Efficient image blocking using perceptive hashes

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***Abstract*—Providing a platform for commerce makes you a desirable target for spam and scam. Many tools have been created to tackle the issues of content filtering, but efficiently blocking images has been a rather complex problem to solve.**

***Index Terms*—Spam, scam, perceptual hash, hash, image blocking.**

I. Introduction

THE introduction goes here!!!... you should get a sense of what is it we don in this article in the intro.

II. Hash Similarity

First we need a similarity measure.

Definition 1. We define the similarity between two hashes as their Cross Correlation.
Let $\mathbf{x}, \mathbf{y} \in \mathbb{R}^N$ be two hashes, composed of N coordinates.
Their cross-correlation $\theta : \{\mathbb{R}^N, \mathbb{R}^N\} \to [0, 1]$ is defined as:

$$\theta(\mathbf{x}, \mathbf{y}) = \max_{0<d<N} [\theta_d(\mathbf{x}, \mathbf{y})] \tag{1}$$

where

$$\theta_d(\mathbf{x}, \mathbf{y}) = \frac{\sum_i (x_i - \mu_{\mathbf{x}})(y_{i-d} - \mu_{\mathbf{y}})}{\sqrt{\sum_i (x_i - \mu_{\mathbf{x}})^2 \sum_i (y_{i-d} - \mu_{\mathbf{y}})^2}} \tag{2}$$

$$\mu_{\mathbf{x}} = \frac{1}{N} \sum_i x_i, \quad \mu_{\mathbf{y}} = \frac{1}{N} \sum_i y_i,$$

III. Search problem

Now that we have a hash function and a similarity function, let's define the Search Problem as follows:

Definition 2. Let $\mathbf{y} \in \mathbb{R}^N$ be the hash of the query image, and $\mathbb{S} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots \mathbf{x}_M\} \subset \mathbb{R}^N$ the corpus of image hashes to search in.
The search function $\lambda : \mathbb{R}^N \to \mathbb{S}$ is

$$\lambda_{\mathbb{S}}(\mathbf{y}) = arg \max_{\mathbf{t} \in \mathbb{S}} [\theta(\mathbf{y}, \mathbf{t})]$$

This search problem can be restated by splitting the search in many searches with a simplified similarity metric.
Let $\rho_d : \mathbb{R}^N \to \mathbb{R}^N$ defined as

$$\rho_d(\mathbf{v}) = (v_{1-d}, v_{2-d}, \ldots, v_{N-d}) \tag{3}$$

a "rotation" function that moves the components of the vector by d positions. In this rotation, if the index $(i - d) \leq 0$ then we use instead $(N + i - d) \bmod N$.

Then the search function can be rewritten as:

$$\lambda_{\mathbb{S}}(\mathbf{y}) = arg \max_{d} [\lambda\prime_{\mathbb{S}}(\rho_d(\mathbf{y}))]$$

where $\lambda\prime_{\mathbb{S}}$ is a search with a simplified similarity function:

$$\lambda\prime_{\mathbb{S}}(\mathbf{z}) = arg \max_{\mathbf{t} \in \mathbb{S}} [\theta\prime(\mathbf{z}, \mathbf{t})]$$

$$\theta\prime(\mathbf{x}, \mathbf{y}) = \frac{\sum_i (x_i - \mu_{\mathbf{x}})(y_i - \mu_{\mathbf{y}})}{\sqrt{\sum_i (x_i - \mu_{\mathbf{x}})^2 \sum_i (y_i - \mu_{\mathbf{y}})^2}}$$

As $\sqrt{\sum_i (x_i - \mu_{\mathbf{x}})^2}$ is constant for the query vector (and always positive), we can pre-calculate it and apply it after the maximum is found:

$$\lambda\prime_{\mathbb{S}}(\mathbf{z}) = \frac{1}{\sqrt{\sum_i (x_i - \mu_{\mathbf{x}})^2}} \lambda\prime\prime_{\mathbb{S}}(\mathbf{z})$$

$$\begin{aligned} \lambda\prime\prime_{\mathbb{S}}(\mathbf{z}) &= arg \max_{\mathbf{t} \in \mathbb{S}} \left\{ \frac{\sum_i (z_i - \mu_{\mathbf{z}})(t_i - \mu_{\mathbf{t}})}{\sqrt{\sum_i (t_i - \mu_{\mathbf{t}})^2}} \right\} \\ &= arg \max_{\mathbf{t} \in \mathbb{S}} \left\{ \sum_i (z_i - \mu_{\mathbf{z}}) \frac{(t_i - \mu_{\mathbf{t}})}{\sqrt{\sum_i (t_i - \mu_{\mathbf{t}})^2}} \right\} \end{aligned}$$

So, finally, it can be rewritten as:

$$\lambda\prime\prime_{\mathbb{S}}(\mathbf{z}) = arg \max_{\mathbf{t} \in \mathbb{S}\prime} \{ \langle \tilde{\mathbf{z}}, \mathbf{t} \rangle \}$$

where

$$\mathbb{S}\prime = \left(\frac{1}{\|\mathbf{x}_i\|} (\mathbf{x}_i - \mu_{\mathbf{x}_i}) \right) \forall \mathbf{x}_i \in \mathbb{S}$$

So, the problem may be represented as a maximum inner product search as defined in XXX.

Appendix A
Proof of the First Zonklar Equation

Appendix one text goes here.

Appendix B

Appendix two text goes here.

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References

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