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Reverse engineering of double compressed images in the presence of contrast enhancement

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Abstract—A comparison between two forensic techniques for the reverse engineering of a chain composed by a double JPEG compression interleaved by a linear contrast enhancement is presented here. The first approach is based on the well known peak-to-valley behavior of the histogram of double-quantized DCT coefficients, while the second approach is based on the distribution of the first digit of DCT coefficients. These methods have been extended to the study of the considered processing chain, for both the chain detection and the estimation of its parameters. More specifically, the proposed approaches provide an estimation of the quality factor of the previous JPEG compression and the amount of linear contrast enhancement.

I. INTRODUCTION

Image forensics is a multidisciplinary science aiming at acquiring information on the history of digital images, including the acquisition chain, the coding process, and the editing operators, and it works on the assumption that any digital processing, although visually imperceptible, alters the underlying statistics of an image. These statistics can be interpreted as *digital fingerprints* characterizing the image life-cycle. The analysis of such traces can be exploited for the verification of the trustworthiness of digital images.

A variety of tools have been proposed for the analysis of fingerprints left by specific processing, like resampling [1], [2], contrast enhancement [3], or compression [4], [5], [6], just to name a few. A common characteristic of most of the proposed works is to consider a single processing step at a time; on the contrary, in realistic scenarios a *chain* of such operations is employed to obtain the final processed image. Thus, to go one step further, the identification of operators in the presence of multiple processing steps has to be studied. As an example in this sense, several methods have been proposed to study the double JPEG compression that can be seen as a chain composed by two codings [4], [5], [6]. But if we consider

heterogeneous chain, i.e. composed by different operators, only a small effort has been made so far, for example in [7], where authors analyze double JPEG compressed images when image resizing is applied between the two compressions, and provide a joint estimation of resize factor and quality of the first compression.

In this work, we consider a chain composed by double JPEG compression interleaved by a linear contrast enhancement. A wide literature has been written about double compression or contrast enhancement artifacts, but these fingerprints were treated separately. Usually, contrast enhancement detectors are based on the analysis of histograms of pixels as in [3], [8], [9], whose performance dramatically decreases when a lossy compression is subsequently applied. We assume the following processing chain: the luminance Y of a JPEG color image with quality QF_1 is linearly stretched and then re-saved in another JPEG color image with quality QF_2 . We propose two approaches, borrowed by double JPEG compression detection and extended for the identification of the considered chain; furthermore, assuming QF_2 to be known, the methods provide the joint estimation of the chain operator parameters, i.e. first quality QF_1 and amount of contrast enhancement.

II. PROPOSED APPROACHES

In [4], [6], [10], [11], the effects of double compression on DCT coefficients are well explained and exploited to detect double or single JPEG compression, to localize forged regions, or for steganalysis. Briefly, double compression involves a double quantization of DCT coefficients. Each quantization introduced a periodic peak-to-valley pattern across DCT coefficients histograms, due to the rounding to integers.

If we denote c^{kl} a generic unquantized coefficient, and q_1^{kl} and q_2^{kl} (where $k, l = 1, \dots, 8$) the quantization matrix of the first and the second compression, respectively, the quantized coefficient c_1^{kl} is

$$c_1^{kl} = Q_{q_1^{kl}}(c^{kl}) = \left\lceil \frac{c^{kl}}{q_1^{kl}} \right\rceil \quad (1)$$

and the corresponding dequantized d_1^{kl} is

$$d_1^{kl} = Q_{q_1^{kl}}^{-1}(Q_{q_1^{kl}}(c^{kl})) = \left\lceil \frac{c^{kl}}{q_1^{kl}} \right\rceil q_1^{kl}. \quad (2)$$

Now we introduce the linear contrast enhancement as a linear mapping of pixel values, namely:

$$Y_{out} = \alpha Y_{in} + \beta. \quad (3)$$

When a *Discrete Cosine Transform* (DCT) is applied to a linear contrast enhanced grayscale image (as could be the luminance Y of a color image) each DCT coefficient is linearly mapped into another value by the same parameters α and β , due to the linearity of the transform, apart from an error term due to the rounding to 8-bit in pixel domain. In order to simplify the model, we can assume that the processing depends on α only, and thus we have $\beta = 0$, and we can neglect the effects of clipping to the range $[0, 255]$. By applying the enhancement considering the relation (3) with $\beta = 0$, and introducing an additive noise term ϵ taking into account the rounding to 8-bit in pixel domain, we have that the DCT coefficient after the processing will become:

$$d_1^{kl} = \alpha \left\lceil \frac{c^{kl}}{q_1^{kl}} \right\rceil q_1^{kl} + \epsilon, \quad (4)$$

and after the second quantization we will obtain the double quantized coefficient:

$$c_2^{kl} = \left\lceil \left(\alpha \left\lceil \frac{c^{kl}}{q_1^{kl}} \right\rceil q_1^{kl} + \epsilon \right) \frac{1}{q_2^{kl}} \right\rceil. \quad (5)$$

A. DCT Coefficients Histograms

The periodic pattern of the histogram of doubly compressed DCT coefficients can be modeled as in [10] by computing the number $n(c_2^{kl})$ of bins of the original histogram contributing to bin c_2^{kl} in the doubly compressed histogram, that in this case is given by

$$n(c_2^{kl}) = q_1^{kl} \left\{ \left\lfloor \frac{1}{\alpha q_1^{kl}} \left(q_2^{kl} \left(c_2^{kl} + \frac{1}{2} \right) - \epsilon \right) \right\rfloor - \left\lfloor \frac{1}{\alpha q_1^{kl}} \left(q_2^{kl} \left(c_2^{kl} - \frac{1}{2} \right) - \epsilon \right) \right\rfloor + 1 \right\} \quad (6)$$

It is possible to demonstrate that $n(c_2^{kl})$ is periodic with a period which can be computed as follows. Let us consider the following function

$$f_a(x) = \lfloor x + a \rfloor - \lfloor x - a \rfloor \quad (7)$$

where a is a real number. It can be easily demonstrated that the period of $f_a(x)$ is 1, for all real a . It is also easy to show that $f_a(x - b)$ has still period equal to 1, whereas the scaled version

$$f_a\left(\frac{x}{\gamma}\right) = \left\lfloor \frac{x}{\gamma} + a \right\rfloor - \left\lfloor \frac{x}{\gamma} - a \right\rfloor \quad (8)$$

has period equal to γ . By using the previous properties, we can write $n(c_2^{kl})$ using f_a as

$$n(c_2^{kl}) = q_1^{kl} \left\{ f_a\left(\frac{q_2^{kl}}{\alpha q_1^{kl}} c_2^{kl} - \frac{\epsilon}{\alpha q_1^{kl}}\right) \right\} \quad (9)$$

where $a = \frac{q_2^{kl}}{2\alpha q_1^{kl}}$ and the period is, as for the function (8),

$$\tau'^{kl} = \gamma = \frac{\alpha q_1^{kl}}{q_2^{kl}} \quad (10)$$

The result can be seen as a generalization of that found in [10], with the difference related to the presence of α and ϵ . In particular, we can observe that the periodicity of the function $n(c_2^{kl})$ depends on the value α , while it is not modified by ϵ . The period could not be an integer but a rational number.

We can now describe a method to detect the presence of such a chain leveraging on the previous analysis. To do this, we need to know the distribution of DCT coefficients histograms of an image in the presence and in the absence of double compression. Let us suppose that we are observing a double compressed image; as in [4], [12], a method to obtain a histogram of DCT coefficients without periodical pattern from a doubly compressed image is to compute the DCT coefficients by misaligning the grid of 8×8 blocks employed in JPEG standard. In such a way, we can observe two histograms for DCT coefficients at frequency kl : the first one, which we name $h(c_2^{kl})$, is obtained directly from the image, whereas the second one, which we name $h_s(c_2^{kl})$, is obtained as explained before and it represents the hypothesis of absence of a double compression (*smoothed* histogram). From these histograms, we estimate the *probability density functions* (pdf) of a given DCT coefficient, $p(c_2^{kl})$ and $p_s(c_2^{kl})$, respectively, as in [12]. Ideally, $p(c_2^{kl}) = p_s(c_2^{kl})$ in a single compressed image, whereas $p(c_2^{kl}) \neq p_s(c_2^{kl})$ in double compressed images, because of the presence of a periodic pattern in $p(c_2^{kl})$ that does not appear in $p_s(c_2^{kl})$.

