Multiscale extraction of non-compressible bit-strings from speckle patterns

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Abstract. Non-compressible signatures are extracted from speckle patterns by refining wavelet analysis with Independent Component Analysis. Only simple operations are involved in addition to fast algorithms implementing these analysis. The extraction method is tested on a set of real speckle patterns.

1. Introduction

Laser speckle can be used as a natural way to authenticate diffusive objects. First of all, reference speckle patterns can be stored for some subsequent direct comparisons [1]. Pappu et al. suggested to produce an identity code by filtering the patterns in a work [2] based on a multiscale Gabor representation using 1D filters [3]. A binary image is produced at each level and each orientation of the complex Gabor filter by thresholding the imaginary part at zero. By this way, out of 240×320 recorded speckle patterns, using only the 4th level of the transform, 2400-bit signatures can be generated by serialization and concatenation of the two 30×40 binarized diagonal detail images. Only the two diagonal directions are retained because the diagonal entries are much less sensitive to small changes in x−y positioning of the token. The choice of the level results from two competing issues: getting a long (low level) and robust (high level corresponding to low bandpass) signature.

However in the sense of Shannon information, these signatures have a reduced content, as less than 10% of bits are shown to be on the average, statistically independent [2]. Thus, even if their bias is close to zero, these bit strings can be severely losslessly compressed. In fact the obtained signatures look like real fingerprints (see figure 1). Consequently they could be dramatically compressed by searching for some "minutiae". In this paper, the goal is rather to extract constant-size, long, non-compressible bit-strings.

Our approach consists in refining multiscale wavelet analysis by Independent Component Analysis (ICA). Some images of wavelet coefficients used as input are decomposed into Independent Components (ICs). Such a way can be used to represent some features of an initial image, especially via multi-resolution analysis as in [4]. A modified wavelet-based IC analysis, taking into account the distribution of the ICs is detailed and discussed in section 2. From this analysis, an algorithm dedicated to the extraction of the searched bit-strings is suggested and tested on real data in section 3.
2. Speckle patterns analysis

2.1. Image analysis

Speckle image analysis is performed by chaining multi-resolution analysis, efficient to to detect spatial structures belonging to certain frequency subbands, with ICA in order to linearly expand the subbands in statistically independent components. A fast method is to combine Mallat’s multi-resolution algorithm [5] with FastICA algorithm [6].

In Mallat’s multi-resolution analysis, a pyramidal decomposition of original image $Y$ is obtained by using an orthogonal or bi-orthogonal basis. Approximation image $A_{2k}Y$ at level $k$ is obtained by filtering lines, then columns with the 1D scale function. Corresponding vertical, horizontal and diagonal details $D_{1k}^{1}Y$, $D_{2k}^{2}Y$, $D_{3k}^{3}Y$ are obtained by successively filtering the lines with the scale function, then the columns with the wavelet, the lines with the wavelet, then the columns with the scale function, the lines then columns both with the wavelet, respectively. The detail images have the advantage of being well decorrelated on vertical and/or horizontal directions due to the wavelet band-pass filtering [7]. Thus the prior data whitening preceding the FastICA optimization procedure may be reduced to variance normalization of wavelet coefficients.

For any given detail image at level $k$, several subband particular realizations $X_{i}^{(k)}$ are required. Once obtained, they are grouped into a certain matrix $X^{(k)}$ as input of FastICA. FastICA maximizes the negentropy of the rows of matrix $S^{(k)}$ in order to obtain statistically Independent Components (ICs) $S_{j}^{(k)}$ ($j=1,\ldots,J$) and quasi-orthogonal vectors $A_{j}^{(k)}$ forming a matrix $A^{(k)}$ of the ICs according to the following linear model:

$$X_{i}^{(k)} = \sum_{j=1}^{J} S_{ij}^{(k)} A_{j}^{(k)} \quad \text{(1)}$$

As ICs negentropy is a function with multiple local maxima, FastICA maximization may provide various solutions depending on the initial guess for $A^{(k)}$ for a fixed $X^{(k)}$. In our application, in order to obtain a solution that is close to wavelet transform (WT), columns of $A_{j}^{(k)}$ were initialized by a wavelet frame consisting of shifted wavelets (the same as needed for the WT preceding ICA).

