New Improvement in Obtaining Monogenic Phase Congruency

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Abstract. Phase congruency is an advanced technique for edge detection in images. However, in the original technique, edge detection errors can occur when at least one side of the image is not a power of two. In this paper, this problem, not reported before, and its origin are exposed and two ways of correction are proposed to reduce this problem. The proposed solutions allow to overcome the presented problem by obtaining more accurate and uniform contours than the original technique.

Keywords: Monogenic Phase congruency · Tile-mirror · Edge detection · Filter bank · Image segmentation

1 Introduction

Automatic edge detection in images is an area of great interest to industry and the scientific community. A problem usually experienced is that edge detectors are sensitive to the magnitude of changes in brightness. However, this disadvantage disappears when employing the technique known as phase congruency (PC), which allows edge detection in an image regardless of its illumination level [5]. This technique is based on phase alignment of frequency components. This principle states that the edges of an image occur when the phases of the Fourier components coincide. By using phase, the direct dependence on brightness intensity in edge detection is avoided.

Generally speaking, phase congruency implementations can be classified into two different groups according to the way the frequency components of the image to be analyzed are calculated. The first one consists in using wavelet filters, so that for each component different directional Log-Gabor filters are applied [6]. The second consists in using monogenic filters, so that only one filter is required for each component, substantially reducing the computational cost [9]. Using directional filters increases the computational cost, but has applications in corner detection [7], which has evolved to point of interest detection [1,12,13]. Regarding phase congruency using monogenic filters (MPC), progress has also

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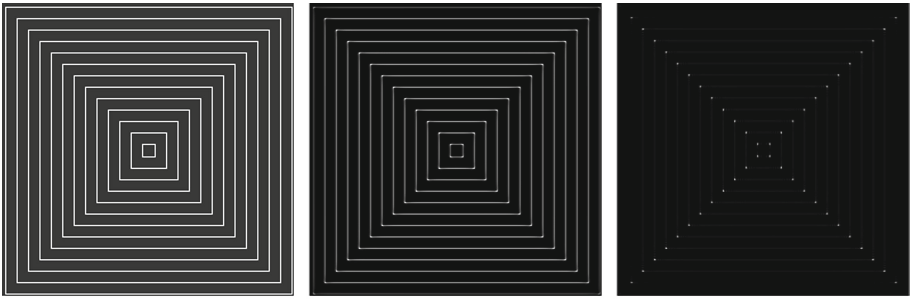
been made to improve detection of contiguous edges [3], estimate noise with greater versatility [2], and extend it to color images [11].

A difficulty with MPC, not previously mentioned, is that edge detection, when these are very close, is affected by the image dimensions. Thus, for example, if the PC of an image of 256×256 pixels is obtained, the result is accurate, but if its width and height are reduced by only one pixel, to 255×255 pixels, the edge detection is highly affected, losing many of the edges, as seen in the example in Fig. 1. To overcome this problem, this paper presents the causes of the error and its solution by increasing the image size or properly adjusting the filter bank.



(a) (b) (c)

Fig. 1. Problem presented in edge detection in MPC. (a) Original image of 256×256 pixels. (b) MPC obtained from the original image. (c) MPC obtained from the original image cropped to 255×255 pixels.

2 Monogenic Phase Congruency

Figure 2 shows the approximation of a square and a triangular signal using four Fourier components. As can be seen, the phases of all the components coincide at the edges of the signals, i.e. in the image of the square signal when there is a sudden change in the signal, and in the triangle at the maximum or minimum. Thus, a phase congruency is present at all edges of an image [6].

PC is defined by Eq. (1), where $\overline{\phi}(x)$ is the phase that maximizes it, defined in terms of the Fourier components A_n of a signal at position x [10].

$$PC(x) = \max_{\overline{\phi}(x) \in [0, 2\pi]} \frac{\sum_{n=1}^{N} A_n \cos\left(\phi_n(x) - \overline{\phi}(x)\right)}{\sum_{n=1}^{N} A_n}, \tag{1}$$

By using monogenic filters it is possible to implement phase congruency [9, 11]. Thus, Kovesi proposed a PC implementation using these filters through the Equation:

$$PC(\vec{x}) = W(\vec{x}).\lfloor 1 - \alpha\,|\delta(\vec{x})| \rfloor.\frac{\lfloor E(\vec{x}) - T \rfloor}{E(\vec{x}) + \varepsilon} \tag{2}$$

