Abstract—The Tor darknet hosts different types of illegal content, which are monitored by cybersecurity agencies. However, manually classifying Tor content can be slow and error-prone. To support this task, we introduce Frequency-Dominant Neighborhood Structure (F-DNS), a new perceptual hashing method for automatically classifying domains by their screenshots. First, we evaluated F-DNS using images subject to various content-preserving operations. We compared them with their original images, achieving better correlation coefficients than other state-of-the-art methods, especially in the case of rotation. Then, we applied F-DNS to categorize Tor domains using the Darknet Usage Service Images-2K (DUSI-2K), a dataset with screenshots of active Tor service domains. Finally, we measured the performance of F-DNS against an image classification approach and a state-of-the-art hashing method. Our proposal obtained 98.75% accuracy in Tor images, surpassing all other methods compared.

Index Terms—Perceptual Hashing, Deep Web, Tor, DCT, F-DNS, Image Classification

Type of contribution: Research already published

I. INTRODUCTION

The Deep Web content cannot be indexed by standard search engines, such as Google, Yahoo, or Bing [1]. Within it, we find darknets that can only be accessed by unique browsers such as Tor (The Onion Router). These domains host various kinds of suspicious content [2].

According to Al-Nabki et al., at least 20% of the content found in Tor domains can be considered as illegal [3], so Law Enforcement Agencies (LEA) are interested in monitor Tor darknets [1], [4], [5]. The manual categorization of the Darknet is not feasible due to the amount of data availability, requiring the use of automatic tools to identify and classify Tor darknet domains.

To support this task, we present and make publicly available Darknet Usage Service Images-2K (DUSI-2K)\(^1\), a dataset with 2500 snapshots of Tor domain home pages, divided into 16 categories.

Furthermore we introduce Frequency-Dominant Neighborhood Structure (F-DNS), a new perceptual hashing method that demonstrates excellent performance against image content-preserving operations, like scaling. Finally, we applied F-DNS to the problem of classifying Tor domains using its screenshots and compare its performance with other state-of-the-art methods [6].

\(^1\)http://gvis.unileon.es/dataset/dusi-darknet-usage-service-images-2k/

II. DARKNET USAGE SERVICE IMAGES-2K (DUSI-2K)

DUSI-2K dataset is built in a semi-supervised way, extending the Darknet Usage Service Images (DUSI) [7] dataset by including snapshots from 16 classes of active Tor domains. All domains were crawled using the labeled domains of Darknet Usage Text Addresses (DUTA) dataset [8].

III. CONSTRUCTION OF F-DNS HASH

The pipeline of our F-DNS method is presented in Fig. 1. In pre-processing, the image is converted to grayscale and smoothed using a Gaussian filter.

After pre-processing, the image features are extracted employing Discrete Cosine Transform (DCT) [9] and the Dominant Neighborhood Structure (DNS), proposed by Khel-lah [10]. Since the DNS is extracted from the DCT of the image, we named the extracted map as Frequency-Dominant Neighborhood Structure (F-DNS).

First, we apply DCT to the pre-processed image and then the DNS [10] is applied on the output of the DCT of the image to extract features from its texture energies. The DNS exploits the high redundancy that is found on images with repetitive patterns.

Given a pixel \(x\), called central pixel, the DNS, \(D\), is obtained by computing the intensity similarity for all pixels \(x'\) which fall within a \(N \times N\) neighborhood around it, called searching window. The similarity of each pixel \(x'\) of the searching window is calculated employing the Euclidean distance between the intensities in the flattened matrices of \(M \times M\) pixels around both \(x\) and \(x'\). This area of \(M \times M\) pixels is called neighborhood window. If the coordinates of \(x'\)
within the neighborhood window are \((i, j)\), then the similarity between \(x\) and \(x'\) is placed in the position \((i, j)\) of the DNS, i.e. \(D(i, j)\). Therefore, the DNS represents the degree of similarity of texture energies between pixel \(x\) and its neighbor pixels.

After obtaining \(N\) F-DNS maps, we compute the Frequency-Global Neighborhood Structure (F-GNS) of the image by summing up all F-DNS maps from the image.

The final image hash is obtained using the coefficients but discarding the first row and column, to avoid including the average of the pixel values, obtained during the DCT calculation process. At the end of the process, the hash code of each image is composed of 64 real values.

In this work, we have considered \(9 \times 9\) pixels (i.e. \(N = 9\)) searching window and \(3 \times 3\) pixels neighborhood window.

IV. EXPERIMENTAL RESULTS

To evaluate the robustness of F-DNS, we used USC-SIPI [11] state-of-the-art dataset to generate visually identical versions of 35 images, applying various content-preserving operations. We calculated the correlation coefficients between the hashes obtained from the altered images and the hash of their corresponding original image.

We compared the performance of F-DNS against RP-IVD (Ring Partition and Invariant Vector Distance) [12], a state-of-the-art perceptual hashing method. The average score of the correlation coefficients obtained in each task can be seen in Table I.

| Operation                  | RP-IVD | F-DNS | Operation                  | RP-IVD | F-DNS |
|----------------------------|--------|-------|----------------------------|--------|-------|
| Brightness adj             | 0.9801 | 0.9998 | Gamma correction           | 0.9570 | 0.9873 |
| Contrast adj               | 0.9920 | 0.9993 | Salt & pepper noise        | 0.9872 | 0.9989 |
| Gaussian filter            | 0.9997 | 0.9999 | Multiplicative noise       | 0.9939 | 0.9999 |
| JPEG compression           | 0.9986 | 0.9993 | Watermark embedding        | 0.9601 | 0.9989 |
| Scaling                    | 0.9773 | 0.9857 |                            |        |       |
| Rotation                   | 0.2599 | 0.9365 |                            |        |       |
|                          |        |       |                            |        |       |

Our proposal performs best against most content-preserving operations, and stands out for its performance in rotation, which is one of its major advantages over similar proposals. Additionally, we tested our proposal using the Tor domain screenshots taken from the DUSI-2K dataset. We took a total of 1624 images, from which we selected 79 templates, i.e. snapshots of domains, which are frequently used in Tor domains with similar topics. Therefore, by determining which template is most similar to each screenshot we can deduce which category each screenshot belongs to.

We calculated the hash codes of the templates and compared them with the hash code of each of the remaining 1545 images. For classification, images are assigned labels based on the template with the highest similarity. We measured performance using the accuracy metric.

We repeated the experiment 20 times, including the random selection of the template from the images in each class, and compared F-DNS against RP-IVD. Since this approach can be considered as an image classification task [13], we also reported the results with state-of-the-art image descriptors, such as Inception-ResNet-v2 [14]. We split split DUSI-2K randomly into 5 disjoint sets, setting 75% of the images for training a Support Vector Machine (SVM) with linear kernel, and 25% for testing. The results are shown in Table II.

Table II

| Methods          | Overall accuracy |
|------------------|------------------|
| RP-IVD           | 93.84%           |
| Inception-ResNet-v2 | 85.19%           |
| F-DNS            | 90.75%           |

V. CONCLUSIONS

In this paper, we presented DUSI-2K, a dataset with 2500 snapshots of Tor domains. We have also proposed a new robust image hashing scheme, called F-DNS, and used it to classify Tor domains.

We compared the performance of F-DNS with other state-of-the-art hashing schemes, as well as image classification models, demonstrating that F-DNS achieved the best results.

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