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Research paper

Extreme Learning Machine Classification of File Clusters for Evaluating Content-based Feature Vectors

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Abstract

In the digital forensic investigation and missing data files retrieval in general, there is a challenge of recovering files that have missing system information. The recovery process entails applying a number of methods to determine the type, the contents and the structure of each data file clusters such as JPEG, DOC, ZIP or TXT. This paper studies the effects of three content-based features extraction methods in improving the classification of JPEG File clusters. The methods are Byte Frequency Distribution, Entropy, and Rate of Change. Consequently, an Extreme Learning Machine (ELM) neural network algorithm is used to evaluate the performance of the three methods in which it classifies the class label of the feature vectors to JPEG and Non-JPEG images for files in different file formats. The files are allocated in a continuous series of clusters. The ELM algorithm is applied to the DFRWS (2006) dataset and the results show that the combination of the three methods produces 93.46% classification accuracy.

Keywords: *Multimedia Clusters, JPEG image, Extreme Learning Machine (ELM), Feature selection.*

1. Introduction

There are many digital devices such as smartphones and computers that deal with several numbers of file types such as PDF, JPEG, EXE and etc. [1]. Over the last few decades, these files are very popular in retaining important documents, evidence or memories [2]. computer devices have storages that are split into fix size of storage units called sectors as shown in Fig 1. The file system groups these sectors into smallest allocation units called clusters or blocks that carries a data of a particular file [3]. The clusters or blocks have markers that includes a start of file "header" and end of file "footer" or signature. This signature labels the file's system metadata of a file [4].

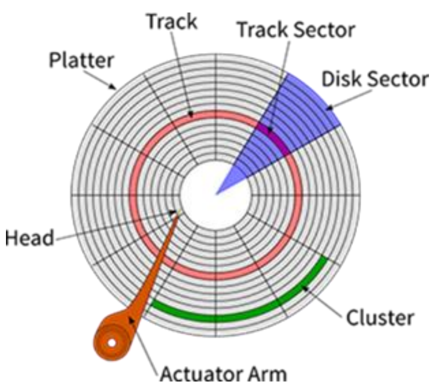

Fig. 1: A computer hard drive architecture [2]

Eventually, data files may have exposed to missing data clusters (damaged or deleted) due to many reasons including operating system storage operations (store data at random places in storage media), human errors, deliberate destruction or device failure [5].

Applying data recovery or file carving techniques is one way to recover such files [6], [7]. In files recovery, file type identification is a primary and important stage [3]. The file type identification is a process of knowing the consecutive blocks that make up the file. File types are commonly identified by two methods which are the file extensions method and the signature method [6], [7]. However, both methods can be easily deceived by changing the file extension or signature. The advanced methods of file type identification explore and analyze the contents or scan area of the files [8]. The content-based nowadays is a promising approach to retrieve files with missing data clusters. This approach extracts features from the scan area of the file in order to identify its type and content. McDaniel [9], [10] propose a content-based method to recover some file types and Li et al. [11], use a multi-centroids technique to improve the McDaniel [9] work.

The main focus of this research is studying the effects of three content-based features extraction methods in improving the classification of JPEG File clusters. The methods are Byte Frequency Distribution (BFD), Entropy and Rate of Change (RoC). Consequently, an Extreme Learning Machine (ELM) classifier is used to evaluate the features extraction methods. It identifies a class label of different file types (feature vectors) to JPEG or Non-JPEG images. The ELM emerges as a prevailing machine learning classifier. It has the potential to produce high accuracy results when handling problems that have a few number of features, e.g., the work of Zhang et al., [8].

This section introduces the paper. The following section presents the related work of image file carving. The rest of the paper is organized such that Section 3 reviews the related methods and dataset of the work. Section 4 view the implementation, testing and the obtained results. The finally Section (5) concludes the paper and suggests a possible future work.

