Recovery of Watermark Using Differential Affine Motion Estimation

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Abstract

Digital watermarking techniques have been proposed to protect the copyright of multimedia data. Robustness against geometric distortion is one of the most important issues to be solved to increase the robustness of digital image watermarking systems. Such attacks are very simple to implement, so they can defeat most existing watermarking algorithms without causing serious perceptual distortion. In this paper, a method for the recovery of watermarks based on differential affine motion estimation is presented. This method models the geometric distortion between images as locally affine but globally smooth. This approach is built upon a differential multiscale framework, allowing us to capture both large-scale and small-scale transformations. Experimental results show that the described method can estimate the distortions quite accurately and allow correct watermark detection.

Keywords: Watermark recovery, differential affine motion estimation, robust watermark.

1 Introduction

A Digital Rights Management (DRM) system compose of information technology (IT) components and services developed along with corresponding law, policies and business models which strives to distribute and control intellectual property (IP) and its rights (Chiariglione 2003). A well-designed DRM system has to provide tradeoffs among the security requirements of the content owners, the privacy of the end users and the cost of the components that will be used to establish trust between the parties. In the digital world, security and privacy are implemented through the use of cryptographic algorithms and protocols. In the case of multimedia intangibles, the lowered cost of reproduction, storage and distribution invites much motivation for large-scale commercial infringement. This is the reason why robust watermarking, the digital insertion of marks to individualize, trace, and control usage of a digital work, will be one of the pillars of future DRM systems (Macq, Dittmann, and Delp 2004).

Digital watermarking is the enabling technology to prove ownership on copyrighted material, detect originators of illegally made copies, monitor the usage of the copyrighted multimedia data, and analyse the spread spectrum of the data over networks and servers. This emerging area has already led to the development of numerous watermarking methods. Many requirements (Kutter, Bhattacharjee, and Ebrahimi 1999) have been recognized and evaluated in the benchmarking of watermarking systems. Among them, some parameters, such as fidelity and robustness, are commonly used in a variety of applications. Others are only employed in specific applications, such as high capacity and complexity. Although not all requirements have to be satisfied for a specific watermarking application, robustness is definitely important because many attacks already exist, and new types of attacks will appear in the future.

Several problems related to robustness of watermarking techniques against malicious or non-malicious attacks still remain unsolved. These problems must be addressed before digital watermarking can be claimed to be the ultimate solution for copyright protection in digital media. In image watermarking applications, it has been pointed out that geometric attacks may hinder the watermark detection without causing noticeable artifacts. For instance, random bending attack (RBA) can defeat most existing watermarking schemes but do not alter the visual quality of an image. The RBA was first introduced by F.A.P. Petitcolas in the benchmarking tool StirMark to model printing/scanning artifacts (Kutter and Petitcolas 1999). The main difficulty in dealing with the RBA comes from the basic assumption that all geometrical alterations introduced by the attacker are modelled as a global affine transform. This does not hold for the RBA where the introduced distortions cannot be described using the parameters of a global affine transform only (Voloshynovskiy, Deguillaume, and Pun 2001). Hence, the design of a watermark resistant to geometrical distortions remains an open problem. To ensure resistance to geometric attacks, more complex approaches have to be designed.

In this paper, an image registration scheme based on differential affine motion estimation between the distorted image and a reference copy is described. By employing an unmarked copy of the original image as a reference, this scheme models the geometric distortion between images as locally affine but globally smooth transformation. This approach is built upon a differential multiscale framework, allowing us to capture both large-scale and small-scale transformations. Without generality, using two classical invisible watermarking methods, described by Cox (Cox 1997) and Barni (Barni, Bartolini and Piva 2001) respectively , to produce a watermarked image, then using "StirMark" to distort the watermarked image, and a copy of the original unmarked image for reference, the registration method is demonstrated to be sufficient by showing successful extraction of the embedded watermark from a registered image. However, these algorithms are sensitive to geometric attack. Although the requirement of a reference image seems to conflict with blind watermark detection, it is not necessary to use the original host image as the reference. In practice, we can use an undistorted image watermarked with a different algorithm as the reference, with little degradation in performance.

The remainder of this paper is organized as follows. Section 2 provides an overview of geometry robust watermarking algorithms. Section 3 provides a brief description of our image registration scheme. Section 4 describes our method of recovering image parameters and appearance, and presents experimental results on images. Conclusions and suggestions about future research are presented in Section 5.