We propose to use two different measures of similarity between two probability distributions: the *Kullback-Liebler divergence* (D_{KL}) [13] and the *Kolmogorov-Smirnov distance* (D_{KS}) [5]. These measure are defined for each DCT coefficient histogram of Y . In order to obtain a scalar value, we assume to sum the Kullback-Leibler distances of each DCT histogram, as for the Kolmogorov-Smirnov divergences.

If the image is considered processed by the supposed chain, it is of interest the estimation of the first compression quality QF_1 and of α . In [14], a Maximum Likelihood Estimation (MLE) approach has been proposed to detect JPEG compression in raster bitmap format images and to estimate the quantizer used. Although MLE approach may seem the trivial way to estimate the triplet (QF_1, QF_2, α) , the computational cost of this approach grows considerably by increasing the number of parameters to be estimated.

Therefore, as in [15], [16] and others, we employ a *Discrete Fourier Transform* based analysis of DCT histograms. Before this, we pre-process $p(c_2^{kl})$ in order to reduce the effects of low-pass frequencies due to the shape of the histograms: the spectrum is then calculated on $p_n(c_2^{kl}) = p(c_2^{kl}) - p_s(c_2^{kl})$. After that, the period $\hat{\tau}'^{kl}$ is estimated by finding the peak with maximum amplitude through a smooth interpolation [7], in order to achieve a better estimate of the frequency $F = 1/\hat{\tau}'^{kl}$.

An exhaustive search is performed over all possible α and QF_1 , by discretizing them, to minimize the distance between

the theoretical period τ'^{kl} , computed according to Equation (10), and the estimated period $\hat{\tau}'^{kl}$. This distance is the median value of residues defined as

$$\rho_{kl} = \left(\frac{\hat{\tau}'^{kl} - \tau'^{kl}}{\tau'^{kl}} \right)^2 \quad (11)$$

for a subset n_c of DCT coefficients c_2^{kl} . The choice of working on a subset of coefficients is due to fact that histograms with a small support don't show detectable peaks in their spectra, as shown in [15]. The median value is employed to bound the effects of ambiguities: it can be easily verified that it is well possible that different (α, QF_1) tuples result in equivalent periodic artifacts in the histogram of a given coefficient. As we have a set n_c of DCT coefficients, these ambiguities can be present on a number of coefficients $n_a \leq n_c$. In all those cases in which $n_a \leq \lfloor n_c/2 \rfloor$, the distance doesn't take into account errors due to the ambiguities.

In our analysis we have to take into account that when the period τ'^{kl} is greater than 2, we observe in the spectrum the fundamental harmonic with frequency $F = 1/\tau'^{kl}$. Conversely, when $1 < \tau'^{kl} < 2$, we don't observe F , but the *aliased* frequency $F = 1 - 1/\tau'^{kl}$. Finally, when $\tau'^{kl} < 1$, we can not observe any fundamental period, because the histogram can be viewed as a sampled signal, where the sample period is 1. However, high order harmonics can still be observed if they are greater than 1, but the peaks associated with them could have undetectable amplitude. Because we do not know if the theoretical period is less or greater than 2, we test both $\tau'^{kl} = 1/F$ and $\tau'^{kl} = 1/(1 - F)$ for each DCT coefficient separately, and the period giving lower residue is taken into account in (11).

B. Mode Based First Digit Features

In [17], it is observed that the distribution of the first digit of quantized DCT coefficients can be used to distinguish singly and doubly JPEG compressed images. Briefly, when an image is singly compressed, it is observed that the magnitudes of DCT coefficients approximately follow an exponential distribution. Hence, the distribution of the first digit of quantized DCT coefficients is well modeled by the *generalized Benford's law* [17]. Instead, in case of double compression, the distribution of the first digit is usually perturbed and it violates the generalized Benford's law.

In [18], the authors introduce a new feature based on the distribution of the first digit of DCT coefficients for each separate DCT frequency, or mode. The features are obtained by measuring the frequencies of the 9 possible nonzero values of the first digit for each of the first 20 DCT modes. The resulting $9 \times 20 = 180$ frequencies form a vector of features named Mode Based First Digit Features (MBFDF).

The approach based on Benford's law can be extended also to images modified by contrast enhancement. Even if contrast enhancement is expected to modify the distribution of the first digit, the resulting distribution will still violate the generalized Benford's law, so that MBFDF can still be used to distinguish

singly and doubly compressed images. Moreover, different parameters of the contrast enhancement operator will produce different patterns on the distribution of the first digit of DCT coefficients. Hence, MBFDF can also be used to discriminate different parameters of the processing chain.

