Prefilter Design for Forensic Resampling Estimation

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***Abstract*—Starting from a theoretical analysis of the resampling estimation problem for image tampering detection, this work presents a study, based on cyclostationarity theory, about the use of prefilters to improve the estimation accuracy of the resampling factor. Considering the methods that perform the estimation by analyzing the spectrum of the covariance of a resampled region, we propose an analytical framework that allows the definition of a cost function that measures the degree of detectability of the spectral peaks. Based on this measure, the design of the optimum prefilters for a particular resampling factor can be solved numerically. Experimental results validate the developed analysis and illustrate the enhancement of the performance in a real scenario.**

I. Introduction

The presence of forged images in the news, in magazines or flowing through the Internet has become prevalent these days. However, even if today anyone can simply manipulate the information represented by a picture without leaving perceptual traces, the subsequent change introduced in the intrinsic properties of the image may enable the detection of such alterations. For instance, the application of a geometric transformation (e.g. scaling, rotation or skewing) to a portion of an image modifies the original sampling grid of this region, producing resampling traces that can be detected and, later on, will allow the estimation of the transformation locally applied.

To solve this problem, several techniques have been proposed in the past few years [1]–[6], providing different ways to detect those resampling traces and estimate the applied transformation. Although different approaches are considered in each case, all the proposed methods work, at some point, in the frequency domain to finally detect or estimate the periodicities that are inherently present when a spatial transformation is carried out in an image. Specifically, in [3]–[6], the spectrum of the covariance of the resampled blocks is computed to detect the frequency peaks that enable the estimation of the applied spatial transformation. Derivative filters are used in these resampling-based methods, to enhance the spectral lines as a way of substantially improving the estimation performance.

Since the use of certain prefilters, like the derivatives, increases the estimation accuracy of tampered regions, the question of whether there exist other prefilters yielding better results becomes very relevant. In a recent work, Dalgaard et al. show analytically that for asymptotically large values of the resampling factor, the use of derivative filters enhances the detection of the resampling traces [7].

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Nevertheless, in order to avoid visible distortions in the tampered image (generated by the employed spatial transformation), the resampling factor is usually near 1 and rarely larger than 2, so the hypothesis of an asymptotically large value of this factor does not hold in a realistic scenario. For this reason, the main goal of this paper is to present an analytical framework that supports the definition of a cost function which gives a measure of the detectability of resampling traces. Using this criterion, we study different prefilters and compute numerically their performance in the mentioned range of resampling factors, so as to reach the optimum prefilter for each factor. Using a database of real images, we also provide empirical results to endorse our analysis.

The paper is organized as follows: the next section is intended to describe the notation we will use along the paper and to introduce the bases of the problem exposed earlier. The description of the model used for natural images and the Fourier analysis for the detection of the resampling traces is presented in Section III. The design of the prefilters is considered in Section IV and the test of those with real images is performed in Section V. Finally, Section VI concludes the paper with comments on further research.

II. Preliminaries and Problem Statement

In order to create a credible image forgery, the manipulated portions of the image must be geometrically adapted to the scene in most of the cases. The spatial transformation applied in such regions maps the intensity value at each pixel location of the original region to a new one. This operation must be followed by an interpolation to get the pixel intensity values in those intermediate locations between source pixels. As it was shown in [6], the resampling process introduces periodically correlated fields in the two-dimensional (2-D) space that make possible the detection of such geometric transformation. Since the analysis of these correlations is more tractable in the one-dimensional (1-D) space, we will present the frequency analysis using a resampled image model in the 1-D space. While optimum results can be achieved following this model, the obtained solution can be not perfect for real images; therefore, in Section V experimental results with natural images are provided to show that the results can be straightforwardly extended to the 2-D case.

A. Notation

A real-valued continuous time signal in the 1-D space will be represented as $z(t)$ (note the parentheses), where $t \in \mathbb{R}$.

We will use the notation $z[n]$ (with brackets) to represent a real-valued 1-D discrete-index signal with $n \in \mathbb{Z}$. The mean of $z[n]$ will be represented by $\mu_z[n] \doteq \mathrm{E}\{z[n]\}$ and the covariance as $c_{zz}[n;\tau] \doteq \mathrm{E}\{(z[n]-\mu_z[n])(z[n+\tau]-\mu_z[n+\tau])\}$ with $\tau \in \mathbb{Z}$.

We will denote the cyclic correlation of a zero-mean process $z[n]$ by $C_{zz}(\alpha_n;\tau)$ and the Fourier Series coefficients if we have a pure cyclostationary process with period Q will be represented by $C_{zz}\left(\frac{2\pi}{Q}k;\tau\right)$, or directly by $C_{zz}[k;\tau]$, with $k\in\{0,\ldots,Q-1\}$. The Fourier Series coefficients of a sequence $z[n]$ will be denoted by $Z[k]$.