2 Overview of geometry robust watermarking algorithms

In watermarking applications, the robustness of the watermark to geometric distortion is a critical issue. Geometric attacks, while very simple, have proven to be both very elusive and harmful, since the spatial movement of the pixels also alters the watermark in such a way that its samples are no longer at the expected positions. This can be compared to losing synchronization in a communication system. Yet so far, the designing of a watermark resistant to geometrical distortions remains an open problem (Voloshynovskiy, Deguillaume and Pun 2001). To ensure resistance to geometric attacks, more complex approaches have to be designed. These schemes can be roughly divided into exhaustive search, invariant watermark, synchronization, autocorrelation, and the correction or registration of the geometrical distortion.

The simplest approach for watermark detection after a geometric distortion is an exhaustive search. After defining a range of likely values for each distortion parameter, and a search resolution for it, every combination of distortion parameters is examined. Computation and false positive probability are two practical forces that limit the size of the search space. Thus, effective uses of exhaustive search rely on techniques that result in small searches.

Invariant watermark is robust against rotation, scaling, and translation (RST). A promising approach was proposed by Ruanaidh (Ruanaidh and Pun 1998), in which the watermark is embedded in the Fourier-Mellin transform domain. This transformation is equivalent to mapping the Fourier spectrum of an image into a Log-Polar coordinate system and taking again a Fourier transform of the result. The resulting domain is invariant to RST. Thus, embedding the watermark in this domain will make it robust against rotation, translation and scaling. One of the drawbacks of this method is that mapping the Fourier spectrum into a Log-Polar coordinate system may imply severe loss of quality to the watermarked image. Moments and invariant functions of moments have been extensively used for invariant feature extraction in computer vision for pattern recognition for a long time. (Hu 1962) derived seven moment invariants, which are RST invariant from the regular moments. The same invariants were used for watermark. (Alghoniemy and Tewfik 2000) hide watermarks by modifying image content iteratively to produce the mean value of several invariant moments in a predefined range. The detector verifies the presence of the watermark by checking the mean value of these moments.

To address the requirements of invariant watermarking, another approach for resisting geometric attacks is based on synchronizing (in terms of position, orientation and scaling) the watermark that is embedded in an image with the correlating watermark using image features. The extracted features of image content can be used as reference points for both watermark embedding and detection. (Bas, Chassery, and Macq 2002) described an algorithm based on the detection of salient features in an image and the insertion of signals relative to these salient features. Experimental results indicated that the method is robust to mirror reflection and rotation. Corner points and facial feature points (Nikolaidis and Pitas 2000) have also been used for this purpose in other approaches of this category.

The fourth set of techniques introduce a known template in some domains which allows its recovery after the transformation, or exploit the self-reference principle based on an auto-correlation function (ACF) or the Fourier magnitude spectrum of a periodical watermark. (Pereira and Pun 2000) proposed an approach to embed a template into the DFT domain besides the intended watermark. The drawback of the template is that it can be discovered, damaged or removed. They limit the payload of the watermark as well. In (Kutter 1998), the watermark is replicated in the image in order to create four repetitions of the same watermark so that the experienced geometrical transformation can be detected by applying autocorrelation to the investigated image. There are three important drawbacks of the ACF-based watermarking methods. In the first place, embedding a second repeating pattern after a geometrical distortion will confuse the watermark detector. The second drawback is that the regular peak grids in the ACF are accessible without any knowledge of secret information. The third drawback is that the autocorrelation of a watermarked image may have additional peaks, missing peaks, and peaks that are slightly moved from their ideal positions.

The correction of geometrical distortions can be done by an assessment of the differences between a reference image and the distorted image (Johnson, Duric and Jajodia 1999, Loo and Kingsbury 2001, Delannay et al. 2001). Image registration and motion estimation are widely used to assess and correct the distortions. Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors. It geometrically aligns two images - the reference and sensed images. The process of image registration aims to resynchronize the watermark in distorted watermarked images. The analysis of the compensation of geometrical deformations based on image registration for watermark recovery has received increasing attention, since it has been recognized that embedding a watermark in an invariant domain and embedding a watermark without spatial synchronisation - spatial resynchronisation by inverting the distortion have the widest range of applications (Doets, Setyawan and Lagendijk 2003).

