International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 06 Issue: 05 | May 2019 www.irjet.net p-ISSN: 2395-0072

Digital Image Watermarking via Adaptive Logo Texturization

Ms. Jagruti D. Ghatole[1], Dr. S.L. Badjate[2]

---***---

***Abstract*—** Grayscale logo watermarking is a quite well-developed area of digital image watermarking which seeks to embed into the host image another smaller logo image. The key advantage of such an approach is the ability to visually analyze the extracted logo for rapid visual authentication and other visual tasks. However, logos pose new challenges for invisible watermarking applications which need to keep the watermark imperceptible within the host image while simultaneously maintaining robustness to attacks. an algorithm for invisible grayscale logo watermarking that operates via adaptive texturization of the logo. The central idea of our approach is to recast the watermarking task into a texture similarity task. We first separate the host image into sufficiently textured and poorly textured regions. Next, for textured regions, we transform the logo into a visually similar texture via the Arnold transform and one lossless rotation; whereas for poorly textured regions, we use only a lossless rotation. The iteration for the Arnold transform and the angle of lossless rotation are determined by a model of visual texture similarity. Finally, for each region, we embed the transformed logo into that region via a standard wavelet-based embedding scheme. We employ a multistep extraction stage,in a watermark image.

Index Terms— Watermarking, logo watermarking, texturiza- tion, texture similarity, Arnold transform, Discrete wavelet transform

I. INTRODUCTION

ADVANCEMENTS in digital-imaging and processing technologies have not only given rise to the now ubiqui-tous use of digital imagery, but they have also led to an increas- ing number of tools and techniques for digitally manipulating the images. The increased feasibility of digital tampering has underscored the need for improved methods of copyright protection and prevention of unauthorized copying and distribution. Owing largely to its practicality and effectiveness, digital image watermarking has become one of the most widely accepted solutions to this problem Algorithms for digital watermarking embed into the original media specific identifying information the "digital water- mark" such as a logo, fingerprint, or serial number

Watermarking has been widely used for proof of ownership and copyright protection; however, it has also been applied to applications such as broadcast monitoring, data integrity verification, and image indexing and labeling Digital watermarking has been investigated for the last several decades and is a mature field of research. However, current efforts try to improve its performance, as new requirements and challenges posed by new applications motivate the need for continued research in this area.

One new requirement is the ability of a watermark to survive multiple, consecutive attacks. Over the last five years, MMS and online sharing of digital imagery on sites such as Facebook, Twitter, and other social and traditional media outlets, have become standard ways of disseminating photos. Typically, the original image is subjected to various forms of manual and/or automated processing before being posted, particularly when using popular sharing software such as Instagram. Such photos are typically resized (resulting in slight blurring), then cropped, then contrast-adjusted, then rotated (e.g., to make horizon lines horizontal), and then compressed via JPEG (resulting in blurring and blocking). Furthermore, if the images are transmitted over lossy communication channels, further degradation may result from transcoding, packet loss, and/or attempted corrections for such loss. The ability to survive multiple consecutive attacks was not a mainstream requirement 10-15 years ago, but it is clearly important today.

One popular thrust in digital image watermarking is *logo watermarking*, in which the watermark is itself an image, typically a small and user-specified image representing a symbol or a trademark. There has been significant research devoted to logo watermarking over the last 15 years. *Invisible* logo watermarking further requires that the watermark is visually imperceptible when placed within the host image, yet is visually recognizable when extracted. The primary advantage of logo watermarking is the ability to visually compare the extracted logo with the original logo during verification It is well-known that the human visual system is unmatched in its ability to perform visual recognition, even for small thumbnail-sized images Thus, even an untrained viewer can often effortlessly determine whether the extracted logo matches the original logo.

Invisible logo watermarking is particularly useful for more recent applications, such as watermarking for automated quality monitoring of multimedia transmission; for embedding QR codes in images and for embedding hospital and/or calibration logos in medical imagery In particular, watermarking has recently emerged as a promis- ing approach to no-reference image and video quality assess- ment No-reference quality assessment algorithms seek to estimate the quality of an image/video without having access to the original, undistorted image/video, which is a challenging research area that has traditionally relied on the use of statistical image features Watermarking hasshown recent promise for this task, and further improvements could be realized via the use of logo watermarking, which would allow the use of a full-reference quality assessment algorithm applied to the original and extracted logos.

