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Detection of Biometric systems by enhancing the image quality measure

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Abstract—Image de blurring (ID) is an ill-posed problem typically addressed by using regularization, or prior knowledge, on the unknown image (and also on the blur operator, in the blind case). ID is often formulated as an optimization problem, where the objective function includes a data term encouraging the estimated image (and blur, in blind ID) to explain the observed data well (typically, the squared norm of a residual) plus a regularizer that penalizes solutions deemed undesirable. The performance of this approach depends critically (among other things) on the relative weight of the regularizer (the regularization parameter) and on the number of iterations of the algorithm used to address the optimization problem. In this paper, we propose new criteria for adjusting the regularization parameter and/or the number of iterations of ID algorithms. The rationale is that if the recovered image (and blur, in blind ID) is well estimated, the residual image is spectrally white; contrarily, a poorly de blurred image typically exhibits structured artifacts (e.g., ringing, over smoothness), yielding residuals that are not spectrally white. The proposed criterion is particularly well suited to a recent blind ID algorithm that uses continuation, i.e., slowly decreases the regularization parameter along the iterations; in this case, choosing this parameter and deciding when to stop are one and the same thing. Our experiments show that the proposed whiteness-based criteria yield improvements in SNR, on average, only 0.15 dB below those obtained by (clairvoyantly) stopping the algorithm at the best SNR. We also illustrate the proposed criteria on non-blind ID, reporting results that are competitive with state-of-the-art criteria (such as Monte Carlo-based GSURE and projected SURE), which, however, are not applicable for blind ID.

Key words - Image deconvolution/ de blurring, blind de blurring, whiteness, stopping criteria, regularization parameter.

I. INTRODUCTION

Image de blurring (ID) is an inverse problem where the observed image is modeled as the convolution of a sharp image with a blur filter, possibly plus some noise (often assumed spectrally white and Gaussian). With applications in many areas (*e.g.*, astronomy, photography, surveillance, remote sensing, medical imaging), research on ID can be divided into *non-blind* ID (NBID), in which the blur filter is assumed known, and (more realistic) *blind* ID (BID), in which both the image and the blur filter are (totally or partially) unknown. Despite its narrower applicability, NBID is already a challenging problem to which a large amount of research has been (and still is) devoted, mainly due to the ill-conditioned nature of the blur operator: the observed image does not uniquely and stably determine the underlying original image [38]. If this problem is serious with a known blur, it is much worse if there is even a slight mismatch between the assumed blur and the true one. Most of the NBID methods overcome this difficulty through the use of an image regularizer, or prior, the weight of which has to be tuned or adapted. Most state-of-the-art regularizers exploit the sparsity1 of the high frequency/edge components of images; this is the rationale underlying wavelet/frame-based methods (see, *e.g.*, [21], [48] and the many references therein) and total variation (TV) regularization. With application not only in ID, but also in other inverse problems, several optimization techniques have been proposed to handle sparsity-inducing regularizers. A popular class of such techniques belongs to the class of *iterative shrinkage/*thresholding (IST) algorithms, and their recent accelerated versions . The iterative nature of these methods requires, in addition to the regularization parameter, the choice of an adequate stopping criterion; often, there is a delicate interplay between these two choices. In BID, even if the blur operator was not ill-conditioned, the problem would still be inherently ill-posed, since there is an infinite number of solutions (pairs of image and blur estimates) compatible with the blurred image. In order toobtain reasonable results, most BID methods restrict the class of blur filters, either in a hard way, through the use of parametric models], or in a soft way, through the use of priors/regularizes]. In contrast, a recent BID method does not use prior knowledge about the blur, yet achieves state of-the-art performance on a wide range of synthetic and real problems. That method is iterative and starts by estimating the main features of the image, using a large regularization weight, and gradually learns the image and filter details, by slowly decreasing the regularization parameter. From an optimization point of view, this can be seen as a continuation method designed to obtain a good local minimum of the underlying non-convex objective function. The drawback of the method is that it requires manual stopping, which corresponds to choosing the final value of the regularization parameter. In fact, adjusting the regularization parameter and/or finding robust stopping criteria for iterative (blind or not) ID algorithms is a long standing, but still open, research area. A crucial issue in the regularization of ill-posed inverse problems is the choice of the regularization parameter, a subject to which much work has been devoted [53]. The *discrepancy principle* (DP) chooses the regularization parameter so that the variance of the residual (*i.e.*, the difference between the observed image and the blurred estimate) equals that of the noise; the DP thus requires an accurate estimate of the noise variance and is known to yield over regularized estimates [28]. A recent extension of the DP uses not only the variance, but also other residual moments . Local residual statistics have also been used to obtain locally adaptive TV regularizers for NBID], Two other popular criteria are *generalized cross validation* (GCV) and the *L-curve*, which, although developed and mainly applied to linear methods, can also be used with nonlinear methods, but are outperformed by more recent criteria based on *Stein's unbiased risk estimate* (SURE). SURE provides an estimate of the *mean squared error* (MSE), assuming knowledge of the noise distribution and requiring an accurate estimate of its variance [59]. While methods for automatically adjusting the regularization parameter are relatively developed for denoising and NBID (as reviewed in the previous paragraph), the same is not true for BID, with most existing methods requiring the regularization parameters to be somehow tuned or empirically selected. For example, SURE-based approaches assume full knowledge of the degradation model, thus are not suitable for BID. There are a few methods that address the adjustment of the regularization parameter; however, some of those approaches were developed for Bayesian formulations , and do not fit iterative BID algorithms such as that of [3]. Finally, we should mention no-reference image quality measures; although proposed for adjusting the regularization parameter in de noising , they can in principle be used in NBID or BID methods.