3 Proposed strategy

3.1 Geometrical transforms

A geometrical transformation attack can take many forms, from relatively simple to complex. One of the simplest forms of geometrical transformation attacks is RST transformation. A superset of the RST transform is the general affine transform. An affine transform is a linear coordinate transformation that includes the elementary transformations: translations, rotations, uniform and non-uniform scaling (stretching the axes by some constant scale factor), reflections (flipping objects about a line) and shearings (which deform squares into parallelograms). Such a transform can be expressed by vector addition and matrix multiplication. These transforms are illustrated in Fig. 1. The affine transformation of $\Re^n$ is a mapping F: $\Re^n \rightarrow \Re^n$ of the form:

$$F(p) = Ap + q \qquad (1)$$

where $p, q \in \Re^n$ and A is a linear transformation of $\Re^n$.

Note that a non-singular map A: $\Re^n \rightarrow \Re^n$ is orientation preserving if det(A) > 0 and orientation reversing when det(A) < 0. In a 2-D space, the affine transformation between point pair **x'** and **x** is given by:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = AX + d \qquad (2)$$

Affine transformation of the entire image can be described using equation (2) and is called a global transformation. On the other hand, affine transformation can be operated locally, such as in several small locations of the image. In this case, the mathematical expressions are different for each particular location. It is possible that the same equation be used in several different places, but the parameters used in these equations may be different for each particular location. This is called local transformation, for example the RBA in StirMark (Kutter and Petitcolas 1999) (see Fig. 2).

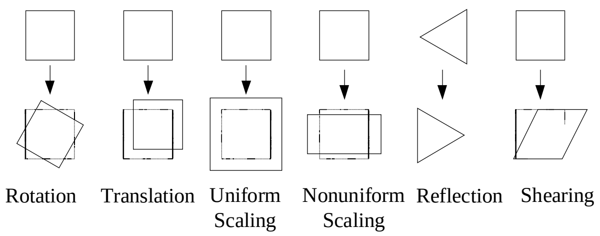
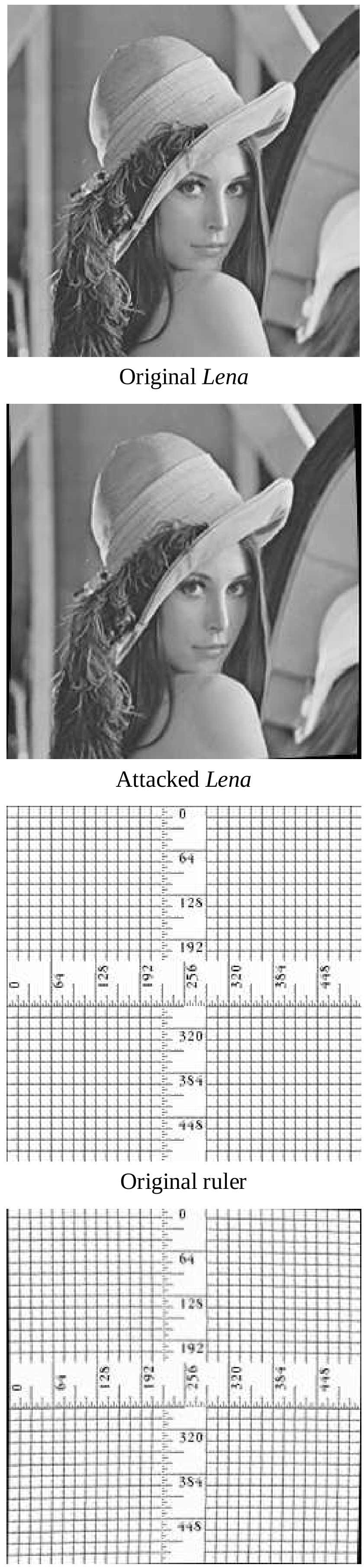


Fig. 1 Examples of affine transformation



Original *Lena*

Attacked *Lena*

Original ruler

Attacked ruler

Fig. 2 Small random distortions (StirMark 4.0)