To identify the coefficients of a digital filter of order P with $l\in\{0,\ldots,P\}$, we will use p_l. For a compact notation, we will use $\mathrm{mod}(a,b)$ to denote the modulo operation: $a \mod b$. Floor and ceiling functions will be represented by $\lfloor\cdot\rfloor$ and $\lceil\cdot\rceil$, respectively.

B. Problem statement

As it was stated before, the role of prefiltering as a way to enhance the detectability of resampling traces in the frequency domain has been analytically supported for asymptotically large values of interpolation factors in [7]. However, considering that commonly the tampered regions are just slightly rotated, scaled or skewed to mitigate the generated visual distortions, we are more interested in the study of which are the prefilters that provide better results for resampling factors in the range $1<N_s<2$ (downsampling, i.e. $N_s<1$, is not considered in this work).

The general case of sampling rate conversion of an input signal $u[n]$ by a factor $N_s=\frac{L}{M}$ (with L and M integer values and relatively primes[1]), is carried out by first performing interpolation by the factor L and then decimating the output of the interpolator by the factor M. The resulting resampled signal $x[n]$, using any interpolation filter $h(t)$, can be expressed as:

$$x[n]=x(n\Delta)=\sum_k u[k]h(n\Delta-k), \tag{1}$$

where $\Delta=\frac{M}{L}=N_s^{-1}$ represents the interval between samples in the resampled signal. The low-pass filter used to preserve the desired spectral characteristics of the input signal $u[n]$ can be linear, cubic or a truncated sinc among others; but, in this case, with the aim of having a simplified model, we will only consider the linear filter, i.e.

$$h(t)=\begin{cases}1-|t|, & \text{if } |t|\le 1\\ 0, & \text{otherwise}\end{cases}.$$

Hence, considering this linear interpolator filter, the expression of the resampled signal (1) can be formulated as follows:

$$\begin{aligned}x[n]&=\begin{cases}\begin{array}{l}u\left[\lfloor n\Delta\rfloor\right]h\left(n\Delta-\lfloor n\Delta\rfloor\right)\\ +u\left[\lceil n\Delta\rceil\right]h\left(n\Delta-\lceil n\Delta\rceil\right)\end{array}, & \text{if } n\Delta\notin\mathbb{Z}\\ \\ u\left[n\Delta\right]\ , & \text{if } n\Delta\in\mathbb{Z}\end{cases}\\ &=u\left[\lfloor n\Delta\rfloor\right]\left(1-\mathrm{mod}(n\Delta,1)\right)+u\left[\lceil n\Delta\rceil\right]\mathrm{mod}(n\Delta,1).\end{aligned} \tag{2}$$

Assuming that the input signal $u[n]$ is zero-mean, the covariance of the resampled signal corresponds to the correlation $c_{xx}[n;\tau]=E\{x[n]x[n+\tau]\}$. Thus, considering the simplified version of $x[n]$ in (2) and using $v[n]\doteq\mathrm{mod}(n\Delta,1)$, we get

$$\begin{aligned}&c_{xx}[n;\tau]\\ &=E\left\{u\left[\lfloor n\Delta\rfloor\right]u\left[\lfloor(n+\tau)\Delta\rfloor\right]\right\}\left(1-v[n]\right)\left(1-v[n+\tau]\right)\\ &\quad+E\left\{u\left[\lfloor n\Delta\rfloor\right]u\left[\lceil(n+\tau)\Delta\rceil\right]\right\}\left(1-v[n]\right)v[n+\tau]\\ &\quad+E\left\{u\left[\lceil n\Delta\rceil\right]u\left[\lfloor(n+\tau)\Delta\rfloor\right]\right\}v[n]\left(1-v[n+\tau]\right)\\ &\quad+E\left\{u\left[\lceil n\Delta\rceil\right]u\left[\lceil(n+\tau)\Delta\rceil\right]\right\}v[n]v[n+\tau],\end{aligned} \tag{3}$$

that represents the general expression of the correlation of a zero-mean signal interpolated by a linear filter.

[1]Note that if $1<N_s<2$, then $L>2$ with $L>M$.

In order to determine if the resampled signal $x[n]$ is (wide-sense) cyclostationary, we have to check if the above expression (3) varies periodically. Sathe and Vaidyanathan showed in [8] that the resampled signal, in this case, will be a cyclostationary signal with period $L/\gcd(L,M)$ if the input signal $u[n]$ is wide-sense stationary and the interpolation filter is not ideal. Note that, in the case that we are considering, L and M are coprime, i.e. $\gcd(L,M)=1$, and consequently this is equivalent to saying that the resampled signal $x[n]$ will be a cyclostationary process of period L if $u[n]$ is wide-sense stationary and the interpolator is not ideal.