A. Contributions

We propose a criterion that can be used to adjust the regularization parameter and stopping criterion of iterative ID methods; although motivated by BID problems, it is of general applicability to both NBID and BID problems. The cornerstone of the proposed approach is the assumption that the noise in the observed image is spectrally white. The implementation of this rationale is based on measures of spectral whiteness to assess the fitness of the current estimates to the degradation model. Residual whiteness has been used for a long time to assess model accuracy, namely in modeling time series and dynamical systems [9], [39]; more recent applications can be found in spectroscopy [18] and signal detection [50]. However, to the best of our knowledge, criteria based on residual whiteness have not been used before in image de convolution/ deblurring. Our criteria are particularly suited to the BID method of [3], where stopping and choosing the regularization parameter are one and the same thing. The results reported in this paper, show that, on a large set of synthetic experiments, the proposed criteria lead to an average decrease of 0.15 dB in ISNR2, compared to what is obtained by stopping the algorithm at the maximum ISNR (which, of course, cannot be done in practice, as it requires the original image), outperforming in this sense both the DP and the measure of [59]. We also show tests on color images and on various real blurred images; although with these images, no quantitative results can be reported, we believe the results can be (subjectively) considered good. We show that the proposed criteria are also suitable for adjusting the regularization parameter and stopping criterion of NBID methods. In particular, we report experiments with two recent algorithms, using different blurs and noise variances. In this scenario, our approach is shown to be adequate, but does not outperform SURE-based methods.

II. IMAGE DECONVOLUTION/DEBLURRING

In ID problems, the degraded image is usually modeled as

$y = h * x + n,$ (1)

where *y* is the degraded image, *x* is the (unknown) original image, *n* is noise, and *h* is the *point spread function* (PSF) of the blur operator (assumed to be known in NBID and unknown in BID) and ∗ denotes convolution. Both BID (finding *x* and *h*, from *y*) and NBID (finding*x*, from *y* and *h*) are normally addressed by adopting a regularizer expressing prior information about the image *x* and considering an objective function of the form

Cλ(x, h) = 12_*y* − *h* ∗ *x*_22+*λ* _*(x)*; (2)

the first term in (2) is the classical data fidelity term that results from assuming that the noise *n* is white and Gaussian, _*(x)* is a regularization function embodying the prior information about *x*, and *λ* is the regularization parameter. Typically, too large values of *λ* lead to over-regularized images (*e.g.*, over smoothed or cartoon-like), while too small values of *λ* lead to under-regularized images dominated by the influence of the noise. An adequate choice of the regularization parameter *λ* is thus clearly crucial to obtain a good image estimate.