3.2 Differential affine motion estimation

Image registration is the process of aligning two similar images of the same scene so that points from one scene lie in the same positions as corresponding points in the other scene. For alignments involving only rotation, translation, and changes of scale, differential affine motion estimation techniques reported in the image registration literature have been shown to be quite powerful. The process of image registration aims to resynchronize the watermark in a distorted watermarked image. Existing approaches always assume the underlying transformation is global affine transformation, which does not necessarily hold for deliberately localized transforms like RBA in StirMark. An improved version of differential affine motion estimation registration scheme has been used in the past in registering medical images (Periaswamy and Farid 2003). Instead of modeling the distortion as a global affine transform, this method models the distortion between images as locally affine but globally smooth. This approach is built upon a differential multiscale framework, allowing one to capture both large-scale and small-scale transformations. The aim of this paper is to show that these methods can be used in image watermarking domain to yield fast and accurate estimates of the distortion in a watermarked image. The differential affine motion estimation registration scheme examined is summarized as follows.

Assume the motion between images that can be modelled locally by an affine transform:

$$f(x,y,t) = f(m_1x + m_2y + m_5, m_3x + m_4y + m_6, t-1) \quad (3)$$

where $f(x,y,t)$ and $f(x,y,t\text{-}1)$ are the source and target images respectively. m_1, m_2, m_3, m_4 are the linear affine parameters, and m_5, m_6 are the translation parameters. In order to estimate these parameters, we define the following quadratic error function to be minimized:

$$E(\vec{m}) = \sum_{x,y\in\Omega} [f(x,y,t) - f(m_1x + m_2y + m_5, m_3x + m_4y + m_6, t-1)]^2$$

where $\vec{m} = (m_1 \cdots m_6)^T$, and Ω denotes a small spatial neighbourhood. The differential techniques compute the minimization of the error function directly from the image pixel intensities by expanding the right side of the equation in a Taylor series to obtain:

$$\begin{aligned} E(\vec{m}) \approx & \sum_{x,y\in\Omega} (f(x,y,t) - [f(x,y,t) + \\ & (m_1x + m_2y + m_5 - x) f_x(x,y,t) + \\ & (m_3x + m_4y + m_6 - y) f_y(x,y,t) - \\ & f_t(x,y,t)])^2 \\ \approx & \sum_{x,y\in\Omega} [f_t(x,y,t) - (m_1x + m_2y + m_5 - x) f_x(x,y,t) - \\ & (m_3x + m_4y + m_6 - y) f_y(x,y,t)]^2 \end{aligned} \quad (4)$$

This error function can be expressed more compactly in vector form as:

$$E(\vec{m}) = \sum_{x,y\in\Omega} \left[k - \vec{c}^T \vec{m}\right]^2 \quad (5)$$

where the scalar k and vector $\vec{c}$ are given as:

$$\begin{aligned} k &= f_t + xf_x + yf_y \\ \vec{c} &= (xf_x \; yf_x \; xf_y \; yf_y \; f_x \; f_y)^T \end{aligned} \quad (6)$$

This error function can be minimized by differentiating with respect to the $\vec{m}$:

$$\frac{dE(\vec{m})}{d\vec{m}} = \sum_{x,y\in\Omega} -2\vec{c}[k - \vec{c}^T \vec{m}] = 0 \quad (7)$$

And then:

$$\vec{m} = \left[\sum_{x,y\in\Omega} \vec{c}\vec{c}^T\right]^{-1} \left[\sum_{x,y\in\Omega} \vec{c}k\right] \quad (8)$$

This solution assumes that the matrix is invertible. It can be guaranteed by integrating over a large enough spatial neighborhoods Ω with sufficient image content.

To account for intensity variations, equation (3) takes the form:

$$\begin{aligned} m_7 f(x,y,t) + m_8 = f(& m_1x + m_2y + m_5, \\ & m_3x + m_4y + m_6, t-1) \end{aligned} \quad (9)$$

where m_7 and m_8 are two new parameters that embody a change in contrast and brightness, respectively. The scalar k and vector $\vec{c}$ are now given as:

$$\begin{aligned} k &= f_t - f + xf_x + yf_y \\ \vec{c} &= (xf_x \; yf_x \; xf_y \; yf_y \; f_x \; f_y - f \; -1)^T \end{aligned} \quad (10)$$

