A Watermark Recognition System: an Approach to Matching Similar Watermarks

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Introduction and Problem Analysis

Watermarks are small images that are embedded in historical paper and are frequently used to identify the paper's manufacturers [1]. Under ideal circumstances, researchers may use watermarks to determine a historical document's origins and context. To identify a watermark, it is matched to a previously archived watermark. Currently, this matching must be done manually, which is neither scalable nor parallelizable. Existing studies explore digital reconstructions of watermarks, but do not focus on a comparison-based setup. This report discusses a system that can automatically identify similar watermarks using traditional image processing techniques.

Watermark images have been provided by the German Museum of Books and Writing. The first is "untraced" watermarks, which are scans taken directly from the watermarked paper (Fig. 1). The second is "traced" watermarks, which are scans of tracings of watermarks (Fig. 2).

Figure 1. An untraced watermark

Figure 2. A traced watermark

Objective

The goal of this research was to create a system to automatically identify similar watermarks in an accessible way, that works for small datasets of images, and can be processed quickly.

Method

The similarity matching pipeline takes an input image and tries to extract useful information about the watermark, then calculates its similarity with the comparison watermarks. The steps of the pipeline are detailed in Figure 3. There are four main steps: user interaction, harmonization, feature extraction, and similarity matching. These are described in further detail in this section.

User Interaction

Users can interact with the pipeline in two ways, either through a graphical user interface (GUI), or a command-line interface (CLI). Both allow the user to upload an image and see its similarity scores to images from the database. However, in a GUI, users can alter intermediary steps in the process by choosing the best-denoised and best-thresholded image. Ideally, this input leads to more accurate results.

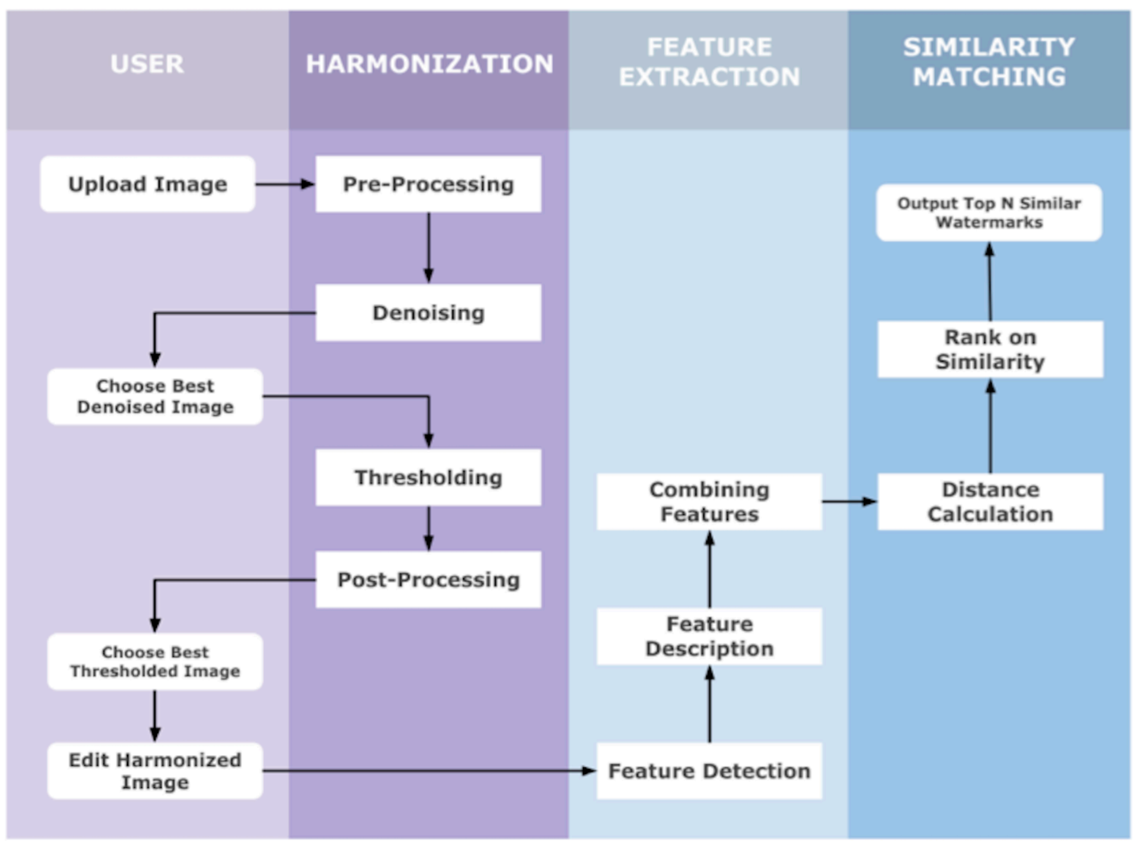

Figure 3. A high-level diagram of the watermark similarity pipeline.

Harmonizations

The harmonization step takes the input image and isolates the watermark from it. Since traced and untraced watermarks have different characteristics, their harmonization processes differ in some ways. However, both use the same key processes and steps, including, pre-processing, denoising, thresholding, and post-processing (Fig. 3).

