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Review on Application of Adaptive Watermarking by Hi-Fidelity Image Annotation for Data Embedding

Kirti Kshirsagar[1], Dr. Sunil Phulre[2], Dr. Vineet Richhariya[3]
[1]M. Tech Scholar, [2]Associate Professor, [3]Professor, Dept. of CSE, LNCT, Bhopal, M.P., India

***Abstract*- In this paper authors cover the survey report of 23 papers that's worked only on data embedding for image annotation. In first paper described hi-fidelity image annotation for 32 bit metadata into a single image over all PSNR 38 dB. In paper second and soft and hard watermarking are used for image imbedding.**

***Keyword* - hi-fidelity, image annotation, MSE.**

I. Introduction

Most of the related work on visual models has focused on establishing a function over the visual features of two images to establish how similar they are, or how closely they appeal to the human eyes. While simple heuristics such as mean squared error (MSE) and peak signal-to-noise ratio (PSNR) are easy to compute and integrate in optimization scenarios, they have been abandoned long ago for high-quality image quality assessment. On the other hand, novel sophisticated models have been mainly focusing on combining feature statistics [1]. The proposed model combines the outputs of two simple filters: entropy and a differential standard deviation filter to estimate visual sensitivity to noise. The two outputs are mixed using a non-linear function and a smoothing low pass filter in a post-processing step. In this paper, we focus on the latter one with an objective to create a tool that annotates images with 32 bits of meta-data. Note that we do not impose any security requirements for the watermarking technology. The developed watermarking technology embeds two watermarks, a strong direct-sequence spread spectrum (SS) watermark tiled over the image in the lapped bi-orthogonal transform (LBT) domain [2]. The number of digital images grows rapidly and it becomes an important challenge to organize these resources effectively. As a way to facilitate image categorization and retrieval, automatic imageannotation has received much research attention. Considering that there are a great number of unlabeled images available, it is beneficial to develop an effective mechanism to leverage unlabeled images for large scale imageannotation. Meanwhile, a single image is usually associated with multiple labels, which are inherently correlated to each other.

A straightforward method of imageannotation is to decompose the problem into multiple independent single label problems, but this ignores the underlying correlations among different labels. In this paper, we propose a new inductive algorithm for imageannotation by integrating label correlation mining and visual similarity mining into a joint framework. We first construct a graph model according to image visual features. A multi-label classifier is then trained by simultaneously uncovering the shared structure common to different labels and the visual graph embedded label prediction matrix for imageannotation. We show that the globally optimal solution of the proposed framework can be obtained by performing generalized eigen-decomposition. We apply the proposed framework both to web imageannotation and personal album labeling using the NUS-WIDE, MSRA MM 2.0 and Kodak image datasets and the AUC evaluation metric. Extensive experiments on large scale image databases collected from the web and personal album show that the proposed algorithm is capable of utilizing both labeled and unlabeled data for imageannotation and outperforms other algorithms[3].

II. Applications And Requirements Watermarking

Watermarking has wide range of application. They can be used for copyright protection of digital images, fingerprinting, adding additional information to digital documents. The author of a digital image wants to "sign" the image so that no one else canclaim the authorship of the image to himself. The signature cannot be appended to the image file, nor can it be visibly imprinted on the image because such signatures can be easily removed or replaced. Cryptographic digital signatures cannot be applied because images are to be viewed by others and, therefore, will be distributed "in plain". Cryptographic digital signatures can be used for authentication of a communication channel but cannot protect an image posted on a web page.

The solution is to put a robust, secure, invisible watermark on the image and the watermarked image W is distributed. The author keeps the original image I.

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To prove that an image W'or a portion of it has been pirated, the author shows that W'contains his watermark (to this purpose, he could but does not have to use his original image I). The best a pirate can do is to try to remove the original watermark (which is impossible if the watermark is secure), or he can embed his signature in the image. But this does not help him too much because both his "original" and his watermarked image will contain the author's watermark (due to robustness property), while the author can present an image without pirate's watermark. Thus, the ownership of the image can be resolved in the court of law. The watermark must be robust, secure, invisible, and it has to depend in a non-invertible manner on the original image. The watermarking technique can use the original image for watermark detection. This simplifies image registration before watermark detector can be applied. Other requirements: relatively small capacity (1-100 bits).

2.1Annotation Watermark

Additional data-related information is embedded into the host data as content annotation. Thus, more information is conveyed together with the transmission of the host data. The embedded information can be anything related to the content. For example, an image or a song could contain additional embedded information on its author, type, copyright or a link to a Web address where more related information can be retrieved. Annotation watermarks require a moderate robustness against the common signal processing and the lowest security level.