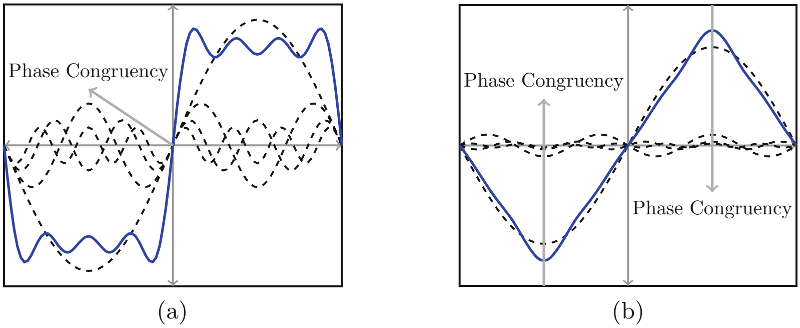


Fig. 2. Approximate signals with four Fourier components. (a) Square signal. (b) Triangular signal.

where the noise threshold T allows, for lower energy values E, the PC to become zero, avoiding producing false edges due to noise. This noise compensation is used by involving the positive part function, denoted as $\lfloor\cdot\rfloor$, in Eq. (3).

$$\lfloor f(x) \rfloor = \max(f(x), 0) = \begin{cases} f(x) & \text{if } f(x) > 0 \\ 0 & \text{if } f(x) \leq 0 \end{cases} \tag{3}$$

$W(x)$ is the phase weighting function [6]. To calculate it, a sigmoid function is used according to Eq. (4), where s is the quantification of the frequency distribution given in Eq. (5). The most important variables used for the calculation of the PC, i.e. the energy, the average phase deviation and the noise threshold can be represented in a geometrical scheme, as illustrated in Fig. 3,

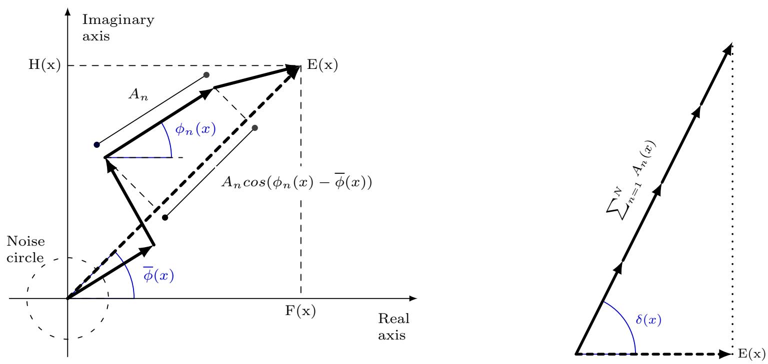
$$W(x) = \frac{1}{1 + e^{\gamma(c - s(x))}}, \tag{4}$$

$$s(x) = \frac{1}{N}\left(\frac{\sum_{n=1}^{N} A_n(x)}{\varepsilon + A_{max}(x)}\right), \tag{5}$$

3 Incorrect Edge Detection in MPC

Edge detection, when borders are very close, is affected by the dimensions of the image. In Fig. 4 the result and the vertical profile of the MPC on a square image of side 256, the edges are detected correctly. On the contrary, when the same image, but with 255×255 dimensions, the result is drastically deteriorated, as seen in Fig. 5, where, as can be seen in the profile plotted on the right, the value of the detected phase congruency is reduced almost twenty times, from about 0.1 to 0.005. This problem arises from the way the FFT interprets the periodicity of the incoming signal and the distribution and shape of the filter bank.

Thus, on the one hand, because the FFT is a discrete approximation of the Fourier transform, it does not produce results identical to the continuous one.



(a) (b)

Fig. 3. Geometric scheme of Phase Congruency. (a) Relationship between phase congruency, local energy, and the sum of the Fourier amplitudes, adapted from [6]. (b) Representation of the PC by a triangle inequality where the $\sum_n A_n(x)$ is always greater than or equal to $E(x)$.