Similarly to [18], in order to distinguish enhanced and recompressed images from singly compressed images, we propose to apply a two-class classification to MBFDF according to Fisher's linear discriminant analysis (LDA). The parameters of the processing chain, i.e., QF_1 and α , can be estimated by using a "one-against-one" multi-classification strategy, where each possible combination of values for QF_1, α is considered as a different class. Given N_C possible classes, we construct $N_C(N_C - 1)/2$ two-class LDA classifiers, where the classifiers consider every possible combination of two classes. Each classifier "votes" for its winning class, and the class obtaining more votes corresponds to the estimated values QF_1, α .

The above approach works well in presence of a finite set of possible parameters, like in the case of QF_1 . However, for continuous valued parameters, like α , it requires a quantization of the parameter space, with a proper choice of the quantization step, since a fine search of parameter values may be impractical due to the fact that the number of required classifiers grows quadratically with the number of parameter values.

III. EXPERIMENTAL RESULTS

Here, we show the results about the detection of the considered processing a chain, i.e., we verify the presence/absence of double compression interleaved by contrast enhancement, and about the estimation of the parameters which characterize it. The proposed algorithms have been tested on a dataset composed by 300 TIFF images coming from 3 different cameras (*Nikon D90, Canon 5D, Panasonic DMC-G2*), cropped to 1024×1024 pixels, and representing landscapes, buildings and people, avoiding uniform content and with different degrees of texture. We fix $\alpha \in \{1.05, 1.15, 1.35, 1.55, 1.75\}$. For each α , we generate two datasets: the first dataset contains TIFF images which are first enhanced and then compressed (i.e. single compression scenario) with a quality factor QF_2 , whereas the second dataset contains TIFF images compressed with a quality factor QF_1 , whose luminance is enhanced, and then re-compressed with a quality factor QF_2 (i.e. double compression scenario). We compress images by applying the Matlab function `imwrite` at different quality factors chosen in $[50, 55, \dots, 100]$, for each α . This policy is then repeated for images with size 256×256 and 64×64 .

A. Detection

To compare histogram based features (as D_{KL} and D_{KS} ones) and MBFDF in detecting the presence of a double compression, we evaluate the performance of detectors by measuring the *true positive rate* and the *false positive rate*. The overall performance is evaluated by plotting their *receiver operating characteristic* (ROC) curves, obtained by thresholding the distributions of each feature in both hypotheses using

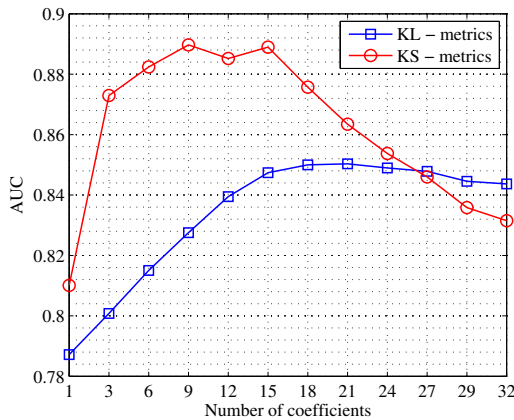


Fig. 1. AUCs of KS and KL metrics, evaluated for different number of coefficients, by starting from the DC coefficient and obtained by averaging over all possible α , QF_1 and QF_2 .

a varying threshold value, and recording the corresponding value of true positive and false positive rate. Finally, the *area under the ROC curve* (AUC) is used as a scalar parameter: an AUC close to one indicates good detection performance, whereas an AUC close to 0.5 indicates that the detector has no better performance than choosing at random.

First of all, we evaluated the best performance between D_{KL} and D_{KS} , by varying the number of coefficients n_c . As shown in Figure 1, the best detection capability, in terms of AUC, is recorded by employing D_{KS} with the first $n_c = 9$ DCT coefficients; we then decided to fix this configuration for the successive detection analysis.

To compare histograms based versus MBFDF approach, AUC values have been evaluated for different couples (QF_1, QF_2) , by mediating over all possible values of α . The results are reported in Table I and Table II. For lack of space, only the subset $\{50, 60, 70, 80, 90, 100\}$ of all couples (QF_1, QF_2) is shown. When $QF_1 \leq QF_2$, both approaches have a very high capability of detecting double compression, but when $QF_1 > QF_2$, MBFDF method clearly outperforms histogram based ones.