Logo watermarking has to overcome multiple challenges. One challenge is that the extracted watermark must be visually meaningful in order to facilitate a visual comparison, as opposed to simply catering to a present/not-present decision. Thus, the watermark must be able to survive attacks such that the visual quality of the extracted logo gracefully degrades as the attack intensity increases. Another challenge to logo water- marking and some other non-logo watermarking algorithms, such as copy protection codes, stems from the fact that the logo (or watermark in general) is specified by the end-user and not by the watermarking algorithm; thus, the algorithm designer cannot choose which data to embed. A successful logo watermarking algorithm must be able to handle a variety of logos, which largely restricts the algorithm from employing approaches which are tailored to particular data patterns.

Much of the early work in invisible logo watermarking has concentrated on using binary logos. In Zeng *et al.* proposed a multiresolution binary logo extractor, which is capable of retrieving different resolutions of the embedded logo. In Voyatis and Pitas use toral automorphism to scramble a binary watermark via a set of parameters con- trolled by the logo owner. Two chaotic maps are employed in to encrypt the embedding position of the host image, and to determine the pixel bit of host image for watermark embedding.

Binary logo watermarking has also been performed in the discrete cosine transform (DCT) and discrete wavelet trans- form (DWT) domains. In Abdulfetah *et al.* combined a Just Noticeable Difference visual model with the DWT and DCT to adaptively embed the binary watermark in the original image. In Ramanjaneyulu *et al.* applied a two-level DWT to the original image and selected horizontal sub band (LH2) for embedding a binary watermark. A genetic algorithm is used for parameter optimization to maximize the imperceptibility and robustness of the method. In Reddy and Varadarajan embed a pseudo-randomly shuffled version of the logo in either the LH, HL, or HH subband of the host image. The subband with the maximum entropy is chosen for embedding.

In addition to binary logo watermarking, algorithms for invisible logo watermarking have also been designed to operate with grayscale logos, and there has been significant research devoted to both categories. In the work by Kundur and Hatzinakos a multiresolution fusion-based watermarking method is proposed for embedding grayscale logos in the DWT domain via a single-level DWT, and adding the four subbands of the logo to the same-orientation blocks of the host image.

Ganic and Eskicioglu combined the DWT and singular value decomposition (SVD), where they modified singular values of the host image by the singular values of the water- mark using specific strength. Although similar procedures have been followed in some other methods including and these methods do not embed the watermark completely in the host image. The reason is that these methods modify only the singular value matrix, and leave intact the two unitary matrices resulting from the SVD; these unitary matrices con- tain a significant portion of information regarding the logo. In the extraction stage, the non-attacked unitary matrices are employed, thus leading to seemingly high robustness measures.

Bhatnagar and Wu extended the size of host image using the reversible extension transform, which is followed by embedding the grayscale logo in the middle singular values of the extended image. Next, the watermarked image is shuffled using toral automorphism followed by automatic thresholding to get a binary image, which is also embedded in the host image to enhance the security and chance of logo retrieval.

Algorithms for grayscale logo watermarking have also been designed based on properties of the human visual system (HVS), most notably, visual masking. Reddy and Chatterji embed a small logo into the host images in the DWT domain using a single-level decomposition for the logo and a four-level decomposition for the host image. A model of visual masking is used for calculating the watermark embedding weights for individual wavelet coefficients.

Hien *et al.* encrypt the logo into a random noise signal for security. Then, the host image is decomposed by redundant discrete wavelet transform (RDWT), and the logo is embedded into the mid-frequency RDWT subbands. A noise visibility function is employed to model visual masking for adaptively varying the watermarking strength.

Jin *et al.* perform grayscale logo watermarking by using the DWT and visual masking. To enhance security, the logo is first shuffled by the Arnold transform Then, the shuffled logo is embedded into blocks of the LL subband which contain the largest-magnitude coefficients. The embedding is performed via a weighted addition, where the weights are determined based on models of luminance and noise masking. Foriš and Levický utilized three HVS models in combination with the DWT and DCT for watermarking. Three HVS models are used to select "perceptually significant" transform coefficients: (1) A model based on luminance masking and contrast sensitivity; (2) a model based on regions of interest and contrast masking; and (3) a model based on noise masking.

First and Qi proposed a composite watermarking algorithm which embeds the logo in the DWT subbands of the host image via modulus- and additive-based insertion. A pseudo-randomly shuffled and scaled version of the logo is embedded in the LL subband of the image via a modulus- based addition. The DCT of the logo is embedded in the "perceptually significant" blocks of the LH, HL, and HH subbands via a weighted addition of coefficients, where the weights are determined based on visual masking.