Therefore, if the period of the fundamental signal is considered equal to the total of acquired samples, the FFT result will be given directly in frequency units. In this sense, if pure frequency components are desired, the quotient between the number of samples and the period of the signal measured in samples must be an integer. Therefore, for 256 samples there are more integer divisors than for 255, thus offering a wider range of signals that can be approximated with pure components, as illustrated in the example of the Fig. 6, which shows the FFT result obtained from a sinusoidal signal of frequency 64, sampled 256 Hz, taking 256 and 255 samples. As can be seen, when the number of samples is 255, the discrete approximation of a non-integer frequency, between 63 and 64 and real and imaginary components, is obtained as transformed, while if the number of samples is 256, a signal with a single frequency component, equal to 64, is obtained as transformed. On the other hand, due to the fact that the joint response of the filter bank is not completely uniform and the phase congruency quantification is non linear, incorrect responses are generated, as shown in Fig. 1c.

Thus, since to obtain the PC of an image it is required to convert it to frequency space by using the FFT, and subsequently obtain the A_n components through a bank of filters whose joint response is not linear, as shown in Fig. 7, when performing the inverse process to obtain the resulting image is affected by its dimension, as illustrated in Fig. 6. In other words, if the processing in the frequency space were a linear process, this problem would not occur.

4 Materials

For this work, a synthetic image was created, which allows to clearly observe the studied problem, and six images of different specialties were used to illustrate

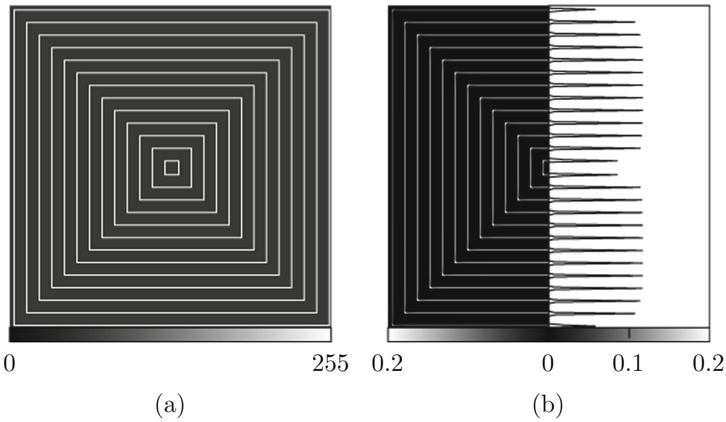


Fig. 4. MPC of a synthetic square image of side 256. (a) Original image. (b) MPC and vertical profile.

the obtained results. The MPC method, in which the proposed corrections are included, was developed in java as a plugin of the open source software imageJ and is available for free use in [4]. The study of the Fourier transform and MPC profiles was performed in Octave, using the code developed by Kovesi [8].

5 Problem Solution

A solution usually employed in 1d signal processing to solve the problem explained above, when the signal does not fit the desired size q, it is resized and padded with zeros to become equal to q. This solution is adequate when the signal at the cutoff point is zero or close to it, since it does not generate noticeable discontinuities in the signal that can generate high frequency spurious components. In the case of MPC, this solution is not adequate due to its high sensitivity to discontinuities, detecting edges independently of their amplitude, accentuating the nonlinear response of the filters, as shown in Fig. 8, which shows the profile obtained by traversing the image in the middle from top to bottom. As can be seen, the response at the edges located at the upper and left ends of the image are much greater, due to the fact that they are located next to the padded zone, which is also observed in the profile, which shows that the PC value of the upper edge is more than twice as large as that of the others. To avoid affecting the MPC values and resize the image to the desired dimensions, the signal continuity must be preserved. For this purpose, the signal is mirrored on each side of the image until the desired size is reached. Thus, it is now possible to correctly detect edges within the image preserving the PC value for all edges. In the case of the synthetic image in Fig. 5, the same MPC will be obtained, since the mirror image results equal to the original one.