2. Related Work

The literature provides several classification methods that are capable of classifying binary or multi-classes problems [12]. [13] Some well-known classifiers are k-nearest neighbour, neural network, and SVM [14], [15]. Nevertheless, there are a few numbers of related work that deploy these methods in files recovery in which a classifier classifies data file clusters in the scan area i.e., content-based recovery [16], [17]. This section describes some of these works.
McDaniel (2001) makes one of the first attempts on content-based file recovery [10]. Subsequently, McDaniel and Heydari [9], propose three features extraction methods for content-based file recovery. The methods are Byte Frequency Cross-correlation (BFC), Byte Frequency Analysis (BFA), and File Header/Trailer (FHT) analysis. The methods are used to produce fingerprints for the contents of files. Later, Li et al. [11], works on improving the work of McDaniel and Heydari [9]. The improvement is represented by using a multi-centroids technique for some of the file types.
Karresand and Shahmehri [18] model the file types based on data fragments of files without the need for metadata. They use a BFD features extraction method based on mean and standard deviation measures. Similarly, Ahmed et al. [19], use the BFD features extraction method but based on a frequency of appearance rate measures. The features vectors are classified by several classification methods. The highest recorded classification accuracy result is 90.5% [20]. Finally, Sportiello and Zanero [21], use BFD methods to extract files features. The feature vectors are classified by support vector machines. The aim of the work is to investigate the impact of the features on the classification accuracy. The results show that the features of file clusters tremendously affect the results.
Dunham et al. [22] use a neural network to classify file types of encrypted files. The features vector of a class consists of 32 bytes of file header data, byte frequency, and byte frequency of autocorrelation. Similarly, Harris [23], uses a neural network to classify files clusters. The features vector is content-based and not file header dependent. The recorded classification accuracy of this work is not more than 20%. Amirani et al. [16], uses a Principle Component Analysis (PCA) method for feature extraction of file clusters in scan area. The method obtains a fingerprint for each file of a type. The extracted feature vectors are classified by unsupervised Multi-Layer Perceptron (MLP) neural network. The classification results show relatively good accuracy. However, the method can only cover limited file types.
Rahmat et al. [24], propose a Longest Common Subsequence (LCS) method to identify the file types of file fragments. The method operates based on training, testing and validation steps. The method achieves 92.91% identification accuracy in average for PDF, RTF, DOC data types. Rahmat et al. endorse BFD in their future work.

3. Methods and Materials

This research includes applying different combinations of content-based features extraction methods which are Entropy, Byte Frequency Distribution (BFD) and Rate of Change (RoC) to multimedia files. The ELM classifies the files to JPEG and Non-JPEG images. The files are allocated in a sequence of fragmented data clusters. The conducted steps to undertake and complete this work are presented in Fig.2 and detailed in the following subsections.

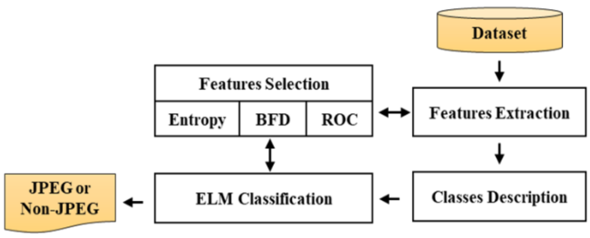

Fig. 2: The research methods flow diagram

Table 1 describes the attributes of the three methods. The aim of this work is to identify the best combination of features for file cluster identification. The features are evaluated based on Extreme Learning Machine (ELM) classification.

Table 1: Definition

Features	*Entropy*	*BFD*	*RoC*
Number	1	2→257 (256)	258→513(256)
Range	[0,1]	[0,1]	[0,1]
Type	Float	Float	Float

3.1. Datasets Description

In this work, the DFRWS (2006) dataset is used to test different combinations of feature extraction methods. The DFRWS (2006) is a 50MB multimedia files. The target file type is a JPEG file, but there are other file types such as ZIP, HTML, TXT, and DOC files [25]. Fig. 3 shows DFRWS (2006) dataset example of files.

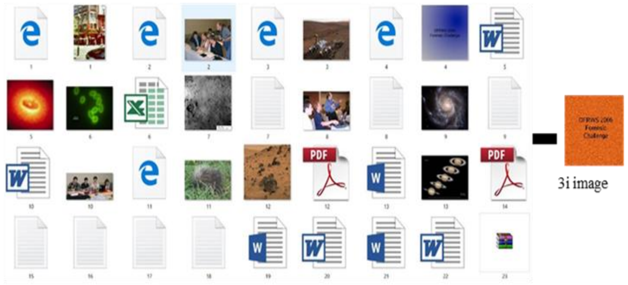

Fig. 3: The DFRWS (2006) dataset samples

The DFRWS (2006) has 23639 JPEG images clusters and 23639 non-JPEG images clusters. Each cluster includes 513 features and the clusters acquire 512 bytes. The class of the cluster is represented in the final column of each row of features (i.e., 514).