Mohanty and Bhargava proposed a watermarking algo- rithm which operates based on visual masking and salience. First, a region of interest is detected in the host image for watermark embedding. Next, a compound logo is created by using the fusion of the logo and a statistical image synthesized from the region of interest to make the watermark less visible. Clearly, properties of visual masking have proven useful for image watermarking. However, current understanding of visual masking in natural images is still relatively immature Recent studies using natural images as masks have shown that natural images can impose unique masking effects that cannot be predicted by existing computational models of masking Therefore, in watermarking, the use of exist- ing masking measures can potentially give rise to erroneous estimates of masking in images; thus resulting in watermarks which are either (1) visible due to overestimates of masking, or (2) unnecessarily far below the threshold of detectability due to underestimates of masking.

We present an algorithm for invisible grayscale logo watermarking, called *ALT-MARK* (*Adaptive Logo Texturization* Watermarking), that builds on the strengths of previous techniques, but which takes a fundamentally different approach. The main idea of our approach is to recast the watermarking task into a texture-similarity task by adaptively transforming the logo into a set of textures that visually match the textures of the host image. Specifically, during embedding, we utilize all possible regions within the host image to improve robustness against a wide range of attacks, since different attacks affect specific areas inside an image. We first separate sufficiently textured and poorly textured regions in the host image. Next, for textured regions, we transform the logo into a visually similar texture using the Arnold transform (which is invertible) and one lossless rotation; while for poorly textured regions, we use only a lossless rotation. The iteration for the Arnold transform and the angle of lossless rotation are determined via a model of visual texture similarity. Finally, for each region, we embed the transformed logo into that region via a standard wavelet-based embedding scheme. We employ a multi-step extraction stage, where affine parameter estimation is performed to compensate for possible geometrical trans- formations, which leads to higher robustness against such attacks.

Figure 1 illustrates the advantage of scrambling (texturizing) the logo based on the Arnold-transform iteration and lossless rotations of 90°, 180°, and 270° which yields the most visually similar texture. Here, the original and texturized versions of the logo *Peppers* have been embedded in a potential region within the host image (a segment of the pants on image *Barbara*). The first column shows the original region of the host image before embedding. The second column shows the watermarked versions of this region using the original and texturized logos from the third column, all embedded in the same manner, with the same weights. As shown in the first row, without texturization, the outlines of the peppers are visible after the embedding. As shown in the second and third rows, selecting

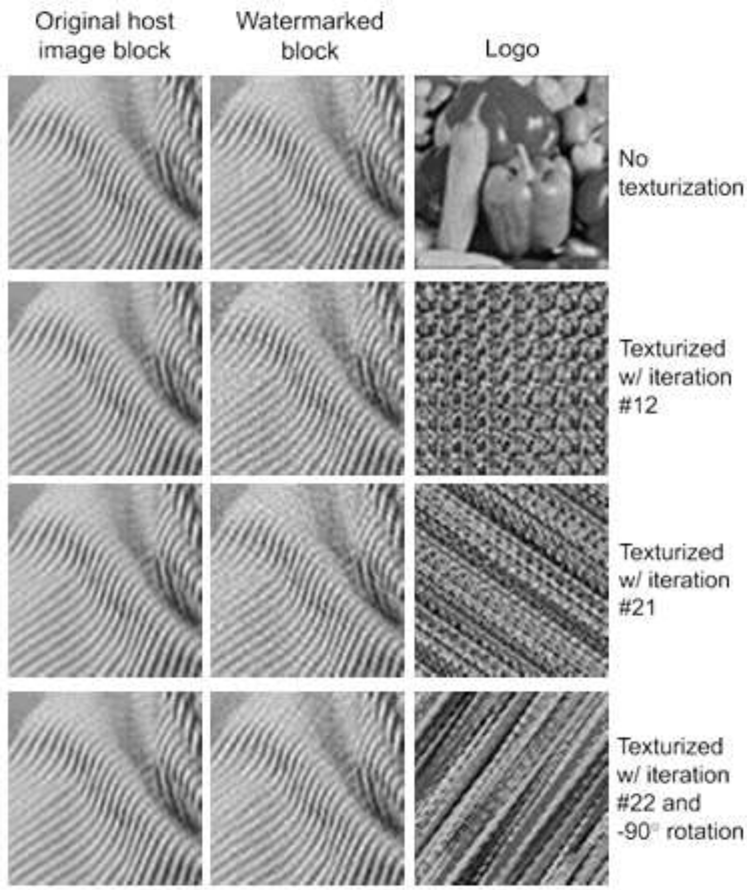


Fig. 1. Demonstration of adaptively texturizing a logo to visually match a region of the host image.