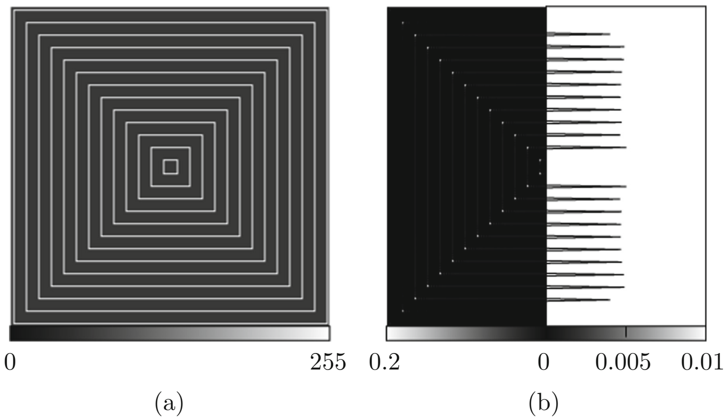


Fig. 5. MPC of a synthetic square image of side 255. (a) Original image. (b) MPC and vertical profile.

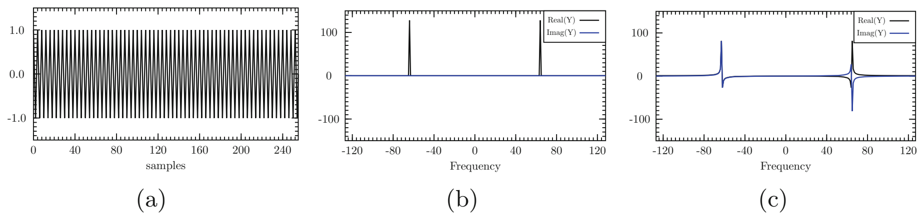


Fig. 6. FFT of 64 Hz cosine signal sampled at a frequency 256 Hz. (a) Original signal. (b) FFT of (a). (c) FFT of (a) taking only the first 255 samples, i.e., excluding the last one.

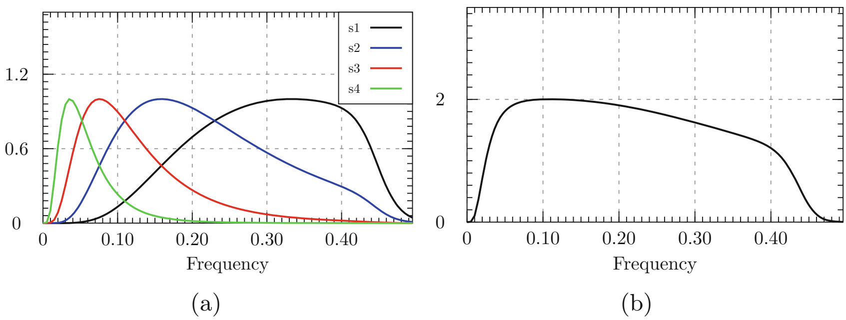
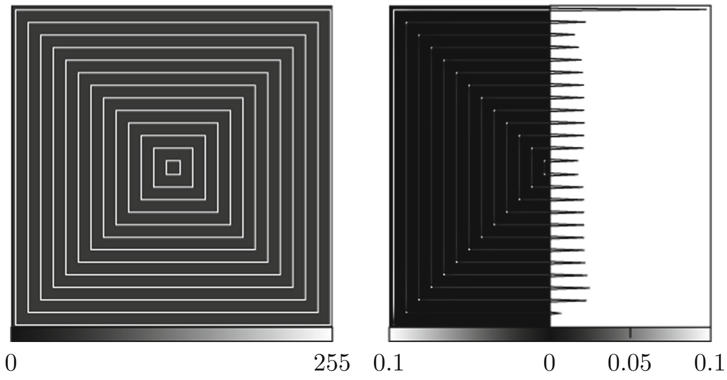


Fig. 7. Filter bank spectra of phase congruency with default parameters. (a) Scales spectra. (b) Sum of scales spectra.

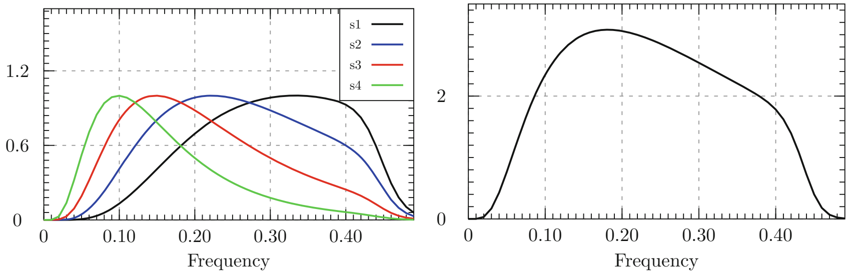
Figure 8 shows the result of the phase congruency of the image in Fig. 1a cropped to 255×255 pixels, after resizing it to 256×256 pixels, by padding it with zeros and mirror extension.