3.2. Features Extraction Methods

The Entropy, BFD and RoC are content-based features extraction methods. These methods provide measures for frequency distribution and entropy of the image content. There are different techniques for advanced features selection, but this work roughly tests all the possible combinations to ensure comprehensive outcomes. The features extraction methods are detailed as follows:

3.2.1. Entropy

The JPEG files are in encrypted or compressed form which make them have high entropy [7]. Entropy-based features are found to be able to identify JPEG files with fragmentation in scan area using a proper classification technique. The entropy method depends on the computer byte value which is between 0 and 255 [7]. It produces a feature with a value between zero and one as follows. Let $B(i)$ represents the probability of byte value B occurrences, $O(i)$ be the occurrences number and L be the size of a file fragment. Then the formula (1) finds $B(i)$ is defined as:

$$B(i) = O(i)/L \quad (1)$$

The Entropy is found by (2):

$$Entropy = -\sum B(i) \log^{B(i)}, 0 < B(i) \leq 1 \quad (2)$$

3.2.2. Byte Frequency Distribution (BFD)

The BFD method creates a histogram for image clusters based on byte value measures. The measures include calculating a number of byte values, and their mean and standard deviation to find a centroid model. This model is used to identify known data of the image clusters. The BFD method generates features vector that consists of 256 basic features i.e., $F_i = \{F_0, F_1, \ldots, F_{255}\}$. The BFD feature considers the values of the bytes and neglects their order [26]. The process is described in (3).

$$F(i) = B(i) \quad (3)$$

3.2.3. Rate of Change (RoC)

The RoC method tracks the relevant bytes in their corresponding clusters from their orders. The RoC measures the difference between two consecutive byte values. The absolute value of the difference represents the rate of change. The RoC method contains ordering bytes mechanism to associate the rate of change. However, it does not specify the direction (positive or negative) of the byte stream change [18]. The following illustrates the measurement of the RoC method.

Let r_i and r_{i+1} be two consecutive bytes. Then, RoC features are represented by (4):

$$R_i = | r_i - r_{i+1} | \quad (4)$$

Let $L2$ be the size of R_i sequence; $O(i)$ to be the number of occurrences of R_i. Then RoC byte frequency is defined in (5).

$$F2(i) = O(i)/L2 \quad (5)$$

3.3. Features Extraction Methods

Above step results in different sets of feature vectors. The feature vectors work as fingerprint and reduce initial data of the files [11], [27]. The feature vectors have class labels of a column number that is used for indexing purposes. Binary classification distinguishes between two classes of a type which are JPEG and Non-JPEG file clusters. The non-JPEG file types such as ZIP, TXT, and DOC have high entropies comparing with the JPEG files. Different combinations of feature vectors are investigated in order to study their effect on the identification of file cluster types. The selection process is manual in which different copies of an independent dataset are used. Table 2 shows the investigated combinations of this work.

Table 2: Features Selection

Choices	Entropy	BFD	RoC
C1	+	-	-
C2	-	+	-
C3	-	-	+
C4	+	+	-
C5	+	-	+
C6	-	+	+
C7	+	+	+

3.4. Classification of JPEG image cluster

There is a wide range of artificial intelligence applications in the literature. Some examples are [12], [13], [14] and [15]. The Artificial Intelligence techniques are found to be not fully utilized in the data recovery field. The main usage of the techniques is in the identification step in which it classifies the clusters based on a number of extracted features [29]. Examples of Artificial Intelligence techniques are Neural Network, SVM, and genetic algorithm. Table 3 presents the application of a number of Artificial Intelligence techniques in clusters classification and file recovery in general.

Table 3: Application of Artificial Intelligence techniques

Technique	Usage
neural network	Predict next fragment to recover JPEG file [29]
	Applied to a classifier for a type detection [16]
genetic algorithm	Predict types of file fragments [30]
	Improving the identification of file cluster [31]
support vector machine	Improve a recovery accuracy of file fragments [17]
	Identifying fragment types [21]
	Clusters classification [31]
kohonen neural networks	Automatic color based 2-D image fragment reassembly [32]
k-nearest neighbor	Distance metric between file fragments [33]
software agent	Perform a number of files recovery tasks [34]
expert system	Assists non-expert users in files recovery [35]

This work adopts Extreme Learning Machine (ELM) for classifying clusters of JPEG files based on the extracted features. The ELM, as well as other classifiers, analyse a set of features to predict the class type of the feature vector then assigns a class label for each of the feature vectors [8,36,37,38]. The ELM architecture has a one hidden layer and works in a feedforward mode as shown in Fig.4. The weights of the ELM has specific setting in which the weights of the hidden nodes are set randomly one time and they are never updated while the output nodes' weights are learned in one cycle [39,40].

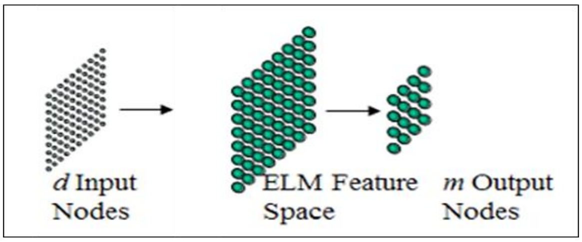

Fig. 4: The architecture of the ELM [13]

Let a set of stochastic samples (x_i, t_i) be the target vector $x_i = [x_1^i \; x_2^i \ldots . x_n^i]^T$ in which there exists a i_{th} training set of a n-dimensional feature vector that have the quantity $t_i = [t_1^i \; t_2^i \ldots . t_n^i]^T$. The target output of the ELM can be calculated by the following equation [8], [26]:

$$T = H\beta \quad (6)$$

where H is represents the output of the hidden nodes and $\beta = [\beta_1, \beta_2, \ldots, \beta_M]_{l\times M}^T$ is the output weights that can be determined through (7):

$$\tilde{\beta} = \arg min_\beta \|H\beta - T\| = H^+T \quad (7)$$

where $\tilde{\beta} = (H^T H)^{-1} H^T T$.