Figure 4. A traced watermark before harmonization

Figure 5. A traced watermark after pre-processing

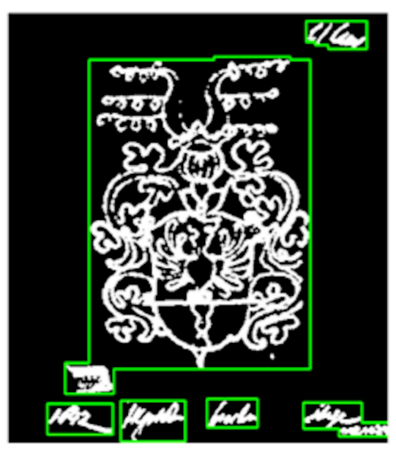

Figure 6. A traced watermark during post-processing

Figure 7. A traced watermark after post-processing

Harmonization begins with the raw watermark image (Fig. 4, 8). Both types of watermarks use similar steps for pre-processing, which includes enhancing the image contrast and removing shadows. Additionally, vertical lines that are not part of the watermark are removed with the combined wavelet-Fourier approach [2] (Fig. 5). For denoising, traced watermarks undergo a Gaussian blur while untraced watermarks utilize BM3D [3] and a Kuwahara filter [4] to blur the background while preserving the watermark. Next, thresholding is done to all watermarks, typically with a Sauvola threshold, although under

Method Continued

Figure 8. An untraced watermark before harmonization

Figure 9. An untraced watermark after harmonization

certain conditions a global threshold is used. Finally, all watermarks undergo post-processing, which seeks to remove all components of an image that are not part of the watermark (Fig. 6). This is accomplished by analyzing connected components and filtering on size and density. Harmonization is completed after post-processing and can be seen in Figures 7 and 9.

Feature Extraction and Similarity

Feature extraction encodes the harmonized image into a series of numbers, making it easier to calculate their similarity. Features were used that would be invariant to scale, translation, and rotation. To create such invariance, three features were combined: SIFT [5], Hu moments [6], and Zernike moments [7].

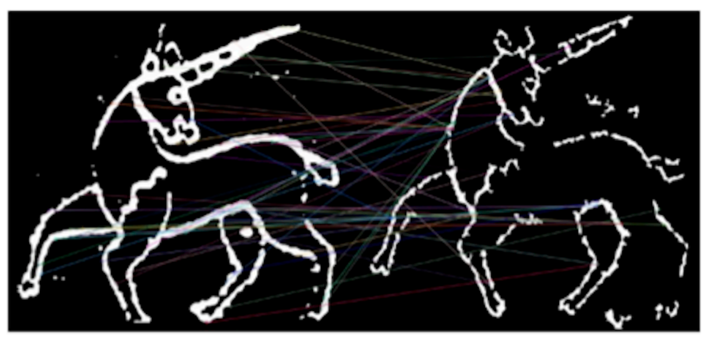

Figure 10. SIFT feature matching of two watermarks

The set of features of two watermarks are compared to determine their similarity. Similarity is calculated differently depending on the type of feature. SIFT uses the k-nearest neighbour with Euclidean distance (Fig. 10), and the two moments use Manhattan distance. These scores are combined into one total score by taking the geometric mean (Fig. 11). The watermarks with the highest similarity scores are then returned.

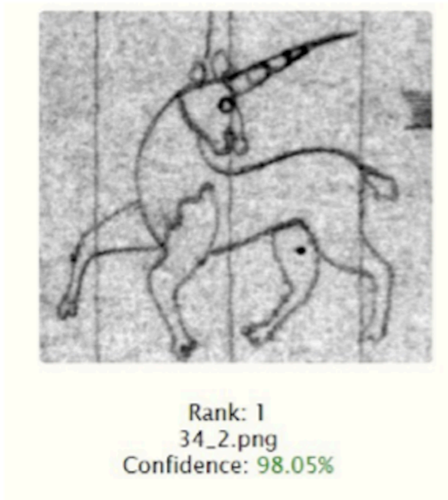

Figure 11. Final similarity score of a watermark

Results and Evaluation

From the provided dataset, 500 images were taken by randomly choosing a watermark and including 2-5 images of that watermark in the dataset. The dataset was randomly divided into 85% for training and 15% for evaluation. Results were evaluated for the GUI (referred to as Manual) and the CLI (referred to as Automatic) (Table 1). To calculate the accuracy of the system, the number of evaluation images with a match found was divided by the total number of images. A match occured if at least one similar watermark is found in the top 10% of returned similar watermarks.

		Traced	Untraced	Overall
Automatic Pipeline	Automatic Database	44%	40%	41%
	Manual Database	61%	35%	41%
Manual Pipeline	Automatic Database	61%	40%	45%
	Manual Database	61%	51%	53%

Table 1. Results for the Evaluation

Unclear watermarks were present in the original dataset due to the random nature of its generation. To test the system further, a new dataset was created of 200 images that contained watermarks all visible to the human eye, which were not randomly selected and therefore not representative. This dataset was then split as 75% and 25% evaluation. This set was only evaluated manually, with results showing an overall accuracy of 82%, with 96% accuracy for traced watermarks, and 68% accuracy for untraced watermarks.

Discussion

As seen from the results of the original dataset, overall automatic works worse than the manual. This was expected since, when automatic, the images were processed with default values, whereas when manual the user interaction allowed for better results to be chosen. Additionally, untraced watermarks typically perform worse. This too is expected, since these watermarks typically contain more noise. It is notable that in the dataset of 200 "clear" images, the results improve greatly. This indicates that the system works most effectively on watermarks that are distinguishable to the human eye.

References

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