(a) (b)

Fig. 8. MPC of a synthetic square image of side 255 and fitted with zeros. (a) Synthetic image adjusted with tile mirror. (b) MPC of (a) and a vertical profile.

Since the nonlinearity of the joint response of the filter bank is, as mentioned above, one of the causes of the problem encountered, another possible solution, although more complex, consists of experimentally adjusting the response of the filter bank until the MPC identifies the edges, which can be achieved by modifying the separation between them, looking for a better response. As shown in Fig. 9, in this example the response of the filter bank is increased in the low frequencies, allowing to reduce the effect introduced by the high ones, obtaining an improvement in edge detection as shown in Fig. 10.



(a) (b)

Fig. 9. Bank filter spectra of MPC with factor between filter at 1.5. (a) Scales spectra. (b) Sum of scales spectra.

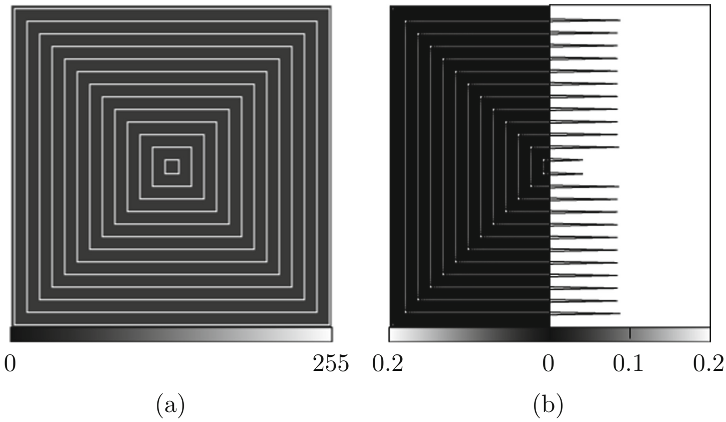


Fig. 10. MPC of a synthetic square image of side 255 with factor between filter at 1.5. (a) Original image. (b) MPC and vertical profile.

6 Experimental Results and Analysis

The example shown in Fig. 1, illustrates a critical case presented in the MPC, when the sides of the image do not have a value equal to a power of two. In practice, this deficiency is reflected in the incorrect detection of edges at the extremes of the image, as shown in Fig. 11b. As can be seen, when comparing the image obtained by mirror reflection of the edges, in Fig. 11d, with the one obtained by padding with zero, the first image allows obtaining a better edge detection at the extremes of the image, while in the second one a false edge is produced, as could be expected due to the abrupt change in the gray levels in that place. Other results are illustrated in the images in Fig. 12, where details can be seen in the red and green boxes, where it can be observed how the proposed correction allows to obtain a better edge detection at the extremes of the images. This correction is of great importance in image stitching in microscopy.

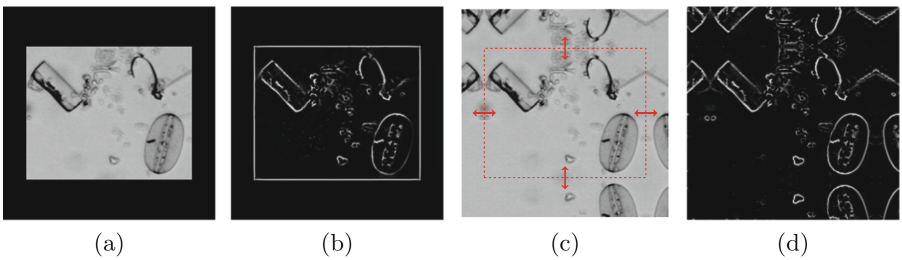


Fig. 11. MPC of diatom image. (a) Image resized using zero padding. (b) MPC of (a). (c) Image resized using tile-mirror. (d) MPC of (c).