A. Non-Blind De blurring

In NBID, *h* is assumed to be known and the cost function (2) is minimized with respect to *x*, given some choice of the regularization parameter *λ*. Many optimization methods for ID minimize the cost function (2) iteratively , computing the image estimate at iteration *t* + 1 as a function of the previous estimate *xt* , the available data (*y* and *h*), and the regularization parameter *λ*:

xk+1 = f (xk, y, h, λ). (3)

Besides requiring a good estimate for the regularization parameter *λ*, these iterative approaches also need stopping criteria, which considerably influence the final results.For fairness, it should be mentioned that some state-of-theart methods don't fall in the category of methods mentioned in the previous paragraph. For example, the method proposed in [16] (arguably the method yielding the current best results) is iterative, but rather than look for a minimizer of an objective function, it looks for a Nash equilibrium between two objective functions. Other NBID methods are not based on iterative minimization of objective functions.

B. Blind De blurring

In BID, both the image *x* and the filter *h* are unknown. A BID problem suffers from an obvious lack of data, since there are many pairs *(x, h)* that explain equally well the observed data *y*. Most BID methods circumvent this difficulty by adding to (2) a regularizer on the blur filter and, usually, by alternatingly estimating the image and the blur filter. A regularizer on the blur naturally involves an additional regularization parameter, also requiring adjustment, while the alternating estimation of the image and the filter requires good initialization (since the underlying objective (2) is non-convex) and a good criterion to stop the iterative process. The recent method in [2], [3] yields good results without regularization on the blur filter, *i.e.*, using a cost function with the form of (2). That method uses an iterative algorithm to minimize (2), by starting with a strong regularization (large *λ*), and gradually decreasing it (see Algorithm 1). The initial estimates are cartoon-like; the sharp edges of these images, when compared with the blurred image *y*, allow to learn and improve the estimate of the filter *h*, which, in turn, allows reducing the weight of the regularization, thus learning finer image details. This slow decrease of the regularization parameter was shown to yield good estimates without the need for a regularizer on the blur filter [3]. A drawback of that method is the need to manually stop the iterations, which corresponds to setting the final value of the regularization parameter. In [3], this was done either based on the ISNR value, in synthetic experiments, or by visual assessment of the restored image, for real blurred images. The whiteness based criteria proposed in this paper will be illustrated in automatically stopping the BID algorithm of.

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Algorithm 1 Blind method of [2], [3]

1 Set λ to the initial value; choose $\alpha < 1$.
2 Set $\widehat{x} = y$
3 **repeat**
4 $\quad \widehat{h} \leftarrow \arg\min_h C_\lambda(\widehat{x}, h)$
5 $\quad \widehat{x} \leftarrow \arg\min_x C_\lambda(x, \widehat{h})$
6 $\quad \lambda \leftarrow \alpha\,\lambda$
7 **until** *stopping criterion is satisfied*

III. THE WHITENESS CRITERIA

A. Rationale

The proposed criteria for selecting the regularization parameter and the stopping iteration are based on measures of the fitness of the image estimate _*x* and the blur estimate _*h*(in NBID, *h* is known, thus _*h* = *h*) to the degradation model (1), by analyzing the estimated residual image:

$r = y - \_h * \_x.$ (4)

The characteristics of the residual *r* are then compared with those assumed for the noise *n* in the degradation model (1). In particular, the noise *n* is assumed to be spectrally white (uncorrelated), thus a measure of the whiteness of the residual *r* is used to assess the adequacy of the estimates (_*x*,*h*) to the model. This is a quite generic assumption, valid for most real situation. Our approach differs from other methods based on residual statistics, such as those in [17], [52], in that those methods do not use spectral properties of the residual, but other statistics, such as variance and other moments. The proposed criterion consists in selecting the regularization parameter and/or final iteration of the algorithm that maximize one of the whiteness measures introduced below. If this measure exhibits a clear peak as a function of the regularization parameter and/or the iteration number, we adopt an oriented search scheme and stop the method as soon as the measure of whiteness starts to decrease. This is the case in the BID algorithm mentioned in the previous section. Also in NBID, if optimizing only with respect to λ, an efficient strategy is to sweep a range of values, using the estimate at each value to initialize the algorithm at the next value; this process is known *warm-starting*, and may yield large computational savings [56]. In our NBID experiments, when optimizing with respect to λ and/or the number of iterations, and since the goal is to assess the ability of the proposed criteria to select these quantities, with no concern for computational efficiency, we simply consider a grid of values and return the image estimate yielding the maximum residual whiteness.