QF1/QF2	50	60	70	80	90	100
50	0.95	1.00	1.00	1.00	1.00	1.00
60	0.91	0.95	1.00	1.00	1.00	1.00
70	0.91	0.94	0.96	1.00	1.00	1.00
80	0.98	0.98	0.98	0.96	1.00	1.00
90	0.83	0.89	0.96	0.98	0.93	0.99
100	0.5	0.5	0.51	0.55	0.69	0.65

TABLE I

DETECTION PERFORMANCE: AUC VALUES OF KS METRICS FOR A SUBSET OF PAIRS (QF_1, QF_2) WITH $QF_1, QF_2 = \{50, 60, 70, 80, 90, 100\}$, BY FIXING $n_c = 9$ AND AVERAGING OVER ALL POSSIBLE VALUES OF α .

B. Estimation

We then evaluate the ability of the two approaches to estimate the parameter α and the first compression quality factor. In order to allow a fair comparison between the

QF1/QF2	50	60	70	80	90	100
50	0.95	1.00	1.00	1.00	1.00	1.00
60	0.99	0.97	1.00	1.00	1.00	1.00
70	1.00	0.99	0.97	1.00	1.00	1.00
80	1.00	0.99	1.00	0.95	1.00	1.00
90	0.90	0.98	0.98	1.00	0.92	1.00
100	0.58	0.60	0.63	0.66	0.82	0.82

TABLE II

DETECTION PERFORMANCE: AUC VALUES OF MBFDF FOR A SUBSET OF PAIRS (QF_1, QF_2) WITH $QF_1, QF_2 = \{50, 60, 70, 80, 90, 100\}$, BY MEDIATING OVER ALL POSSIBLE VALUES OF α .

proposed approaches, we have decided to discretize $\alpha = [1, 2]$ with stepsize 0.05 and $QF_1, QF_2 \in \{50, 60, 70, 80, 90, 100\}$. Whereas the histogram based approach makes an exhaustive search over all couples (QF_1, α) , as explained in II-A, in the MBFDF based approach we trained a LDA classifier over all possible couples (QF_1, α) , so that $N_C = 21 \times 6 = 126$, and the results are obtained by testing a subset of α , as in III, i.e. $\alpha \in \{1.05, 1.15, 1.35, 1.55, 1.75\}$. From preliminary tests on histograms based approach, we fixed $n_c = 5$.

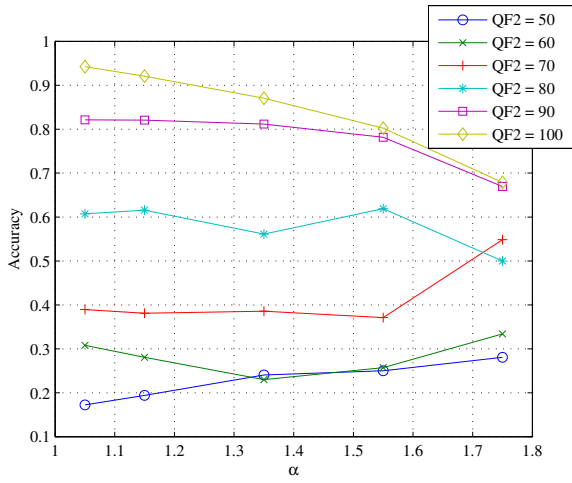
To evaluate estimation accuracy of QF_1 , by fixing QF_2 and α , we define a *confusion matrix* for QF_1 as a matrix where each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. By normalizing by the total number of instances, we obtain the percentage of decisions of each couple of classes. On the main diagonal, we have the percentage of correct decisions, for each value of QF_1 . By averaging the percentage of correct decision over all values of QF_1 (i.e. values on the main diagonal), we obtain an average performance value of the classification of QF_1 , for each couple (QF_2, α) . We name this quantity *accuracy* of the estimate of QF_1 .