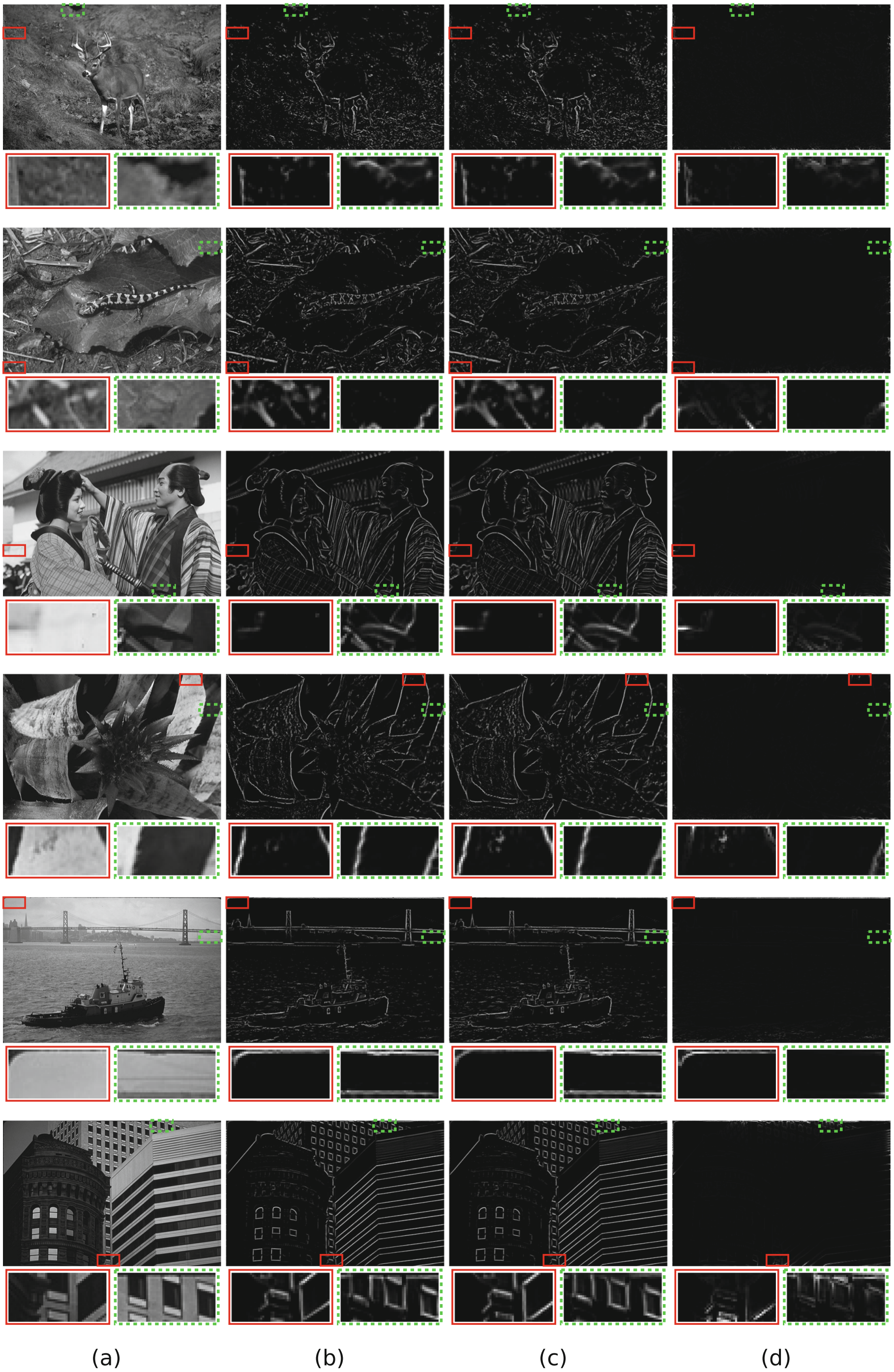


Fig. 12. Results. (a) Sample image. (b) MPC. (c) MPC with tile-mirror. (d) Difference between (b) and (c).

7 Conclusions

MPC is a more efficient technique than the one based on the use of directional filters. However, it presents deficiencies such as incorrect edge detection when any of its dimensions is not a power of two. This deficiency, not mentioned in previous works, is due to the fact that the filter bank and its mode of use for the congruency calculation is not a linear process, which generates poor results in some cases. Two solutions are proposed. The first one consists in enlarging the image by tile-mirror and the second one in readjusting the behavior of the filter bank, being the first one the simplest option and producing optimal results in the whole image, being of interest in cases where image stitching is required and to obtain a homogeneous result of the phase congruency.

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