Moreover, we can generalize this property by proving that the resampled signal is (wide-sense) almost cyclostationary if the above expression satisfies $c_{xx}\left[n+k\frac{L}{M};\tau\right]=c_{xx}[n;\tau]$ with $k\in\mathbb{Z}$. To demonstrate that, we have to show that $v[n]$ is periodic and also that the four terms within expectations $E\{\cdot\}$ in (3) are periodic. Accordingly, starting with the signal $v[n]$, it is easy to see that:

$$\begin{aligned}v\left[n+k\tfrac{L}{M}\right]&=\mathrm{mod}\left(\left(n+k\tfrac{L}{M}\right)\Delta,1\right)\\ &=\mathrm{mod}\left(n\Delta+k,1\right)=\mathrm{mod}(n\Delta,1)=v[n].\end{aligned}$$

On the other hand, considering the expectation term $E\left\{u\left[\lfloor n\Delta\rfloor\right]u\left[\lfloor(n+\tau)\Delta\rfloor\right]\right\}$ and, taking into account that $u[n]$ is wide-sense stationary, we know that this expression depends only on the difference between $\lfloor n\Delta\rfloor$ and $\lfloor(n+\tau)\Delta\rfloor$ and such difference has to be cyclic with period $\frac{L}{M}$, i.e.:

$$\begin{aligned}&\left\lfloor\left(n+k\tfrac{L}{M}\right)\Delta\right\rfloor-\left\lfloor\left(n+k\tfrac{L}{M}+\tau\right)\Delta\right\rfloor\\ &\quad=\lfloor n\Delta+k\rfloor-\lfloor(n+\tau)\Delta+k\rfloor\\ &\quad=(n\Delta+k)-\mathrm{mod}(n\Delta+k,1)\\ &\qquad-((n+\tau)\Delta+k)+\mathrm{mod}((n+\tau)\Delta+k,1)\\ &\quad=-\mathrm{mod}(n\Delta,1)-\tau\Delta+\mathrm{mod}((n+\tau)\Delta,1)\\ &\quad=\lfloor n\Delta\rfloor-\lfloor(n+\tau)\Delta\rfloor,\end{aligned}$$

where we have used the relation:

$$\lfloor n\Delta\rfloor=n\Delta-\mathrm{mod}(n\Delta,1). \tag{4}$$

The same applies for the other three expectation terms in (3), where additionally we have to use that

$$\lceil n\Delta\rceil=n\Delta+\mathrm{mod}(-n\Delta,1). \tag{5}$$

Therefore, since $c_{xx}[n;\tau]$ is cyclic with an almost-integer period $\frac{L}{M}$, we can conclude that if the input signal $u[n]$ is wide-sense stationary then the resampled signal $x[n]$ will be almost cyclostationary.

Several works, i.e. [2]–[4] and [6], have noticed this periodicity, considering a random i.i.d. Gaussian signal as input, but in this case we are generalizing this fact for any wide-sense stationary input signal and a linear interpolator. Our main goal is to analytically characterize the correlation of the resampled signal in the frequency domain, since the estimation of the resampling factor is performed in this domain through the detection of the cyclic frequencies.

Taking into account that we will perform the study of the cyclic correlation in the Fourier domain, it is apparent that a white Gaussian signal will not lead to an accurate model for a natural image, so we need a model that better captures the local correlation of natural images. For this reason, we propose to use a 1-D autoregressive (AR) process of the first order that provides a good fit to the power spectral density of real images [9]. Next section describes the used model and the Fourier analysis carried out that will lead us to the design of the optimum prefilter for resampling estimation.

III. Model Description and Fourier analysis

Since a white Gaussian process is not very representative of a non-compressed natural image, we use a more convenient approximation that corresponds to a first-order AR process with a correlation coefficient ρ that satisfies $|\rho| < 1$. The value of ρ enables the adjustment of the model as necessary. For instance, values of ρ near 1 (e.g. $\rho = 0.95$) can be employed to model the power spectral density of natural images, while values of ρ near zero behave like a Gaussian process, and near -1 (e.g. $\rho = -0.95$) could represent synthetic images with high frequency content [10].

Therefore, in the resampling image model, we consider that the input signal $u[n]$ is a sequence generated by a first-order AR model with parameter ρ, so

$$u[n] = w[n] + \rho u[n-1],$$

where $w[n]$ is a Gaussian process with zero-mean and unit variance. Taking this into account, we have $\mu_u[n] = 0$ and the correlation becomes:

$$c_{uu}[n;\tau] = E\{u[n]u[n+\tau]\} = \frac{\rho^{|\tau|}}{1-\rho^2}.$$

The correlation of the resampled signal $x[n]$, given this input signal, can be directly obtained from (3), resulting in:

$$\begin{aligned} c_{xx}[n;\tau] = \frac{1}{1-\rho^2} \Big[& \rho^{|\lfloor n\Delta\rfloor - \lfloor (n+\tau)\Delta\rfloor|} (1-v[n])(1-v[n+\tau]) \\ & + \rho^{|\lfloor n\Delta\rfloor - \lceil (n+\tau)\Delta\rceil|} (1-v[n])\, v[n+\tau] \\ & + \rho^{|\lceil n\Delta\rceil - \lfloor (n+\tau)\Delta\rfloor|} v[n] (1-v[n+\tau]) \\ & + \rho^{|\lceil n\Delta\rceil - \lceil (n+\tau)\Delta\rceil|} v[n] v[n+\tau] \Big]. \end{aligned} \quad (6)$$

Since $u[n]$ is wide-sense stationary, we know from the previous analysis that the resampled signal will be almost cyclostationary with period $\frac{L}{M}$ and if we consider only pure cyclostationary processes, then $x[n]$ will be cyclostationary with period L.