The above list represents example applications where data hiding and digital watermarks could potentially be of use. In addition, there are many other applications in digital rights management (DRM) and protection that can benefit from data hiding and watermarking technology. Examples include tracking the use of documents, automatic billing for viewing documents, and so forth. From the variety of potential applications exemplified above it is clear that a digital watermarking technique needs to satisfy a number of requirements. Since the specific requirements vary with the application, data hiding and watermarking techniques need to be designed within the context of the entire system in which they are to be employed. Each application imposes different requirements and would require different types of watermarking schemes.

III. ALGORITHM & IMPLEMENTATION

High fidelity is a demanding requirement for data hiding for images with artistic or medical value. This correspondence proposes image watermarking for annotation with robustness to moderate distortion.

To achieve the high fidelity of the embedded image, the model is built by mixing the outputs from entropy and a differential localized standard deviation filter. The mixture is then low-pass filtered and normalized to provide a model that produces substantially better perceptual hi-fidelity than existing tools of similar complexity. The model is built by embedding two basic watermarks: a pilot watermark that locate the existence of the watermark and an information watermark that carries a payload of several dozen bits. The objective is to embed 32 bits of metadata into a single image in such a way that it is robust to JPEG compression and cropping most author implement their won work on the following algorithm shown in Fig.1.

This method takes an image file and 32-bit Meta data and produces a new image file that contains the 32-bit Meta data. The output image is called Annotated image file and it is similar to the input image file. Adaptive Watermark technique identifies parts of the image that are most suited for data hiding. The main objective is to embed 32 bits of metadata into a single image in such a way that it is robust to JPEG compression and cropping. Here we introduce high speed & highly secured image annotation using LBS embedding Algorithm watermarks for image annotation, High fidelity is a demanding requirement for data hiding for images with artistic or medical value. This correspondence proposes image watermarking for annotation with robustness to moderate distortion. To achieve the high fidelity of the embedded image, the model is built by mixing the outputs from entropy and a differential localized standard deviation filter. The mixture is then low-pass filtered and normalized to provide a model that produces substantially better perceptual hi-fidelity than existing tools of similar complexity. The model combines the outputs of two simple filters: entropy and a differential standard deviation filter to estimate visual sensitivity to noise. The two outputs are mixed using a non-linear function and a smoothing low-pass filter in a post-processing step. As a result, image localities with sharp edges of arbitrary shape as well as uniformly or smoothly colored areas are distinguished as "highly sensitive to noise," whereas areas with noisy texture are identified as "tolerant to noise." This ability can be particularly appealing to several applications such as Compression, de-noising, or watermarking. In this paper, we focus on the latter one with an objective to create a tool that annotates images with 32 bits of meta-data. Note that we do not impose any security requirements for the watermarking technology[6].

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The developed watermarking technology embeds two watermarks, a strong direct-sequence spread spectrum (SS) watermark tiled over the image in the lapped bi-orthogonal transform (LBT) domain [7]. This watermark only signals the existence of the meta-data. Next, we embed the meta-data bits using a regional statistic quantization method. The quantization noise is optimized to improve the strength of the SS watermark while obeying the constraints imposed by the perceptual model. We built the watermarks to be particularly robust to aggressive JPEG compression and cropping. With additional improvements, the meta-data could be made robust to other signal processing procedures such as histogram equalization, scaling and certain affine transforms [8]. Finally, within the realm of watermarking, a related focus to high quality imaging has appeared in [9]. Most of the related work on visual models has focused on establishing a function over the visual features of two images to establish how similar they are, or how closely they appeal to the human eyes.

While simple heuristics such as Average Absolute Difference, mean-squared error (MSE), signal to noise ratio (SNR), Image fidelity and peak signal-to-noise ratio (PSNR) are easy to compute and integrate in optimization scenarios, they have been abandoned long ago for high-quality image quality assessment [3]. On the other hand, novel sophisticated models have been mainly focusing on combining feature statistics. An excellent survey of related work prior to year 2009 is given in [4], and a review of most recent work including a novel visual fidelity assessment methodology is reviewed in [5]. We establish the model in the pixel domain for two reasons. First, it can be applied at no transformation cost in applications that require image transforms such as wavelets, lapped transforms, or DCT. Second, it is difficult to model perceptual quality for block transforms such as JPEG's 8 × 8 DCT, as the assessment procedure has to have an understanding of the block interleaving (if any) as well as access to data in the neighboring blocks. In such a setup, it is difficult to predict artifacts like blocking, aliasing, ringing along edges etc.