First column: A sample potential region of the host image *Barbara* before embedding. Second column: Watermarked regions, all embedded in the same manner, with the same weights. Third column: Original and texturized logos. As shown in the first row, without texturization, the outlines of the peppers are visible after the embedding, whereas in this case, the strength of the watermark would have to be reduced in order to lessen these outlines. However, as shown in the last row, by selecting the texurization (iteration of the Arnold transform) and lossless rotation to visually match the host region's texture, the visibility of the embedding can be reduced without reducing the strength of the watermark.

Inappropriate texturizations also leads to visible distortions. In both of these examples, to lessen the artifacts, one would need to reduce the strength of the watermark. However, as shown in the last row, by selecting the texturization (iteration of the Arnold transform) and lossless rotation to visually match the host region's texture, the visibility of the embedding can be reduced without reducing the strength of the watermark.

As in previous algorithms [34], [35] the use of an Arnold transform in ALT-MARK results in a scrambled version of the logo. However, as opposed to previous approaches in which the scrambling is performed only for increased security, our objective in scrambling the logo is to perform texturization to transform the logo into a set of textures that best match the corresponding textures of the host image. Again, this technique of transforming the logo into textures allows us to recast the watermarking task into a texture similarity task, thereby facilitating the use of recent research in visual texture similarity. As a result, and as we will demonstrate, the ALT-MARK algorithm can generate watermarked images in

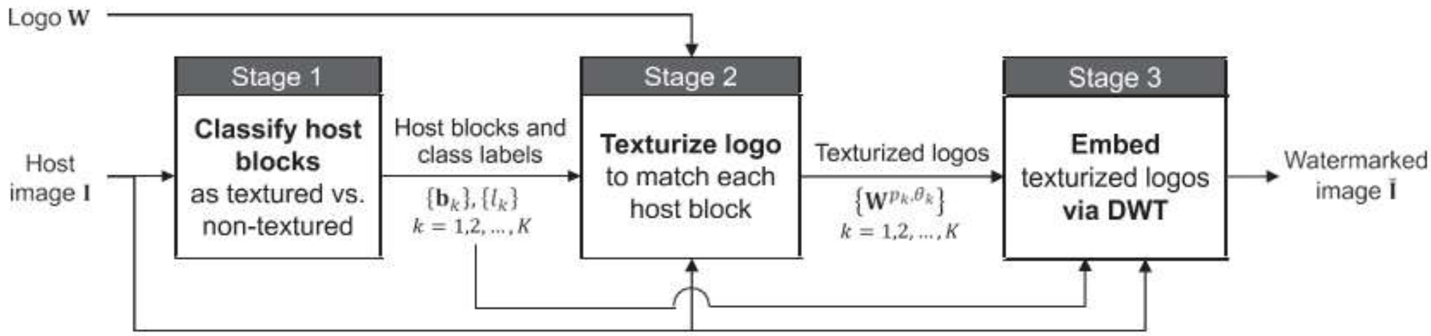


Fig. 2. Block diagram of the stages used in ALT-MARK to generate the watermarked image.

In summary, ALTMARK employs the best of existing methods to improve the performance of digital image water- marking. It utilizes the Arnold Transform, not only for security purposes, but also to texturize the logo for improving robust- ness against attacks, while maintaining invisibility. The new texturization technique benefits from pattern masking rather than contrast masking used in a large number of watermarking publications, and allows us to recast logo watermarking into a texture similarity task, where we employ an HVS appearance model supplemented by histograms of gradients, a well-known and effective method in the texture analysis literature. As in previous approaches, we embed the logo in the DWT domain which has been shown to provide higher impercep- tibility, while avoiding host image quality reduction. Finally, we attempt to compensate for affine distortions to improve robustness against this category of prevalent attacks.

This paper is organized as follows: Section II provides details of the algorithm. In Section III, we evaluate the performance of the algorithm on various images, and we com- pare with other approaches. General conclusions are provided in Section IV.

II. ALGORITHM

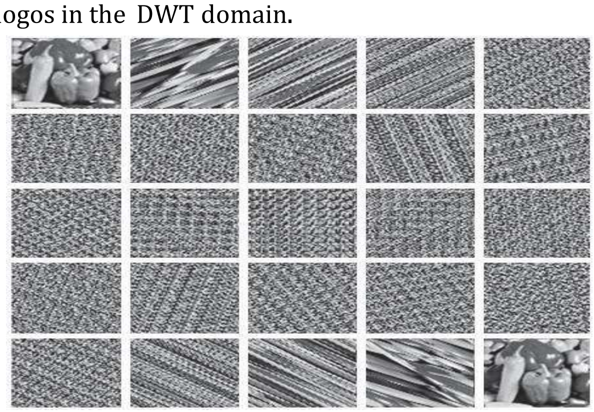
Because most images contain both textured and non- textured content, we use a spatially selective texturization process. For sufficiently textured blocks, the logo is adaptively texturized via the Arnold transform followed by a rotation in an attempt to provide a good visual match between the texturized logo and host block's texture. For host blocks which are non-textured or poorly textured, the Arnold transform would generally make the logo more visible, and therefore we employ only the rotation these latter blocks. Thus, as discussed next, we first employ a texture segmentation to distinguish sufficiently textured blocks from poorly textured blocks.