Fig. 1(a) shows an example of the normalized version of $c_{xx}[n;\tau]|_{\tau=0}$ for $N_s = \frac{11}{10}$ and different values of ρ. Two periods of size $L = 11$ are represented and, as we can see, the periodicity becomes apparent for $\rho = -0.95$ and also for $\rho \approx 0$, whereas for $\rho = 0.95$ the correlation of the resampled signal seems to be constant. From this example, it can be inferred that the estimation in the frequency domain of the resampling factor for an AR process with $\rho = 0.95$ (i.e. natural images) will be more challenging than for $\rho = 0$ or $\rho = -0.95$ (i.e. synthetic images). In order to study the complexity of finding the resampling traces, we have to analyze the correlation in the frequency domain.

In view of the correlation $c_{xx}[n;\tau]$ is periodic over n with period L, such signal accepts a Fourier Series expansion whose spectral coefficients are $C_{xx}[k;\tau]$ with $k \in \{0,\ldots,L-1\}$. The development of a closed-form expression is not straightforward, but we can derive the spectral coefficients of (6), by determining the Discrete-Time Fourier Series (DTFS) of the signal $v[n]$ and then writing each term $\rho^{|\cdot|}$ as a function of $v[n]$.

Starting from the signal $v[n]$, we know that his DTFS corresponds to:

$$V[k] = \begin{cases} \frac{(L-1)}{2L}, & \text{if } k = 0 \\ -\frac{1}{2L} + j\frac{1}{2L\tan\left(\frac{\pi \tilde{M}^{-1}}{L}k\right)}, & \text{if } 1 \le k \le (L-1) \end{cases},$$

where $\tilde{M}^{-1}$ is the modular multiplicative inverse of M. From the previous relations (4) and (5), it is possible to formulate each one of the terms $\rho^{|\cdot|}$ as a function of $v[n]$. As an example, for the first term we obtain the following relation:

$$\begin{aligned} & \rho^{|\lfloor n\Delta\rfloor - \lfloor (n+\tau)\Delta\rfloor|} \\ & = \rho^{\lfloor \tau\Delta\rfloor} \left(1 + (\rho-1)(1 - v[\tau] + v[n] - v[n+\tau])\right). \end{aligned}$$

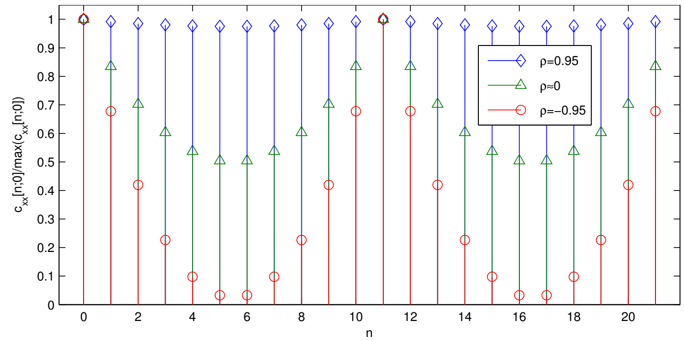
A similar analysis for the remaining $\rho^{|\cdot|}$ terms allows us to write $c_{xx}[n;\tau]$ as a function of ρ, $v[n]$ and some constants. Consequently, by using several properties of the discrete-time Fourier series we can obtain the theoretical expression of the Fourier coefficients $C_{xx}[k;\tau]$. For the sake of brevity, we only give the expression of the spectral coefficients for the particular case $\tau = 0$:

$$\begin{aligned} C_{xx}[k;0] = \frac{1}{1-\rho^2} \Bigg[& B[k] - 2V[k] + 2\sum_{l=0}^{L-1} V[l]V[k-l] \\ & + 2\left(G[k] \circledast \left(V[k] - \sum_{l=0}^{L-1} V[l]V[k-l] \right)\right) \Bigg], \end{aligned} \quad (7)$$