B. Measures of Whiteness

The first step of our method is to normalize the residual image3 to zero mean and unit variance; for simplicity of notation, let this normalized residual still be denoted as *r* ,

$$r \leftarrow \frac{r - \overline{r}}{\sqrt{\mathrm{var}(r)}},$$

where *r* and var(*r*) are, respectively, the sample mean and sample variance of *r* . The auto-correlation (and auto-covariance, since the mean is zero) of the normalized residual *r*, at the two-dimensional (2D) lag *(m, n)*, is estimated by

$$R_{rr}(m,n) = K \sum_{i,j} r(i,j)\, r(i-m, j-n), \qquad (5)$$

where the sum is over the residual image, and *K* is an irrelevant constant. The auto-covariance of a spectrally white image is a delta function at the origin ($\delta(m, n) = 1$, if $m = n = 0$, $\delta(m, n) = 0$, otherwise). A measure of whiteness is thus the distance between *Rrr* and a delta function. Considering a $(2L + 1) \times (2L + 1)$ window, the first proposed whiteness measure is simply the energy of *Rrr* outside the origin,

$$M_R(r) = -\sum_{\substack{(m,n)=(-L,-L)\\(m,n)\neq(0,0)}}^{L,L} \Big(R_{rr}(m,n)\Big)^2, \qquad (6)$$

where the minus sign is used to make *MR* larger for whiter residuals. In our experiments, we have used *L* = 4.For a typical process that exhibits mainly short-range correlations, the auto-covariance for large lags (for long-range dependencies) is usually smaller than for small lags. This observation suggests that it makes sense to give more weight to the auto-covariance for small lags. Based on that, a weighted version of the measure in (6) is also considered,

$$M_{RW}(r) = -\sum_{\substack{(m,n)=(-L,-L)\\(m,n)\neq(0,0)}}^{L,L} W(m,n)\Big(R_{rr}(m,n)\Big)^2, \qquad (7)$$

where *W(m, n)* is a matrix of weights. In all our experiments,we have used *L* = 4 and the *gausswin* function in MATLAB:

$$W(m,n) = \exp\big(-1.25(m^2+n^2)\big). \qquad (8)$$

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Let $S_{rr}(\omega, \nu)$ denote the power spectral density of r, at 2D spatial frequency (ω, ν),

$$S_{rr} = \mathcal{F}(R_{rr}), \quad (9)$$

where F denotes the magnitude of the 2D *discrete Fourier transform* (2D-DFT). Since the auto-correlation of a white process is a delta function, a white signal has a flat power spectral density. To assess the flatness of S_{rr}, we measure its Shannon entropy, after normalization; recall that the maximum entropy is achieved by a flat distribution. The resulting measure is

$$M_H(r) = -\sum_{\omega,\nu} \widetilde{S}_{rr}(\omega,\nu) \log \widetilde{S}_{rr}(\omega,\nu), \quad (10)$$

where $\widetilde{S}_{rr}(\omega,\nu) = S_{rr}(\omega,\nu) / \sum_{\omega',\nu'} S_{rr}(\omega',\nu')$.

C. Local Measures of Whiteness

The approach described in the previous subsection implicitly assumes that the residual image r is a sample of a stationary and ergodic process, since we estimate the auto-covariance (5) by averaging over the whole image. In practice, the residual may not be stationary, which lead us to consider also local versions of the previous measures of whiteness, based on local auto-covariance estimates,

$$R^b_{rr}(m,n) = \sum_{i,j \in B_b} r(i,j)\, r(i-m, j-n), \quad (11)$$

where b indexes an image block, and B_b is the set of pixels in that block. In the experiments reported below, we have used partially overlapping 9 ×9 blocks, separated horizontally and vertically by 5 pixels, and only those that are fully contained in the image domain. Of course, in this case, the residual is normalized to zero mean and unit variance on a block-by block fashion, rather than globally. Given this block partition, the three local measures of whiteness, M_{lR}, M_{lRW} and M_{lH} are obtained by computing the corresponding local measures M_R, M_{RW}, and M_H, respectively, at each block, and then averaging over all the blocks of the image.