There is a natural trade-off in choosing the size of the neighborhood. A large area makes it more likely that the matrix $\sum_{x,y\in\Omega} \vec{c}\vec{c}^T$ in equation (8) will be invertible. A small area makes it more likely that the brightness constancy assumption will hold. To avoid balancing these two issues, we assume that the model parameters $\vec{m}$ vary smoothly across space. We augment the error function in equation (5) as follows:

$$E(\vec{m}) = E_b(\vec{m}) + E_s(\vec{m}) \quad (11)$$

where $E_b(\vec{m})$ is defined as in equation (5) without the summation:

$$E_b(\vec{m}) = \left[k - \vec{c}^T \vec{m}\right]^2 \quad (12)$$

with k and $\vec{c}$ as in equation (10). The new quadratic error function $E_s(\vec{m})$ embodies the smoothness constraint:

$$E_s(\vec{m}) = \sum_{i=1}^{8} \lambda_i \left[\left(\frac{\partial m_i}{\partial x}\right)^2 + \left(\frac{\partial m_i}{\partial y}\right)^2\right] \quad (13)$$

where λ_i is a positive constant that controls the relative weight given to the smoothness constraint on parameter m_i. To minimize this error function, we have:

$$\frac{dE(\vec{m})}{d\vec{m}} = \frac{dE_b(\vec{m})}{d\vec{m}} + \frac{dE_s(\vec{m})}{d\vec{m}} = 0 \quad (14)$$

where

$$\frac{dE_b(\vec{m})}{d\vec{m}} = -2\vec{c}\left[k - \vec{c}^T\vec{m}\right]$$
$$\frac{dE_s(\vec{m})}{d\vec{m}} = 2L(\overline{\vec{m}} - \vec{m}) \qquad (15)$$

where $\overline{\vec{m}}$ is the component-wise average of $\vec{m}$ over a small spatial neighborhood, and L is an 8×8 diagonal matrix with diagonal elements λ_i , and zero off the diagonal. In equation (14), solving for $\vec{m}$ at each pixel location yields an enormous linear system which is intractable to solve. Instead $\vec{m}$ is expressed in the following form:

$$\vec{m}^{(j+1)} = (\vec{c}\vec{c}^T + L)^{-1}(\vec{c}k + L\overline{\vec{m}}^{(j)}) \qquad (16)$$

An iterative scheme to solve for $\vec{m}$ is employed. On each iteration *j*, $\overline{\vec{m}}^{(j)}$ is estimated from the current $\vec{m}^{(j)}$. The initial estimate $\vec{m}^{(0)}$ is estimated from the closed-form solution of equation (9).

To implement the formulation given above, a more accurate estimate of the actual error function can be determined using a Newton-Raphson style iterative scheme. In each iteration, the estimated transformation is applied to the distorted image, and a new transformation is estimated between the newly warped distorted and reference image. A coarse-to-fine scheme is adopted to cope with large motion. A Gaussian pyramid is built for both distorted and reference images, and the local affine and contrast parameters estimated at the coarsest level. These parameters are used to warp the distorted image in the next level of the pyramid. A new estimate is computed at this level, and the process repeated through each level of the pyramid. The transformations at each level of the pyramid are accumulated yielding a single final transformation.

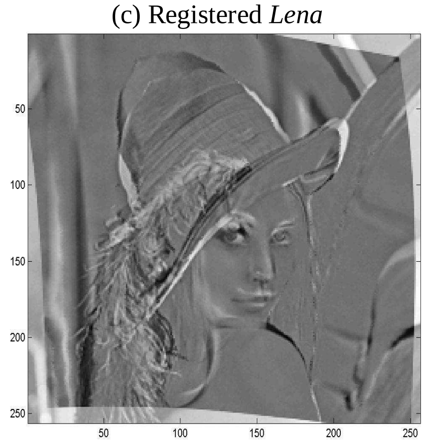
4 Experimental evaluation

The effectiveness of the proposed registration scheme is tested using the watermarking system described in Cox's work, which is a spread spectrum-based watermarking scheme in DCT domain, with several test images. All the images were 8-bit grayscale and of size 256×256. In the registration examples, we follow Periaswamy's work (Periaswamy and Farid 2003): a four-level pyramid was constructed for both the distorted and reference images using a 5-tap lowpass filter. At each scale, a single global affine transform is first estimated and Ω is defined to be the entire image. Then, the local affine parameters are estimated with Ω = 5×5 pixels. In each iteration, $\lambda_i = 1\times10^{11}$, $i = 1,\cdots,8$ and $\overline{m_i}$ is computed by convolving with the 3×3 kernel. After forty iterations, the distorted image is warped according to the final estimate, and this process is repeated five times. This entire process is repeated at each level of the pyramid. Figure 3 shows an example of registering "Lena", which has been attacked by StirMark with a relatively high bending factor.