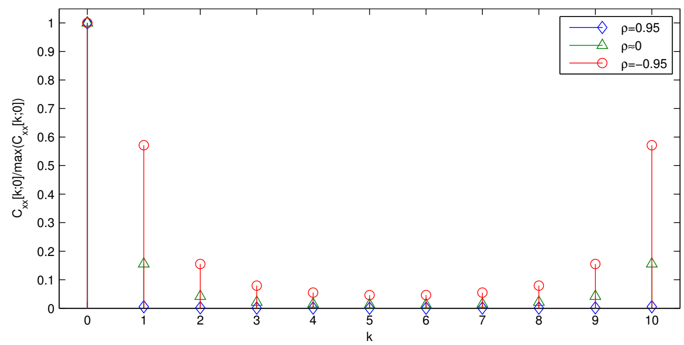
where $\circledast$ stands for the circular convolution operation of period L, $B[k]$ corresponds to the DTFS of a constant signal equal to 1 and $G[k]$ describes the following Fourier coefficients:

$$G[k] = \begin{cases} \frac{1+(L-1)\rho}{L}, & \text{if } k = 0 \\ \frac{1-\rho}{L}, & \text{if } 1 \le k \le (L-1). \end{cases}$$

In Fig. 1(b), we represent the normalized magnitude of the cyclic correlation $C_{xx}\left[\frac{2\pi}{L}k;\tau\right]|_{\tau=0}$ with $k \in \{0,\ldots,L-1\}$, through the Fourier coefficients in (7), for the different values of ρ considered before and keeping the resampling factor at $N_s = \frac{11}{10}$. From the drawn results, we can assert that the magnitude of the spectral



(a) Correlation of $x[n]$.



(b) Cyclic correlation of $x[n]$.

Fig. 1. Normalized version of the correlation and cyclic correlation of the resampled signal $x[n]$ for $N_s = \frac{11}{10}$, $\tau = 0$ and different values of ρ.

coefficients (excluding the DC component at $k = 0$) is very small for $\rho = 0.95$. This is due to the fact that the correlation $c_{xx}[n; 0]$, as it was shown in Fig. 1(a), is almost constant and then the periodicity is hidden. Given that the estimation of the resampling factor depends on the magnitude of those frequencies, it is evident that those peaks must be enhanced for a correct operation.

IV. Prefilter design

As it has been shown in [2]–[7], the use of a prefilter before the estimation of the cyclic correlation improves the detection ratio of the correct resampling factor. In this section, we define a measure that makes possible the design of prefilters that improve the estimate of the resampling rate.

The prefiltering of a resampled signal $x[n]$, with a FIR filter of order P, gives a new signal $y[n]$ with the form

$$y[n] = \sum_{l=0}^{P} p_l x[n-l],$$

where p_l denotes the real-valued coefficients of the prefilter. The output correlation of this filtered version of the resampled signal $x[n]$ becomes

$$\begin{aligned} c_{yy}[n;\tau] &= \sum_{l=0}^{P}\sum_{m=0}^{P} p_l p_m E\left\{x[n-l]x[n+\tau-m]\right\} \\ &= \sum_{l=0}^{P}\sum_{m=0}^{P} p_l p_m c_{xx}[n-l;\tau+l-m], \end{aligned}$$

that is, a linear combination of shifted versions of the correlation described in (6), evaluated in different values of τ. In the Fourier domain, the general expression of the spectral coefficients $C_{yy}[k;\tau]$ can be directly expressed as

$$C_{yy}[k;\tau] = \sum_{l=0}^{P}\sum_{m=0}^{P} p_l p_m C_{xx}[k;\tau+l-m] e^{-j\frac{2\pi k}{L}l},$$

where $C_{xx}[k;\tau]$ corresponds to the Fourier series coefficients of (6), that have been analitically characterized in the previous section.

As we have seen before, the resampled signal $x[n]$ is almost cyclostationary with period $\frac{L}{M}$ and since the prefilter used is a linear time-invariant system, this also applies for the prefiltered signal $y[n]$. From this periodicity and considering the fact that spectral coefficients are symmetric for real-valued signals (i.e. $|C_{yy}[i;\tau]| = |C_{yy}[L-i;\tau]|$), the corresponding cyclic frequencies $\alpha_y \doteq 2\pi\frac{M}{L}$ and the replica $\alpha'_y \doteq 2\pi\frac{L-M}{L} = -2\pi\frac{M}{L}$ will have a larger magnitude than the rest of frequencies (excluding the DC component). For example, given the cyclic correlation with period $N_s = \frac{11}{10}$ shown in Fig. 1(b), we can check that the AC spectral coefficients with largest magnitude are $C_{xx}[1;0]$ and $C_{xx}[10;0]$ that match with the corresponding cyclic frequencies $\alpha'_x = 2\pi\frac{1}{11}$ and $\alpha_x = 2\pi\frac{10}{11}$, respectively.