The watermark embedding algorithm in ALT-MARK con- sists of three main stages:

1) Basic texture segmentation to distinguish sufficiently textured regions from poorly textured regions in the host image.

2) Adaptive-iteration logo scrambling via the Arnold trans- form, employing lossless rotations, and texture similarity analysis.

3) Embedding of the texturized logos in the DWT domain.



Logo *Peppers* of size 64 64 pixels (top-left corner) and results of the Arnold transform using different iterations. The iteration numbers increase in a raster-scan fashion (i.e., from left to right in a row, and then from top to bottom). The original logo is recovered at $P = 24$ iterations.

B. Texturizing the Logo to Match Each Host Block

Given the host blocks $\mathbf{b}_1$, $\mathbf{b}_2$, , $\mathbf{b}_N$ from Stage 1, we now proceed to texturize the logo to provide the best possible visual match to each block. To perform this adap- tive texturization, we use a combination of the Arnold transform, lossless rotations, and a visual texture similarity estimator.

1) *Texturization via the Arnold Transform:* The generalized 2D Arnold transform [29], [37] is a mapping which transforms each coordinate *(x, y)* in an *L L* image to a new location

To maximize the robustness of the watermarked image, we embed the logo in all blocks of the host image. This approach helps improve the ability of the watermark to survive different types of attacks. For example, embedding the logo in each host block improves the robustness to spatially selective attacks such as cropping and blurring (which generally affects higher frequency regions more than lower frequency regions). Furthermore, by using all host blocks, the extraction process entails averaging a larger number of extracted logos, and such averaging can neutralize random effects of the attack on different

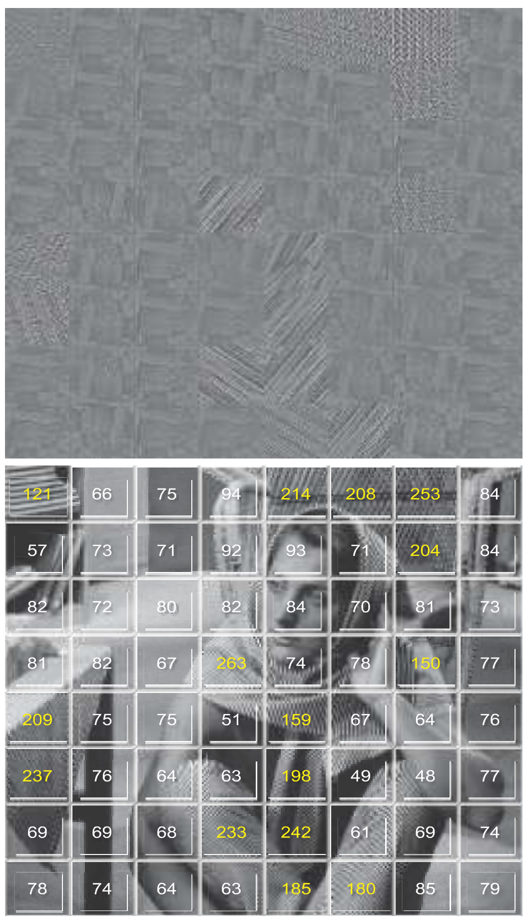


Fig. 6. *Left*: Texturized and/or rotated versions of the logo *Peppers* selected for host image *Barbara*. To promote visibility, each logo has been scaled to a suprathreshold contrast which is proportional to the block's weight α_k . *Right*: Labels of each block's weight scaled by 1000 to promote readability; values in yellow denote textured regions.

A feature points. This procedure is repeated a fixed number of times (see [41] for further details).

Note that if no affine attack has been delivered to $\breve{\mathbf{I}}$,matrices **A** and **B** would be calculated to be the identity matrix and zero matrix, respectively. Moreover, geometrical attacks other than those described by an affine mapping, such as projective transformation might be delivered to a watermarked image. Because prior knowledge about the type of delivered attack(s) is not possible, the technique used here can be employed to compensate for other assumed attacks, while replacing (19) with other transformations.