To evaluate the estimation of α , we adopt the *root mean square error* (RMSE): let $\hat{\alpha}_{ij}$ with $i = 1, \dots, N$ a set of estimated values of α_j , where $j = 1, \dots, N_\alpha$ (i.e. $N_\alpha = 1$ when estimating a single value of α , otherwise $N_\alpha = 5$, equal to the number of tested α), we define the RMSE as:

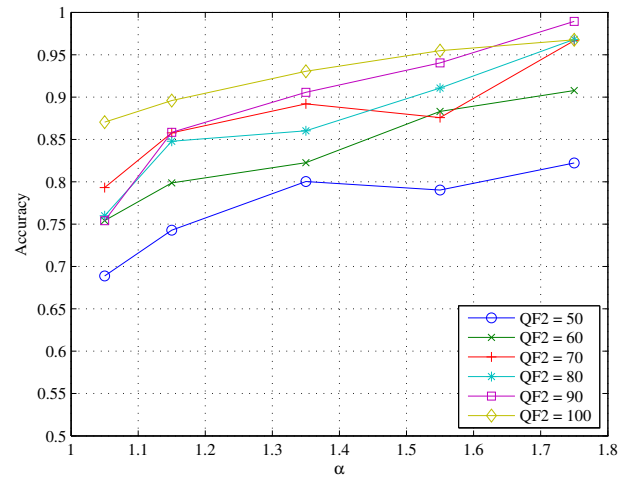
$$RMSE = \sqrt{\frac{1}{N_\alpha \cdot N} \sum_{j=1}^{N_\alpha} \sum_{i=1}^N (\hat{\alpha}_{ij} - \alpha_j)^2} \quad (12)$$

The first comparison is about the *accuracy* of the classification of QF_1 , by varying α and for different QF_2 . The results shown in Figure 2, averaged over all QF_1 values, demonstrate that MBFDF based approach exhibits better performance than the histogram based one.

The second comparison is about the RMSE of the estimate of α , for each couple (QF_1, QF_2) . The results presented in Figure 3, averaged over all α values, show again that MBFDF based approach has better performance than the histogram based one: the latter method shows performance almost comparable to the first one only when the second compression is greater than 90%, but it decreases for lower values of QF_2 , whereas the performance of MBFDF remains good. To

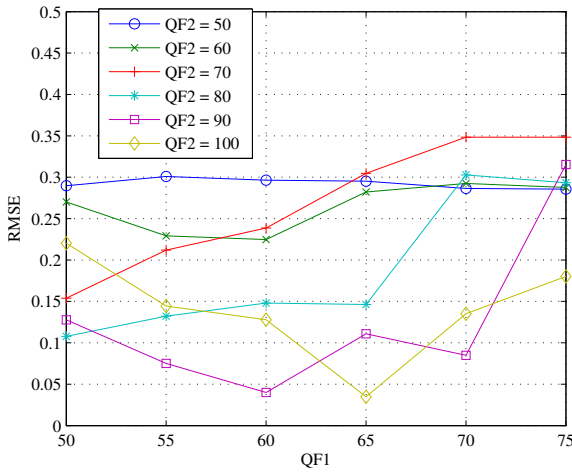


(a) Histogram based approach

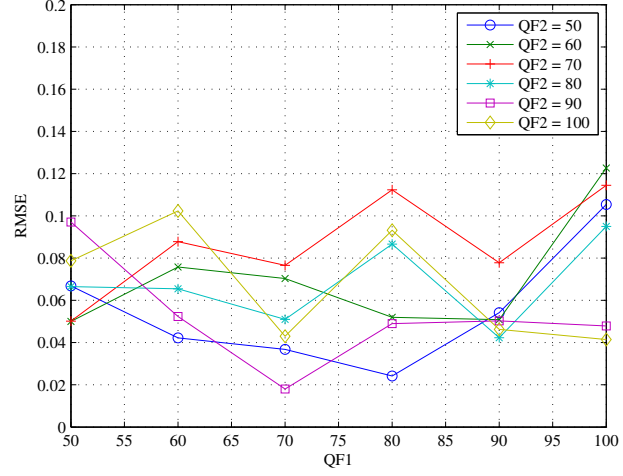


(b) MBFDF

Fig. 2. Accuracy of classification of QF_1 , for different QF_2 and α values.