Therefore, given that the estimation of the resampling rate can be carried out from the AC spectral coefficients with largest magnitude, because they identify the cyclic frequencies, we use the following criterion to define the target function Θ as:

$$\Theta(L, M, \rho, p_0, \ldots, p_m) \doteq \frac{\frac{1}{2}\left(|C_{yy}[M;0]|^2 + |C_{yy}[L-M;0]|^2\right)}{\frac{1}{L-2}\sum_{\substack{k=0\\ k\neq M, L-M}}^{L-1} |C_{yy}[k;0]|^2},$$

where, viewing this expression as an SNR, the magnitude of the cyclic frequencies $\alpha_y = 2\pi\frac{M}{L}$ and $\alpha'_y = 2\pi\frac{L-M}{L}$ represent the signal part and the remaining spectral coefficients are considered as noise. In fact, Θ can be interpreted as a measure of the detectability of the resampling traces.

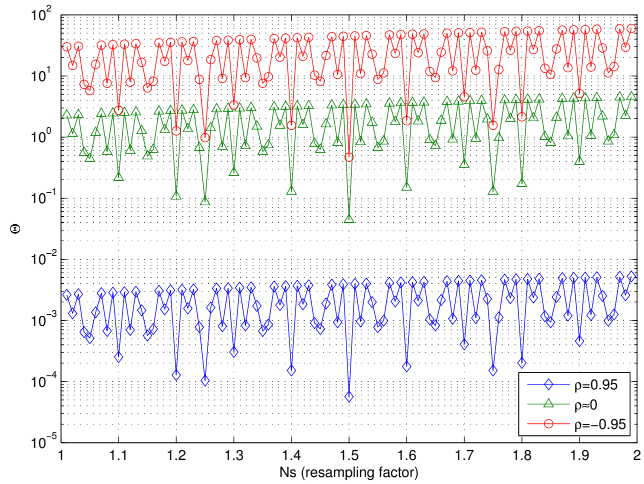


Fig. 2. Objective function Θ for resampling factors in $1 < N_s < 2$ and for different values of ρ.

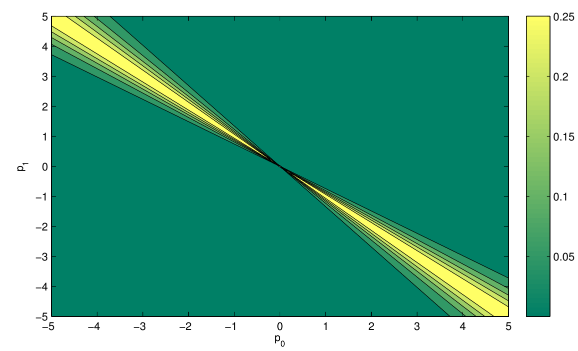


Fig. 3. Objective function Θ considering a first-order prefilter, varying the coefficients p_0 and p_1 in the range $[-5, 5]$, for $N_s = \frac{11}{10}$ and $\rho = 0.95$.

Our main goal is to maximize this objective function Θ for given values of ρ and the resampling factor $N_s = \frac{L}{M}$, so as to obtain the optimum prefilter. The lack of a closed-form solution to the maximization of Θ makes it difficult to find the fixed optimum prefilter for a range of values of N_s and ρ. Nevertheless, since all the cyclic correlations can be straightforwardly evaluated from their analytical expressions, we can numerically find the optimal prefilter maximizing Θ.

In Fig. 2 we evaluate the target function for three different values of ρ and resampling factors in the range $1 < N_s < 2$, when no prefilter is applied. As it was expected, we can observe that the worst performance is reached when the AR process approximates that of natural images, that is, when the correlation coefficient is $\rho = 0.95$.

Focusing on the case $\rho = 0.95$, we start considering a prefilter of order 1 and we analyze the target function Θ for a particular resampling factor, e.g. $N_s = \frac{11}{10}$. Fig. 3 shows the values of Θ for the coefficients p_0 and p_1 in the range $[-5, 5]$. From the representation, it is easy to perceive that the filters that satisfy the condition $p_0 = -p_1$ reach the maximum value of Θ. So, in this particular case, the first-order derivative with $p_0 = 1$ and $p_1 = -1$ is optimal.

The same analysis is carried out for a FIR filter of order 2, but

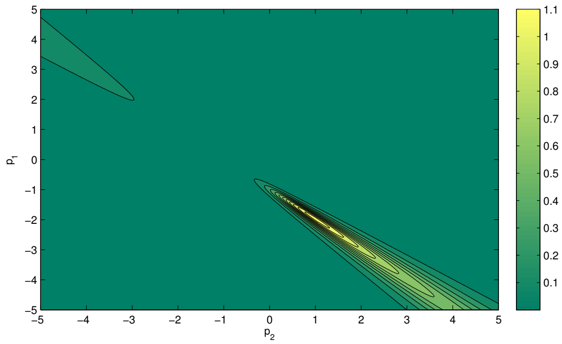


Fig. 4. Objective function Θ considering a second-order prefilter, fixing $p_0 = 1$ and varying the coefficients p_1 and p_2 in the range $[-5, 5]$, for $N_s = \frac{11}{10}$ and $\rho = 0.95$.