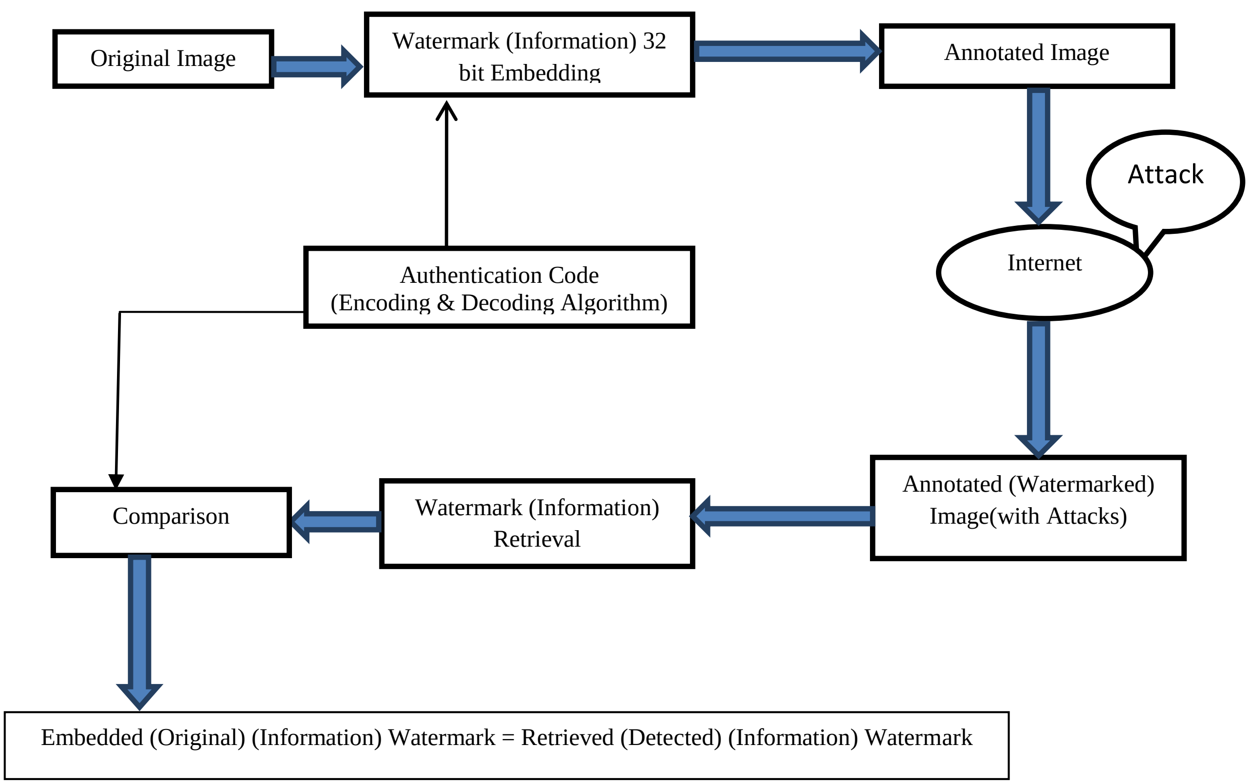

Figure 1: Block Diagram View of Implemented Model

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3.1 Noise Tolerance of Model

The proposed visual perceptual model is evaluated in the pixel luminance domain. It relies on several localized statistics to quantify the noise tolerance of each pixel. Specifically, we choose two filters: one that computes the differential standard derivation and another that calculates the entropy of a local region centered at the pixel-of-interest. Given an image I $\in \{Z^*\}^{m\times n}$, for each of its pixels k(x, y) ∈ I where x and y denote pixel coordinates, we examine its r-by-r neighborhood[1] Π(k) centered at k and define the following metrics:

$$S(k,r) = \sqrt{\frac{1}{r^2-1}\sum_{i\in\pi(k)}\left(i-\frac{1}{r^2}\sum_{j\in\pi(k)} j\right)^2} \quad (1)$$

$$E(k,r) = -\sum_{i=1}^{256} p(k,i)\log\left[p(k,i)\right] \quad (2)$$

$$p(k, i) = \Pr[k = i \mid k \in \Pi(k)]. \quad (3)$$

The entropy map E (k, r) indicates the complexity of the neighborhood for a given pixel. This is a simple heuristic to identify pixels that are perceptually less tolerant to noise. Empirically, this claim usually holds true for pixels with low E (k, r), i.e., regions with smoothly changing luminosity. It is important to stress that high value of E (k, r) does not necessarily imply strong tolerance to noise.