After the affine parameter estimation and compensation, the logo is extracted via the following steps:

2) For each embedded logo $\mathbf{W}^{pk,\theta k}$ $(k1, 2, ..., N)$ and corresponding embedding information $(\alpha_k, p_k, \theta_k)$: =

a) Apply a one-level Haar DWT to the k^{th} block in the original image ($\mathbf{b}_k$), and corresponding block in the retrieved watermarked image after affine transformation compensation ($\mathbf{b}_k$).

b) Subtract all four subbands of $\mathbf{b}_k$ from the cor- responding subbands of $\mathbf{b}_k$, and then divide the difference subbands by the corresponding weights $0.2\alpha_k$, α_k , α_k , α_k to obtain the subbands of the k^{th} texturized logo.

c) Apply an inverse one-level Haar DWT to the resulting subbands to extract the texturized logo

d) De-texturize $\widehat{\mathbf{W}}^{k,\theta k}$ by using the stored angle θ_k a feature point. Therefore, we create a Q 2 matrix M, in which the i^{th} feature point in the watermarked image ($d_{1,i}$) is matched to the j^{th} feature point in the attacked watermarked image ($d_{2,j}$) if $(d_{1,i}\ d_{2,j})^2 < tr$.

Because there could be more than one match for each feature point and outliers exist, we use the Random Sample Consensus (RANSAC) to estimate the affine parameters [41]. RANSAC estimates the affine parameters by iteratively select- ing a random subset of the matched feature points in M. These data are assumed to be hypothetical inliers, then all entries of the matrices **A** and **B** in are calculated from this sample using least-squares techniques. Next, all other feature points are tested against the fitted affine transformation, and those feature points that sufficiently fit the estimated transformation are considered as part of the consensus set. The estimated parameters are sufficiently fit if sufficiently many points have been classified as part of the consensus set. Afterwards, the transformation may be improved by re-estimating it using all and Arnold transform iteration p_k.

3) After the logos from all regions are extracted, average all extracted logos.

4) Among all extracted logos and the average of extracted logos in 2), deem the final extracted logo ($\widehat{\mathbf{W}}$) to be the one with the highest normalized correlation coefficient.

As we will demonstrate next, the affine parameter estimation and compensation allows ALT-MARK to be robust to many geometrical attacks. Furthermore, by utilizing all blocks of the host image in addition to employing averaging of the extracted logos, ALT-MARK is robust to a wide variety of non-geometrical attacks.

III. RESULTS AND ANALYSIS

In this section, we analyze the qualitative and quantitative performance of ALT-MARK. Results for four benchmark images containing varying amounts of texture are provided in Subsection III-A, which presents watermarked images and extracted logos for various types of attacks. In Subsection III-B, we compare the performance of ALT-MARK to other modern logo watermarking algorithms for different types of attacks and different attack intensities, using multiple logos and a large database of host images.

To quantify the imperceptibility and robustness of images generated by ALT-MARK and other watermarking algorithms, we used peak signal-to-noise-ratio (PSNR) and normalized cross-correlation coefficient (NCC). These measures are admittedly imperfect; however, PSNR and NCC are the most frequently utilized in the literature and they thus provide a means for comparison with results published by other