TABLE I
OPTIMUM PREFILTERS OF ORDER 3 FOR SOME VALUES OF N_s.

Range of N_s	Coefficients of the prefilter			
	p_0	p_1	p_2	p_3
1.05 - 1.1	1	-2.4	2.4	-1
1.3 - 1.35	1	-2.75	2.75	-1
1.4 - 1.45	1	-2.8	2.8	-1
1.6 - 1.65	1	-5	7.5	-3.5
1.85 - 1.95	1	-2	1.1429	-0.1429

in order to get representable results, we fix the first coefficient $p_0 = 1$, without loss of generality. Fig. 4 represents the variation of the objective function Θ with respect to the prefilter coefficients p_1 and p_2 in the range $[-5, 5]$. The largest value of Θ is achieved at $p_1 = -2$ and $p_2 = 1$. Then, in this case, the optimum prefilter corresponds to the second-order derivative filter.

Thus, these results support the idea of using derivative filters to enhance the spectral peaks. In Fig. 5, we show the values of Θ considering different order for the derivatives. As we can see, there is a huge gap between the results obtained without any prefilter and the cases where the derivative filters are used. From these plots we can conclude that the derivative filters improve the detectability of the cyclic frequencies for all the resampling rates in the range $1 < N_s < 2$.

Interestingly, the third-order derivative present lower performance than the second-order filter for values of $N_s > 1.6$. Hence, the question is, can we obtain better results with other kinds of filters? The answer is positive, in fact, as we increase the order of the filter, the optimum prefilter becomes more dependent on the considered resampling rate and other types of prefilters show up. Performing an exhaustive search for the first and second order prefilters, the optimizers of Θ turn out to be respectively the first and second order derivative filters. On the other hand, for third-order prefilters, the optimal filters turn out to be dependent on the resampling factor. Table I, shows some of the prefilters achieved for the different values of N_s.

V. EXPERIMENTAL RESULTS

While the obtained prefilters in the previous section can be optimal for a 1-D AR process with $\rho = 0.95$, it remains to evaluate how the prefilters so-designed perform with real images. To this end, we carried out an experiment with natural images where we study the estimation accuracy for different scaling factors separated by a

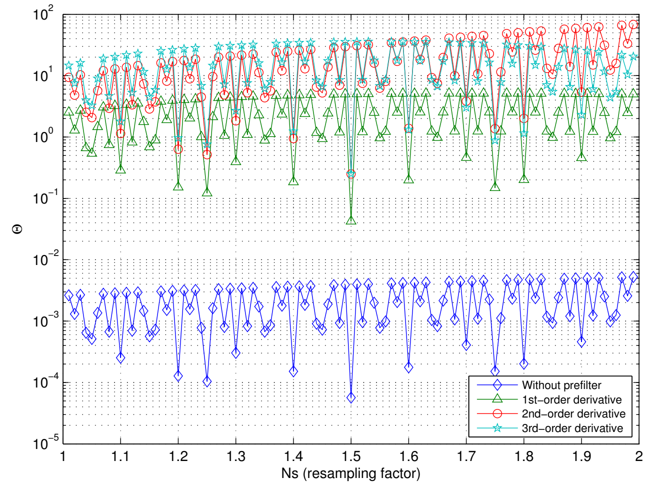


Fig. 5. Objective function Θ, considering different prefilters, for resampling factors in $1 < N_s < 2$ and for $\rho = 0.95$.

distance of 0.05, i.e. $N_s \in \{1.05, \ldots, 1.95\}$. For the evaluation of the prefilters, we use 150 images from a personal image database composed of several realistic scenarios with different indoor and outdoor scenes. All the images in this collection have been captured in a RAW format by a Nikon D60 digital camera and have been converted into uncompressed grayscale TIFF images. Each image has been downsampled by a factor of two in order to avoid the interpolation carried out by the camera, due to the color filter array, obtaining images of size 1936×1296.

To reproduce the conditions of the considered model, we first resize each image by the corresponding factor N_s with a bilinear interpolation filter and then we take a large image block of size 1024×1024 pixels. Next, we subtract the mean value of this portion of the image in order to get a zero-mean block, we subsequently apply the corresponding prefilter and, finally, we compute the 2-D Fourier transform of the correlation of the block for $\tau = 0$ (i.e. the cyclic correlation). Be aware that to exclude the DC component, we just subtract the mean value of the correlation before the computation of the Fourier transform. Considering this 2-D spectrum, the resampling rate is obtained from that frequency pair (ω_1, ω_2) with the largest magnitude. Note that ω_1 represents the horizontal frequency axis and ω_2 the vertical one. Since the range of resampling factors that we employ is $1 < N_s < 2$, the estimated value is computed as follows:

$$\hat{N}_s = \frac{2\pi}{2\pi - \max_{i \in \{1,2\}} |\omega_i|},$$

where we use $\max_{i \in \{1,2\}} |\omega_i|$ to avoid the case when one of both components is equal to zero (i.e. the cyclic frequency is located over one of the axes). We consider that the estimation is correct if the detected cyclic frecuency (ω_1, ω_2) is in the range defined by the resolution in the frequency domain, i.e.

$$\left| \max_{i \in \{1,2\}} |\omega_i| - \alpha \right| \leq \frac{2\pi}{1024},$$

where $\alpha \doteq 2\pi - \frac{2\pi}{N_s} = 2\pi \frac{L-M}{L}$ is the theoretical value of the cyclic frequency.