The particular realizations in matrix $X^{(k)}$ are obtained with a shifting window. The window is shifted in the same direction as the wavelet providing the subband (for instance, vertically on the subband of the horizontal details, the choice for the shifting direction is unimportant for the diagonal details). For each window position, one particular realization is obtained by serializing column by column and placed on a new row in matrix $X^{(k)}$. The window size may be as large as the optimization procedure of FastICA allows.

From ICA model 1, each row $S_{j}^{(k)}$ ($j=1,\ldots,J$) may be considered as a realization of an independent source of the rows in $X_{i}$ to be weighted according to the coefficients of mixing matrix $A^{(k)}$:

$$X_{i}^{(k)} = \sum_{j=1}^{J} A_{ij}^{(k)} S_{j}^{(k)} \quad \text{(2)}$$
The sources given by FastICA have all a unit variance and a zero mean. Let us point out that, as shown in figure 3, sources $S_j^{(k)}$ of a subband can be considered as having Generalized Gauss Distributions (GGDs) with zero mean. This will be assumed in the following. As GGD with zero mean is commonly used as model of the probability density function (pdf) of the wavelet coefficients [8], this property would mean that the nature of the distributions of the coefficients of the wavelet subband is preserved by ICA. In consequence, the distribution of source $S_j^{(k)}$ is mainly characterized by shape parameter $\beta_j$ of the GGD because the first parameter, $\alpha$, is proportional to the variance of the coefficients.

2.2. Image synthesis
The previous analysis consists in a pyramidal representation of speckle patterns where each subband is expanded in a weighted sum of $J$ sources $S_j^{(k)}$ statistically described by parameter $\beta_j$. The consistency of this representation has been tested by performing some reconstructions where the sources extracted from the wavelet subbands on the first three levels of the multiresolution analysis have been replaced by white noises having the same GGD distribution, respectively (figure 4).

Whereas the wavelet transform is invertible, the invertibility of ICA needs a square mixing matrix. This can be always done by padding with random columns and considering only the ICs that are projections on the columns issued, at the end of FastICA, from wavelets. For each selected IC, maximum likelihood estimates of parameters $\beta$, $\alpha$ have been computed and a random IC with the same distribution has been generated by using the GGD generator described in [9]. Figure 4 shows that the reconstructed subband and the synthetized subband have similar textures and that the reconstructed speckle pattern is very close to the real one (figure 3).

3. Non-compressible bit-strings
3.1. Bit-string extraction
Extraction of non-compressible binary strings from speckle patterns can be obtained in a very efficient way by using as input of the FastICA maximization procedure the diagonal details $D_{2-k} Y$ from level $k = k_0$ to $K$. Only the diagonal details are used because they are issued from a band-pass filtering performed both on the lines and columns, then correspond to highly decorrelated wavelet coefficients. First level $k_0$ can be chosen greater than 1 to be less sensitive to misalignment. At each level $k$, FastICA gives $J$ sources $S_j^{(k)}$ per diagonal subband. Each one of these sources has a number of samples equal to the number of coefficients in the subband. According to ICA model (2), rows $S_j^{(k)}$ are Independent Components of the rows (ICs) in $X^{(k)}$. Number $J$ of the sources is fixed to 2, the minimal number in source separation.
Figure 4. (a) 2nd level vertical wavelet subband of the speckle pattern shown in figure 3, reconstructed from the J=3 sources extracted at the analysis stage (b) the vertical wavelet subband but obtained by synthesis of J=3 GGD noises with the same parameter values $\beta, \alpha$ than the real sources, respectively (c) reconstructed speckle patterns with J=3 synthetized sources per subband.

Rows $S_j^{(k)}$, which are serialized images obtained from a shifted window on the diagonal wavelet subband at level $k$, can be reshaped as images accordingly. Afterwards images $\tilde{S}_j^{(k)}$ are decimated by $2^{K-k+1}$. Decimation is needed to obtain constant-size ICs $\tilde{S}_j^{(k)}$ and to reduce residual correlations between samples in $\tilde{S}_j^{(k)}$ (coming from residual correlations in wavelet coefficients transmitted by ICA).