D. Color Images

The measures of whiteness presented in the previous subsection were defined for gray-scale images. In order to use them with color images, several approaches can be followed. Assuming that the three color channels were degraded by the same blur filter, we adopt a simple procedure in all the examples reported below. At each iteration of Algorithm 1, the image estimate is converted to gray-scale and the residual is computed using a (previously computed) gray-scale version of the blurred image and the current blur filter estimate. In the NBID case (although we don't report any experiments), the degraded and the estimated images are converted to gray scale, where the proposed whiteness measures are computed.

IV. SIMULATION RESULT

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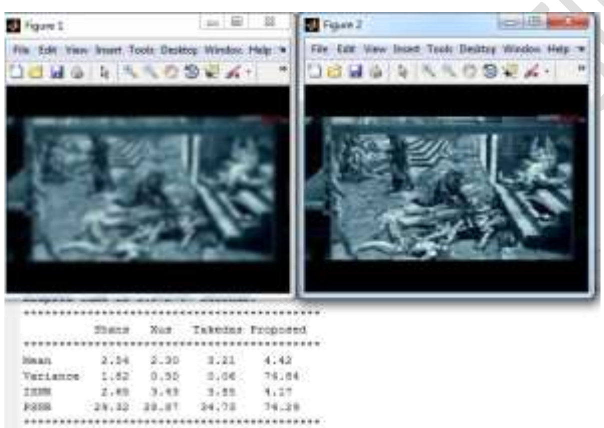
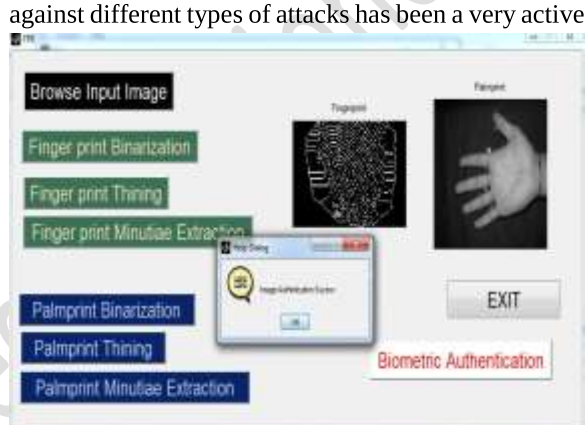


V. CONCLUSION

The study of the vulnerabilities of biometric systems against different types of attacks has been a very active



field of research in recent years. This interest has lead to big advances in the field of security-enhancing technologies for biometric-based applications. However, in spite of this noticeable improvement, the development of efficient protection methods against known threats has proven to be a challenging task. Simple visual inspection of an image of a real biometric trait and a fake sample of the same trait shows that the two images can be very similar and even the human eye may find it difficult to make a distinction between them after a short inspection. Yet, some disparities between the real and fake images may become evident once the images are translated into a proper feature space. These differences come from the fact that biometric traits, as 3D objects, have their own optical qualities (absorption, reflection, scattering, refraction), which other materials (paper, gelatin, electronic display) or synthetically produced samples do not possess. Furthermore, biometric sensors are designed to provide good quality samples when they interact, in a normal operation environment, with a real 3D trait. If this scenario is changed, or if the trait presented to the scanner is an unexpected fake artifact

(2D, different material, etc.), the characteristics of the captured image may significantly vary. For this purpose we have considered a feature space of 25 complementary image quality measures which we have combined with simple classifiers to detect real and fake access attempts. The novel protection method has been evaluated on three largely deployed biometric modalities such as the iris, the fingerprint and 2D face, using publicly available databases with well-defined associated protocols. This way, the results are reproducible and may be fairly compared with other future analogue solutions.

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