Fig. 6 shows the obtained estimation accuracy for the different values of N_s. From this plot we can observe that the proposed analysis and target function yield satisfactory results, as better performance is achieved with those prefilters that reach a larger value of Θ. For

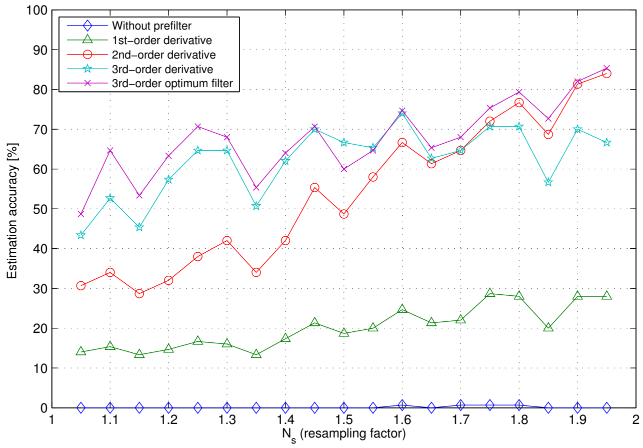


Fig. 6. Estimation accuracy of the resampling factor for image blocks of size 1024×1024 pixels, considering different prefilters.

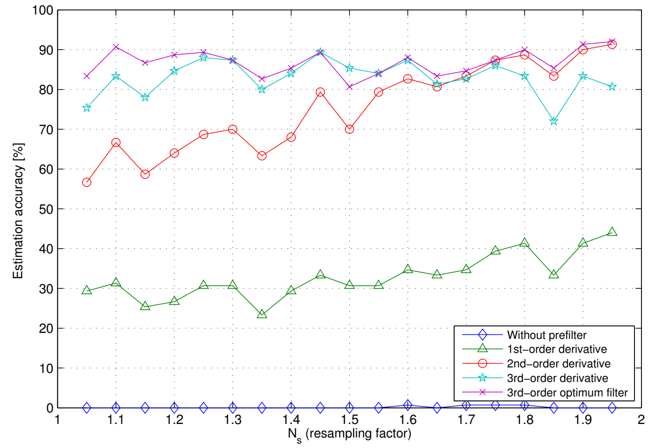


Fig. 7. Estimation accuracy of the resampling rate, excluding near-zero frequencies, for image blocks of size 1024×1024, using different prefilters.

instance, comparing the values obtained for the second and third order prefilters we see that the performance of the former improves when $N_s > 1.6$ as it was shown in Fig. 5. We can also confirm the worse performance of the third-order derivative filter with respect to the numerically computed third-order optimum prefilter, so we can conclude that derivative filters are no longer the best solution once we increase the order of the prefilter above 2.

Focusing on the estimation performance, the obtained results cannot be considered very optimistic, since the prefilter that reach the best results is far from the perfect estimation. This is due to our model only capturing the deterministic value of the cyclic correlation without considering any other effects. In this case, windowing (by taking a block of size 1024×1024) introduces further components at all frequencies, but especially those near DC (i.e. the frequencies included in the main lobe of the window). The magnitude of the latter is heavily influenced by the DC component, so in many cases the cyclic frequency is incorrectly detected, due to the fact that the largest components are located within the DC main lobe. By leaving those components (i.e. $\omega_i \leq 2\pi/1024$) out during the detection process, we obtain the results shown in Fig. 7. As we can see, the estimation accuracy is highly improved for all the prefilters considered, achieving with our porposed design an estimation accuracy close to 90%[2].

VI. Conclusions and Further Work

In this work, the design of prefilters to improve the estimation accuracy of the resampling factor of spatially transformed images has been analytically investigated. Although the proposed analytical framework only models the deterministic value of the cyclic correlation, experimental results validate the use of the defined objective function for the design of prefilters.

However, in order to obtain a better estimate of the cyclic correlation for realistic scenarios, further research will focus on refining the proposed model, taking into consideration the effects of windowing and also the influence of the rounding operation carried out after the resampling of a portion of an image. Moreover, although our study has been limited to the use of a linear interpolator, the proposed framework can be directly applied to other interpolators, such as the cubic or for a truncated sinc. Further research will also focus on extending this analytical framework to other interpolators and to resampling factors less than one.

[2]This comes at the price of missing resampling factors $1 < N_s \leq 1.001$.

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