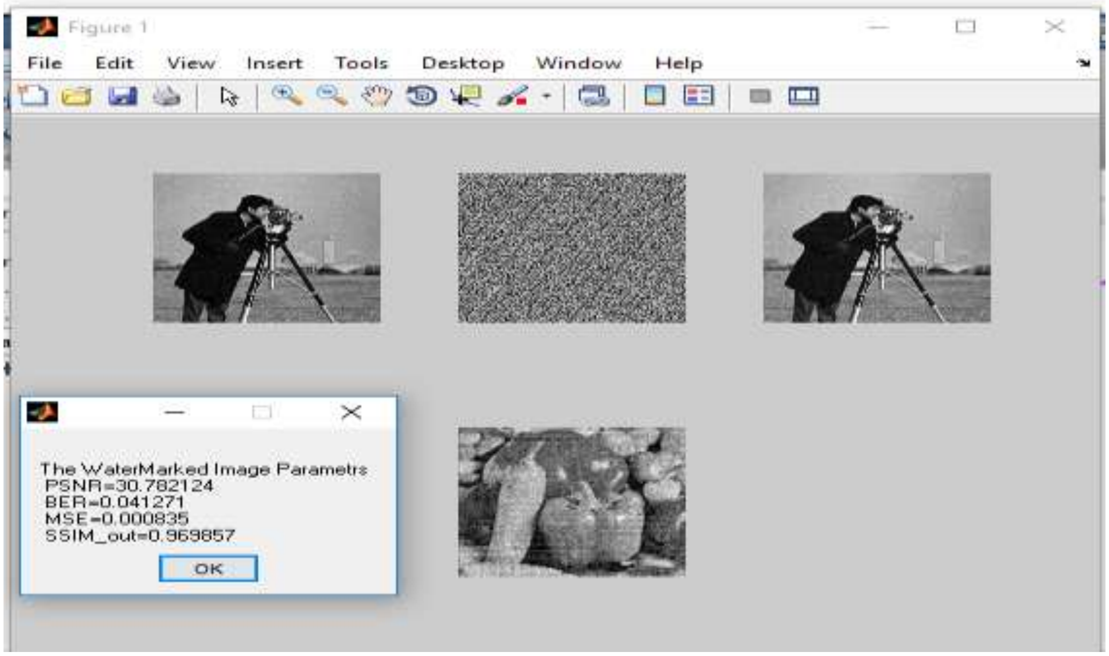


Figure :- Finally Digital Image Watermarking and then extraction concept

IV. CONCLUSION

This paper presented an algorithm for invisible grayscale logo watermarking via adaptive logo texturiza- tion (ALT-MARK). The main idea of our approach is to recast the watermarking task into a texture-similarity task by adaptively transforming the logo into a set of textures that visually match the textures of the host image. As we have demonstrated, the use of all available regions in the host image with varying embedding weights, in addition to the use of affine parameters estimation and compensation, affords significant robustness to a variety of attacks. A comparison of ALT-MARK to other modern logo watermarking algorithms demonstrated that ALT-MARK generally outperforms competing methods in terms of robustness. ALT-MARK is also relatively efficient in terms of computational speed. A basic Matlab implementation running on a modern desktop computer (Intel Core i7 2670QM at 2.2 GHz with 6 GB of system RAM) requires on average 4.8 seconds to embed a 64 64 logo in a 512 512 host image; the extraction process requires on average 0.9 seconds.

REFERENCES

1. A. Z. Tirkel, G. A. Rankin, R. M. Van Schyndel, W. J. Ho,N. R. A. Mee, and C. F. Osborne, “Electronic water mark,” in Proc. DICTA, 1993, pp. 666–673.

2. M. Natarajan and G. Makhdumi, “Safeguarding the digital contents: Digital watermarking,” DESIDOC J. Library Inf. Technol., vol. 29, no. 3, pp. 29–35, 2009.

3. C. I. Podilchuk and E. J. Delp, “Digital watermarking: Algorithms and applications,” IEEE Signal Process. Mag., vol. 18, no. 4, pp. 33–46, Jul. 2001.

4. X. Zhao and A. T. S. Ho, “An introduction to robust transform based image watermarking techniques,” in Intelligent Multimedia Analysis for Security Applications, vol. 282. Berlin, Germany: Springer-Verlag, 2010, pp. 337–364.

5. R. Halder, S. Pal, and A. Cortesi, “Watermarking techniques for rela- tional databases: Survey, classification and comparison,” J. Universal Comput. Sci., vol. 16, no. 21, pp. 3164–3190, 2010.

6. A. Nema and R. Mohan, “Digital image watermarking: A review,” Global J. Multidiscipl. Stud., vol. 3, no. 6, pp. 84–94, 2014.

7. G. W. Braudaway, “Protecting publicly-available images with an invis- ible image watermark,” in Proc. Int. Conf. Image Process., 1997, pp.

8. T. Brandão, "Image communication quality assessment based on watermarking, an overview," Inst. Telecomunicações, Lisboa, Portugal, Tech. Rep. v0.02, 2005.

a. Z. Wang, G. Wu, H. R. Sheikh, E. P. Simoncelli, E.-H. Yang, and C. Bovik, "Quality-aware images," IEEE Trans. Image Process., vol. 15, no. 6, pp. 1680–1689, Jun. 2006.

9. G. Voyatis and I. Pitas, "Digital image watermarking using mixing system," Comput. Graph., vol. 22, no. 4, pp. 405–416, 1998

10. T. Brandão, "Image communication quality assessment based on watermarking, an overview," Inst. Telecomunicações, Lisboa, Portugal, Tech. Rep. v0.02, 2005.

11. Z. Wang, G. Wu, H. R. Sheikh, E. P. Simoncelli, E.-H. Yang, and

a. C. Bovik, "Quality-aware images," IEEE Trans. Image Process., vol. 15, no. 6, pp. 1680–1689, Jun. 2006.