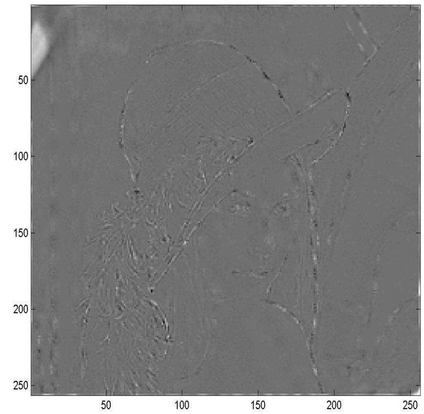
(a) Original *Lena*

(b) Distorted *Lena*

(c) Registered *Lena*



(d) Difference between (a) and (b)



(e) Difference between (a) and (c)

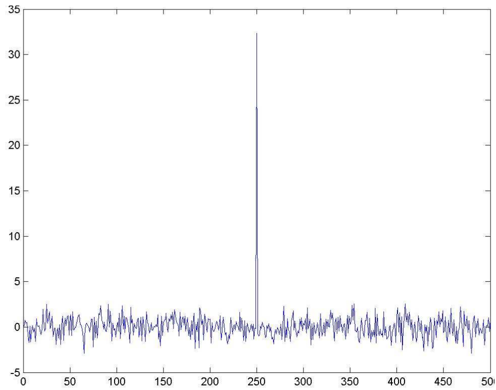
Fig.3 A registration example

Figure 4 shows the detection results for an undistorted watermarked image, a distorted image and a registered image using Cox's algorithm. The watermarked image was attacked by StirMark with a very small bending factor. We can see that, in the absence of registration, the watermark cannot be detected even at very low levels of distortion, and the proposed registration method can realign the image and improve the detector performance significantly.

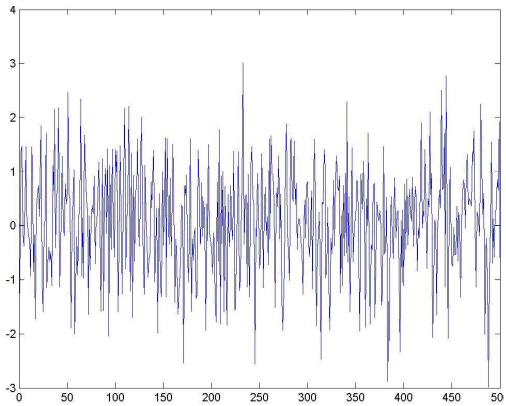
(a) Undistorted watermark image

(b) Distorted watermark image(bending factor 0.3)

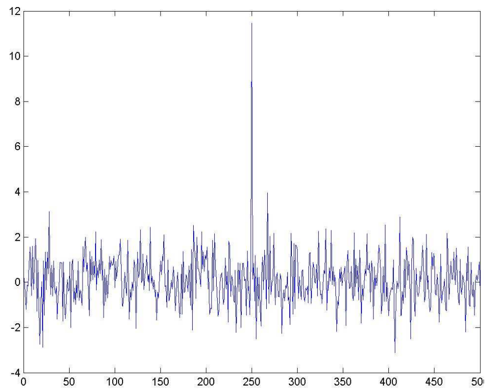
(c) Registered watermark image



(d) Detector response of the undistorted watermark image



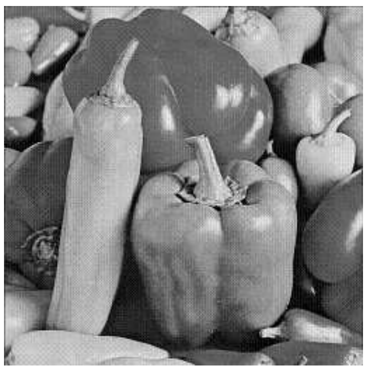
(e) Detector response of the distorted watermark image



