*{001}; *Carpet*{001, 002, 004, 005, 009}; *Chips*{001, 006, 009}; *Crushedstone*{001, 003, 006, 007}; *Flakes*{003, 004, 008, 009}; *Flour*{001, 002, 009, 011, 012}; *Granite*{001, 003, 004, 006, 007, 008, 009}; *Granular*{002, 003}; *Groats*{001, 005, 006, 007}; *Leather*{003}; *Mineral*{003, 004}; *Paper*{001, 003, 004, 005, 006, 007, 008, 009, 010}; *Pasta*{001, 002, 003, 004, 005}; *Pellet*{001}; *Plastic*{001, 003, 004, 005, 006, 009, 011, 016, 017, 018, 019, 021, 022, 024, 025, 026, 027, 028, 029, 030, 031, 032, 034, 035, 036, 044, 045}; *Quartz*{001}; *Rubber*{001}; *Sand*{001, 002}; *Sandpaper*{003}; *Seeds*{001, 002, 003, 004, 005, 006, 007, 008, 009, 011, 012, 013}; *Tile*{003}; *Wallpaper*{001, 002, 003, 006, 008, 012, 013, 018, 019}; *Wood*{003, 004, 005, 007, 008}

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4.3 *Classification and error estimation*

Texture classification was performed using the nearest neighbour rule with the 'Manhattan' ($L1$) distance.

Classification error has been evaluated by split-half validation with stratified sampling [22]: the 1440 textures were divided randomly into two non-overlapping groups of 720 textures each: the *training set* and the *validation set*. For each angle θ the *training set* was formed by textures from the 0° group, while the *validation set* was composed of textures taken from the $\theta°$ group, with $\theta = \{0°, 5°, 10°, 15°, 30°, 45°, 60°, 75°, 90°\}$. The percentage of correct classification was defined as the ratio between the number of textures classified correctly and the number of textures of the validation set. For each angle the estimated percentage of correct classification was averaged over 100 different random partitions of data into training and validation set in order to make the estimation stable.

In order to assess the effectiveness of the DFT method, texure classification was carried out using five different approaches: original feature space (Gabor features with no modification), total energy, circular shift, brute force and Discrete Fourier Transform.

In the total energy approach we sum the response of each filter with different orientations at each frequency [8].

In the circular shift method the dominant orientation d is computed through equation 13, and the feature element in the dominant orientation is moved as the first element of the re-oriented feature vector.

$$d = \underset{\{0,\cdots,Q-1\}}{argmax} \left(\sum_{i=0}^{P-1} \mu_{ij} \right) \tag{13}$$

In the brute force procedure, for each texture to classify, all the Q possible shifts of the feature vector are considered. The texture to classify is assigned the label of the training texture that best matches one of the Q shifts of the original feature vector. In other words the texure to classify is assigned the label of the $c-th$ texture of the training set, which is computed as follows

$$c = \underset{r=\{0,\cdots,R-1\}}{argmin} \left\{ \underset{j=\{0,\cdots,Q-1\}}{min} [D(\mathbf{V}_r, \mathbf{V}_j)] \right\}; \tag{14}$$

where R is the total number of training textures, $\mathbf{V}_r$ is the feature vector of the $r-$th training texture, $D(\mathbf{V}_r, \mathbf{V}_j)$ the distance between the $r-$th training texture and the $j-$th shift of the feature vector of the texture to classify.

5 Results and discussion

Table 1 summarizes, for each filter bank, the results obtained with different rotation angles using the four approaches described in section 4.

First of all we notice that, in accordance with related work [16], the percentage of correct classification shows a consistent decrease if rotation-invariant normalization is not applied. In agreement with the results found in [7], it emerges that, switching from 4 to 6 frequencies, produces an increase in classification performance, and that increasing the number of orientations from 6 to 10 does not improve classification results.

The results show that, in general, the percentage of correct classification obtained with the DFT method is higher than that obtained with the other approaches.

In figure 5 we plot the percentage of correct classification averaged over the six Gabor filter banks. It comes out that, on average, the DFT approach outperforms the others.

In our opinion such results can be explained by looking at the intrinsic properties of the method. As we pointed out in section 2, the main problem which afflicts methods based on estimation of the dominant direction (such as the circular shift), is that such direction may not exist or may not be unique.

If we look at the spectral components of the feature vector we remove this dependency from the dominant direction and, more generally, from any rotation of the input image.

The total energy approach shows a consistent lower performance with respect to the other methods. This can be explained with the reduced capability of discriminating textures that is a consequence of removing orientation-dependent data from texture description. In contrast the other methods do not remove orientation-dependent data, but they re-arrange them in a different way.