$K - k_0 + 1$ pairs $(B_1^{(k)}, B_2^{(k)})$ of binary images having equiprobable bits are obtained by thresholding $\tilde{S}_1^{(k)}, \tilde{S}_2^{(k)}$ respectively with respect to zero. Equiprobability comes from the property of an IC distribution to be zero-mean symmetrical (see section 2).

Finally the bit-string is formed by assembling and serializing the bits resulting from the bitwise additions of binary images from different sources and different scales to furthermore remove residual correlation in the samples and scale effects, respectively. Thus, for $J = 2$, $K = 3$, $k_0 = 2$, any bit-string can be expressed as follows:

$$\text{sig} = B_1^{(3)} \oplus B_2^{(2)} \ || \ |B_1^{(2)} \oplus B_2^{(3)}$$

by symbol $\|$ denotes the concatenation operation.

3.2. Experimental results

In order to measure the quality of the extracted bit-strings, a series of real speckle patterns were recorded by transillumination of a diffusive glass. The experimental set-up used a spatially filtered He-Ne laser beam. A lensless 1280×1024 pixel CCD camera recorded the speckle patterns at a distance fixing the speckle size. 8 different areas of the glass were illuminated with a glass-camera distance equal to 30 cm. 12 contiguous subimages 256×256 pixel were cropped in each image. Consequently 96 sample images 259×259 pixel are available for tests. We have used, in our analysis, Daubechies wavelet “db3” and diagonal detail images at scales $k = 2, 3$ were separated into $J = 2$ sources producing $2 \times 30 \times 30 = 1800$ bits per diagonal detail image (Figure 2).

The two-by-two comparison of the extracted bit-strings gives the histogram of the normalized Hamming distance shown in figure 5. The distance has mean value 0.5002 and its standard deviation is 0.0119. By fitting a Binomial probability density function to the histogram, the number of independent bits is estimated to be 1762 which is about 97.8% of the bits in a 1800-bits string. It is a large increase in comparison with the work ?? for a comparable bit-string length. The resulting bit-stream (21.6 kBytes extracted from 96 speckle patterns) appears as non-compressible. The arithmetic mean value of data bits is 0.4988 very close to 0.5, the theoretical value for random bits. The entropy is 7.99 bits per byte and the serial correlation coefficient does not exceed 0.1%.
Figure 5. Pairwise comparisons between bit-strings from different diffusive zones: histogram of Hamming distance (4560 samples).

Figure 6. Influence of object misalignment: Hamming distance vs. subpixel shift obtained by interpolation (mean curve).

In order to test the robustness with respect to misalignment, the Hamming distance between each real speckle pattern and a set of subpixel shifted versions obtained by spline interpolation has been computed. The mean curve is reported in figure 6. The distance varies roughly linearly with the shift in the range $[0.02, 0.1]$ pixel where it is less than 10%. Beyond 0.1 pixel, the distance increases exponentially. The standard deviation is always less than 6%. These experimental results show precision requirements in object positioning is fundamental for bit-string retrieval.
4. Conclusion

This article has detailed how an efficient extraction of searched signatures from speckle patterns can be done using a modified wavelet-based ICA and a direct thresholding of the obtained components. The extraction is a fast algorithm chaining Mallat’s wavelet decomposition and FastICA but without PCA computation (as wavelet decomposition induces a decorrelation of the components). The thresholding of ICs with respect to zero results from an ICA property we have experimentally tested: the preservation of the GGD nature of the wavelet coefficients. Other involved operations, namely decimation and XOR, are low-cost operations. Applied on 259×259 real speckle patterns, the extraction algorithm has generated 1800-bit strings. This length is comparable to the length of strings extracted in [2]. In contrast, optimum compression does not reduce the size of the strings extracted here and correlation is highly residual. However the accuracy required for the positioning of the sample to re-obtain the bit-string is in practice a severe constraint. This constraint is due to the well-known sensitivity of the speckle observation to position (and angle). In the experiment, retrieving the initial bit-string within less than 2% requires a precision of 0.01 pixel in the repositioning of the sample. The algorithm should be tested on patterns recorded by probing the sample according to some other optical techniques.

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