(f) Detector of the registered watermark image

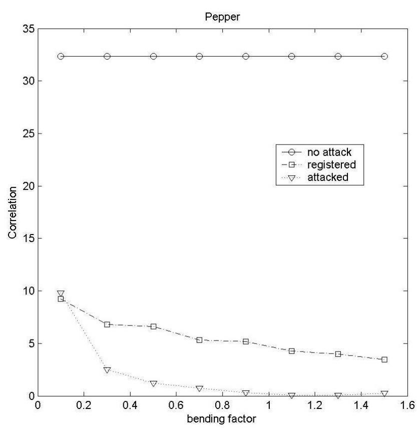
Fig.4 Effect of registration on the watermark detector

Figure 5 illustrates the detection results for an undistorted watermarked image, a distorted image and a registered image for "Pepper" and "Cameraman". Experiments were performed on the attacked watermark with bending factors of 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, and 1.5 (using StirMark 4.0) respectively. The legends for the figures are shown on the right. Although the watermark detector performance drops rapidly with an increase in bending factor, in all cases, the watermark still can be detected after registration. The results show that having the original image is not enough in general to detect watermarks in a distorted image, and registration can improve the detector performance significantly. Furthermore, in order to test the effectiveness of the proposed registration scheme, the same experiment was used to examine some standard images, including the 256×256 pixel Fishing Boat, F16, and Baboon images. In all experiments, the watermark can be detected after registration.

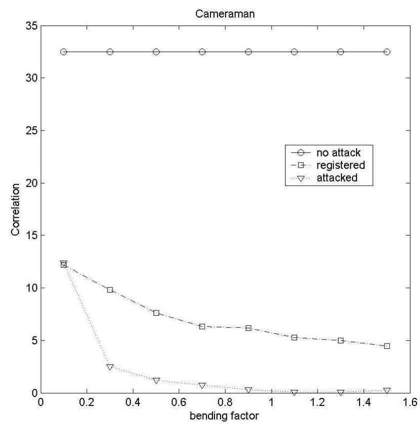


(a) Watermarked *Pepper*

(b) Watermarked *Cameraman*



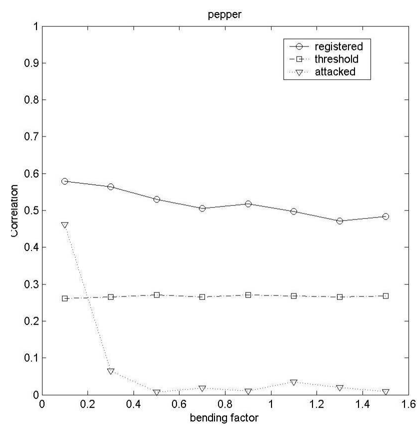
(c) *Pepper* watermark detection



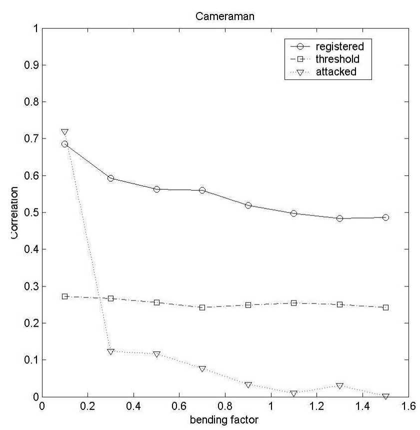
(d) *Cameraman* watermark detection

Fig.5 Effect of registration for two test images

Figure 6 shows the effect of registration on one blind watermark scheme developed by Barni (Barni, Bartolini and Piva 2001). The legends for the figures are shown on the right. The graphs show the correlation between the embedded and the extracted watermark in the distorted images with bending factors of 0.1, 0.3, 0.5, 0.7, 0.9, 1.1, 1.3, and 1.5 (using StirMark 4.0) and the registered images for two test images. In all images, the detector performance is improved significantly after the distorted images are registered.



(a) *Pepper* watermark detection



(b) *Cameraman* watermark detection

Fig.6 Effect of registration on Barni's algorithm

5 Conclusion

In this paper, an image registration scheme based on differential affine motion estimation is used for recovery of watermarks from geometric distortions. The algorithm is capable of handling arbitrary local distortion since it models the geometric distortion between images as locally affine but globally smooth. The main drawback of this scheme is the requirement of a reference image. Experimental results show that the proposed scheme can aid in watermark detection for many watermarking schemes in the presence of geometric distortion attacks. The second drawback is high computation cost. Also, the proposed scheme cannot cope with cropping attack. In order to combat these problems, we suggest a combination of the existing model-based registration techniques with the proposed algorithm. This will be our future work.

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