We use a differential standard deviation filter D (k) = |S (k, r_1) − S (k, r_2)|, $r_1 > r_2$, to expose the effect of edges on visual fidelity. If both S (k, r_1) and S (k, r_2) are low, then we intuitively conclude that the r_1-neighborhood centered on k is not tolerant to noise similarly to the entropy filter. On the other hand, if both S (k, r_1) and S (k, r_2) have high values, one can certainly assume that the visual content around k is noisy and that it more noise-tolerant. The interesting case occurs for disproportionate S (k, r_1) and S (k, r_2); in most cases this signals an edge in the neighborhood of k and low tolerance to noise. In order to reflect these phenomena we empirically selected D( ) as a fast, In order to mix the E( ) and D( ) features, we first normalize both feature matrices and then combine them as follows:

$$m(D,E) = \exp\left[-\frac{(D-1)^2+(E-1)^2}{2s^2}\right] \quad (4)$$

The mixing function is non-linear and has the shape of a 2D Gaussian distribution, where parameter s adjusts the shape of the function. In Fig.2 it resembles a smooth AND operator between E and D. Low values of s raise the complexity value for the pixel with both high E and D while suppressing other pixels. Large s allows pixels with moderate E and D to have moderately high complexity value.

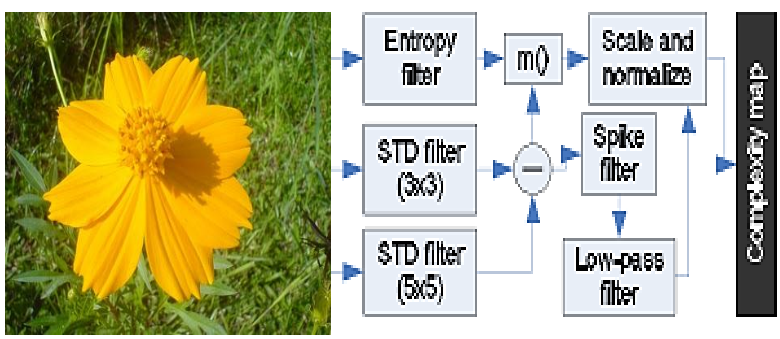

Figure 2: Block diagram of the processing involved in computing a complexity values.

We finalize the process by filtering D(k) with a 3 ×3 spike filter:

$$F1=\left\{-\frac{1}{8},-\frac{1}{8},-\frac{1}{8},-\frac{1}{8},1-\frac{1}{8},-\frac{1}{8},-\frac{1}{8},-\frac{1}{8},\right\} \quad (5)$$

Followed by a low-pass filter to obtain m’(D, E). This processing aims at exposing only strong edge effects.

Finally, by scaling m(D, E)/m’(D, E) and then normalizing the result, we create the final complexity map f(I). Fig.2 illustrates the resulting complexity map Note that the map has minor low-frequency artifacts from using a fast low-pass filter – in all conducted experiments; we were not able to detect these artifacts on the final images.

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IV. Results And Discussions

Author done maximum possible experiments on 5 different images with different characteristics to prove our proposed method and finally we got effective results for efficient image annotation in which we hide 32 bit meta-data in any high fidelity image with medical or any precious value for which used HW and SW. While doing all this we embed same 32 Bit hard watermark in all 5 Images to compare our results with different images:

Results for Image 1 Visual Demonstration of the visual differences between the input image (a), original image in gray scale format with no watermark Fig (b), and annotated image with both soft and hard watermarks augmented Fig(c) & the Detected image after detection of hard watermarks (information) (d). The entire images illustrate the actual pixel value alterations after embedding & detecting both the watermarks:

(a) **(b)** **(c)** **(d)**

Figure 6: Visual difference Image 1(a) Original Input RGB Image (b) original image converted in Gray scale with no watermarks (c) Annotated image with both soft and hard watermarks augmented.(d) Output image after detection of hard watermarks.

Table 1:
First Order statistics for Image 1

Columns 1 To 8	Columns 9 To 16	Columns 17 To 24	Columns 25 To 32
678.0820	288.5996	488.5703	314.3633
657.1191	364.3672	474.7500	359.5273
429.7695	516.0664	518.2813	364.0840
344.8379	545.1660	520.8086	329.8340
340.1719	508.7617	485.3379	327.2910
346.6250	463.4297	483.1094	355.1445
343.4023	454.3340	403.5625	458.4531
273.4199	483.6738	298.2559	616.5840

V. Conclusion

Several experiments to evaluate the different method on a database of 41 challenging images. Figure 1 shows a small portion of one of the original test images with a large smooth region. Most of the semantic content of the image is expressed as an edge. This is an example of an image which is relatively hard to watermark in-perceptively. The same figure illustrates the output of an existing hi-fidelity watermarking scheme compared to the result. The two schemes have approximately the same maximal luminosity noise, however, the overall PSNR in the Y-channel is 42dB. Both the soft and the hard watermark survive a JPEG compression with the quality parameter set to 30.

IV. with €FN= confidence.

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