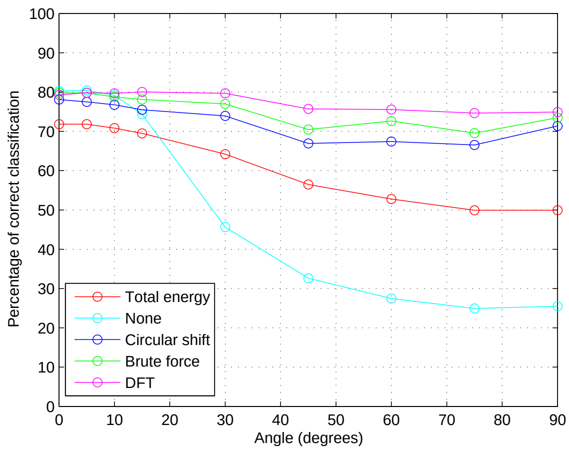

Figure 5: Percentage of correct classification averaged over the six filter banks.

6 Conclusions

In this paper we have evaluated the effectiveness of the DFT technique for rotation invariant texture classification with Gabor features. The DFT method is simple and easy to implement. It consists in substituting the rotation-dependent parts of the Gabor feature vector with their Discrete Fourier Transform, which is

Table 1: Results of the experimental activity.

Filter bank freqs.	Filter bank ornts.	Rotation-invariance method	0°	5°	10°	15°	30°	45°	60°	75°	90°
4	6	None	77,29	76,85	75,51	69,58	40,93	30,53	26,07	23,43	24,41
		Total energy	71,16	70,89	68,25	64,48	53,47	41,27	34,97	32,04	32,02
		Circular shift	74,81	73,52	72,05	66,99	69,06	55,89	60,65	56,18	65,53
		Brute force	76,29	76,17	74,42	69,67	71,77	58,90	67,87	58,42	68,03
		DFT	75,49	76,47	75,95	76,14	75,00	70,52	70,86	68,82	69,16
4	8	None	77,00	76,56	75,09	68,49	41,88	30,06	25,37	23,43	23,80
		Total energy	70,09	69,58	66,96	64,63	54,98	45,19	39,24	33,00	31,67
		Circular shift	74,54	73,65	72,21	72,25	67,89	62,92	60,92	61,19	65,43
		Brute force	76,68	76,20	74,65	75,06	71,89	67,93	66,51	65,28	67,93
		DFT	75,65	76,53	76,27	76,34	75,57	71,55	71,48	69,66	69,74
4	10	None	77,15	76,75	75,50	69,72	41,61	30,22	25,40	23,43	23,80
		Total energy	72,49	72,45	70,93	67,87	53,53	37,76	31,72	28,91	28,37
		Circular shift	74,93	74,18	73,66	73,54	68,74	62,10	60,61	62,93	65,62
		Brute force	76,76	76,55	75,81	76,27	72,06	66,07	66,74	67,23	68,04
		DFT	75,82	76,51	76,43	76,49	75,51	71,69	71,64	69,77	69,98
6	6	None	83,44	84,22	82,78	79,71	49,62	35,48	29,62	26,12	26,85
		Total energy	72,42	72,64	72,98	73,33	74,41	71,49	70,24	68,57	69,26
		Circular shift	81,69	80,96	80,33	78,00	79,17	70,85	73,36	70,19	77,71
		Brute force	82,77	83,35	82,16	80,35	82,25	73,26	78,79	71,63	79,18
		DFT	82,64	83,04	82,93	83,67	84,02	79,75	79,74	79,44	80,02
6	8	None	83,46	83,97	82,99	78,81	49,75	34,80	29,04	26,63	27,07
		Total energy	72,35	72,69	72,88	73,22	74,38	71,53	70,27	68,53	69,09
		Circular shift	81,26	80,97	80,94	81,06	79,16	75,01	74,29	73,72	76,73
		Brute force	83,04	83,06	82,50	83,44	81,77	78,71	77,94	76,85	78,73
		DFT	83,01	83,19	83,17	83,77	83,95	80,39	79,81	80,07	80,19
6	10	None	83,48	84,10	82,98	79,81	49,96	34,77	29,25	26,45	27,08
		Total energy	72,38	72,71	72,93	73,29	74,37	71,51	70,23	68,56	69,14
		Circular shift	81,29	81,65	81,39	81,09	79,54	74,72	74,62	74,99	77,13
		Brute force	83,19	83,33	83,05	83,99	82,14	77,85	77,95	77,81	78,86
		DFT	83,06	83,21	83,33	83,85	83,98	80,41	79,84	80,16	80,33

rotation-independent. Algorithms exist for fast calculation of the Discrete Fourier Transform that makes the computational cost of the method low. An experimental campaign was carried out to evaluate the effectiveness of this technique in comparison with existing methods. The results show that the DFT method provides better results with little computational effort.

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