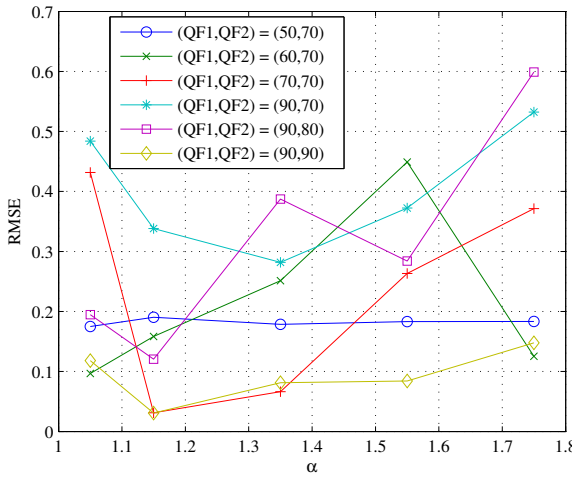


(a) Histogram based approach

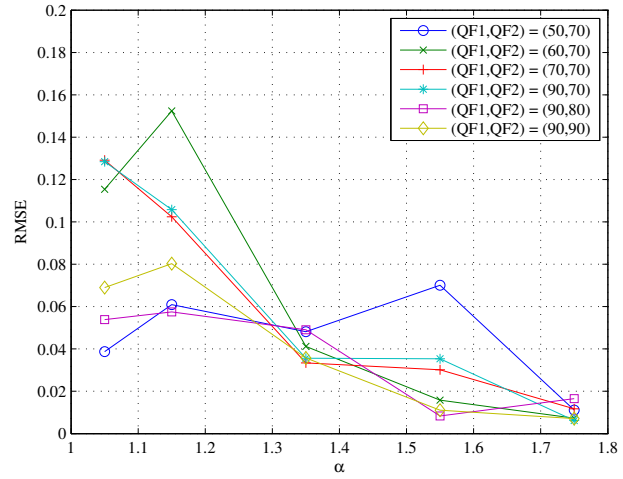


(b) MBFDF

Fig. 3. Estimation of α : RMSE for different QF_1 and QF_2 .



(a) Histogram based approach



(b) MBFDF

Fig. 4. Estimation of α values: RMSE for different fixed couples (QF_1, QF_2) .

Dimension	DCT Histograms			MBFDF		
	1024	256	64	1024	256	64
mean AUC	0.90	0.83	0.72	0.95	0.91	0.85
Accuracy of QF_1	0.52	0.51	0.45	0.86	0.77	0.66
RMSE of α	0.23	0.24	0.26	0.07	0.07	0.06

TABLE III
PERFORMANCES OF THE PROPOSED APPROACHES FOR DIFFERENT IMAGE SIZES (1024 × 1024, 256 × 256 AND 64 × 64).

better understand this latter result, we evaluated the RMSE for different values of α , by fixing some couples of compression quality (QF_1, QF_2). It is possible to observe in Figure 4 that the histogram based approach gives results almost comparable to those obtained by MBFDF approach when $QF_2 \geq QF_1$, but its performance degrades quickly for $QF_2 \leq QF_1$; this behavior is well explained if we take into account the analysis done in II-A, where we discussed the undetectability of the periodic pattern through spectrum analysis whenever $\tau^{kl} < 1$, which corresponds to $QF_2 \leq QF_1$. As a last result, we show in Table III a comparison between the proposed approaches by varying the size of the image. Mean AUC values are obtained by averaging AUC values evaluated for each (QF_1, QF_2) in order to compare trained (i.e. MBFDF) and untrained (i.e. histogram based method) detectors, whereas accuracy of QF_1 and RMSE of α are calculated by mediating over all possible values of QF_1, QF_2 and α . As expected, the performance smoothly degrade by reducing the image size in both approaches, due to the lower number of available features for the detection and estimation procedures.

IV. CONCLUSIONS

In this paper we have demonstrated how it is possible to detect the presence of a common image processing operation like contrast enhancement in the middle of a processing chain composed by two JPEG compressions. Two approaches previously developed to detect the presence of double compression have been properly modified to allow not only the detection, but also the estimation of the quality factor of the first JPEG compression and the parameter of the linear contrast enhancement. Each of the two methods has its own pros and cons: the approach based on the histogram of DCT coefficients has a low computational complexity, but exhibits good performance only when $QF_2 \geq QF_1$ and the second compression is mild; the method based on the distribution of the first digit of DCT coefficients has very good performance for every combination of quality factors, but its “one-against-one” multi-classification strategy may become impractical if a fine search of the processing parameter values is needed. These characteristics could suggest to use the histogram based approach when the image under analysis has a high compression quality, and resort to the other method when this property does not hold.

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