12. N. Baaziz, D. Zheng, and D. Wang, "Image quality assessment based on multiple watermarking approach," in Proc. IEEE 13th Int. Workshop Multimedia Signal Process. (MMSP), Oct. 2011, pp. 1–5.

13. S. Vongpradhip and S. Rungraungsilp, "QR code using invisible water- marking in frequency domain," in Proc. 9th Int. Conf. ICT Knowl. Eng., 2012, pp. 47–52.

14. S. Bhalerao, M. Mehta, N. Dubey, and M. Bhatele, "Digital watermark- ing of medical images," in Proc. India Seminar Biomed. Eng., 2012, pp. 111–116.

15. D. M. Chandler, "Seven challenges in image quality assessment: Past, present, and future research," ISRN Signal Process., vol. 2013, 2013, Art. ID 905685, doi: 10.1155/2013/905685.

16. W. Zeng, B. Liu, and S. Lei, "Extraction of multiresolution water- mark images for resolving rightful ownership," Proc. SPIE, vol. 3657, pp. 404–414, Apr. 1999.

17. G. Voyatis and I. Pitas, "Digital image watermarking using mixing system," Comput. Graph., vol. 22, no. 4, pp. 405–416, 1998.

18. X. Wu and Z.-H. Guan, "A novel digital watermark algorithm based on chaotic maps," Phys. Lett. A, vol. 365, pp. 403–406, Jun. 2007.

19. A. A. Abdulfetah, X. Sun, H. Yang, and N. Mohammad, "Robust adaptive image watermarking using visual models in DWT and DCT domain," Inf. Technol. J., vol. 9, no. 3, pp. 460–466, 2010.

20. K. Ramanjaneyulu and K. Rajarajeswari, "Robust and oblivious image watermarking scheme in the DWT domain using genetic algorithm," Int.

21. J. Adv. Eng. Technol., vol. 2, no. 3, pp. 85–92, 2011.

22. V. P. Reddy and S. Varadarajan, "An effective wavelet-based water- marking scheme using human visual system for protecting copyrights of digital images," Int. J. Comput. Elect. Eng., vol. 2, no. 1, pp. 32–40, 2010.

23. D. Kundur and D. Hatzinakos, "Toward robust logo watermarking using multiresolution image fusion principles," IEEE Trans. Multimedia, vol. 6, no. 1, pp. 185–198, Feb. 2004.

24. E. Ganic and A. M. Eskicioglu, "Robust embedding of visual water- marks using discrete wavelet transform and singular value decomposi- tion," J. Electron. Imag., vol. 14, no. 4, p. 043004, 2005.

25. G. Bhatnagar, B. Raman, and Q. M. J. Wu, "Robust watermarking using fractional wavelet packet transform," IET Image Process., vol. 6, no. 4, pp. 386–397, Jun. 2012.

26. C.-C. Lai and C.-C. Tsai, "Digital image watermarking using discrete wavelet transform and singular value decomposition," IEEE Trans. Instrum. Meas., vol. 59, no. 11, pp. 3060–3063, Nov. 2010.

27. G. Bhatnagar and Q. M. J. Wu, "A new logo watermarking based on redundant fractional wavelet transform," J. Math. Comput. Model., vol. 58, pp. 204–218, Jul. 2013.

28. A. A. Reddy and B. N. Chatterji, "A new wavelet based logo- watermarking scheme," Pattern Recognit. Lett., vol. 26, no. 7, pp. 1019–1027, 2005.

29. T. D. Hien, Z. Nakao, and Y.-W. Chen, "Robust multi-logo watermarking by RDWT and ICA," J. Signal Process., vol. 86, no. 10, pp. 2981–2993, 2006.

30. C. Jin, F. Tao, and Y. Fu, "Image watermarking based HVS characteristic of wavelet transform," in Proc. Int. Conf. Intell. Inf. Hiding Multimedia Signal Process., Dec. 2006, pp. 71–74.

31. V. I. Arnold and A. Avez, Ergodic Problems of Classical Mechanics. New York, NY, USA: Benjamin, 1968.

32. P. Foriš and D. Levický, "Implementations of HVS models in digital image watermarking," Radioengineering, vol. 16, no. 1, pp. 45–50, 2007.

33. E. First and X. Qi, "A composite approach for blind grayscale logo watermarking," in Proc. IEEE Int. Conf. Image Process., vol. 3. Sep./Oct. 2007, pp. III-265–III-268.

34. S. P. Mohanty and B. K. Bhargava, "Invisible watermarking based on creation and robust insertion-extraction of image adaptive watermarks," ACM Trans. Multimedia Comput., Commun., Appl., vol. 5, no. 2, 2008, Art. ID 12.