The complete mathematics representation of the ELM is given in [26]. The ELM application in many classification problems reviles that it can deal with few features, has high generalization and fast training [28].

4. Implementation and Results

The ELM algorithm and the overall carving method are implemented in MATLAB 2017a platform. The method processes the DFRWS (2006) forensic challenge dataset for testing. The dataset is split into 10-Fold cross-validation data. Table 4 shows the main parameters of the ELM and their setting in the performed tests.

Table 4: The ELM classifier details

Dataset	DFRWS (2006)
Size	47278 × 513
Number of hidden neurons	600
Function	Sigmoid
Learning approach	10-Fold cross-validation

The confusion matrix results of the seven choices are summarized in Table 5.

Table 5: The confusion matrix

Choices	File type	Confusion matrix	
C1	JPEG	5347	2532
	Non- JPEG	1783	6096
C2	JPEG	7184	695
	Non- JPEG	483	7396
C3	JPEG	6585	1294
	Non- JPEG	707	7172
C4	JPEG	7180	699
	Non- JPEG	463	7416
C5	JPEG	6688	1191
	Non- JPEG	722	7157
C6	JPEG	7233	646
	Non- JPEG	407	7472
C7	JPEG	7251	628
	Non- JPEG	403	7476

Table 6 shows the accuracy, precision, and recall of the ELM performance for the seven choices.

Table 6: The ELM classification measures

Choices	Accuracy	Precision	Recall
C1	0.7262	0.7499	0.6786
C2	0.9252	0.9370	0.9118
C3	0.8730	0.9030	0.8358
C4	0.9263	0.9394	0.9113
C5	0.8786	0.9026	0.8488
C6	0.9332	0.9026	0.9180
C7	0.9346	0.9473	0.9203

The experimental results show that the ELM algorithm is able to identify JPEG from non-JPEG files including fragmented clusters with a considerably high accuracy results. Table 7 shows the analysis of the classification results for all the conducted tests.

Table 7: The classification results analysis

Choices	File type	Clusters	Classified	Not classified	Accuracy
Ch1	JPEG	7879	5347	1783	72.62%
	Non-JPEG	7879	6096	2532	
Ch2	JPEG	7879	7184	483	92.52%
	Non-JPEG	7879	7396	695	
Ch3	JPEG	7879	6585	707	87.30%
	Non-JPEG	7879	7172	1294	
C4	JPEG	7879	7180	463	92.63%
	Non-JPEG	7879	7416	699	
C5	JPEG	7879	6688	722	87.86%
	Non-JPEG	7879	7157	1191	
C6	JPEG	7879	7233	407	93.32%
	Non-JPEG	7879	7472	646	
C7	JPEG	7879	7251	403	93.46%
	Non-JPEG	7879	7476	628	

It further shows that the ELM delivers viable accuracy results of file type discovery. The difference between the accuracies of the seven combinations of features is relatively not high. The lowest is recorded when using the entropy method alone which is 72.62% and the highest is recorded when using the combination of three features which is 93.46%. This result as compared with the related work is considered significant. Fig. 5 shows the difference between the accuracies of the applied combinations of feature vectors.

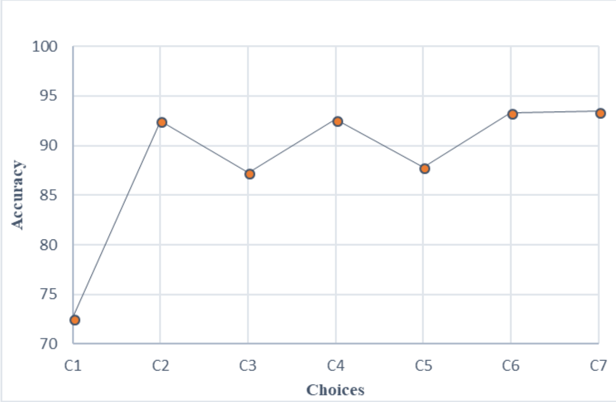

Fig. 5: The classification accuracy

5. Conclusion

This paper focuses on JPEG file recovery when its file system metadata is missing. The aim of the work is to identify the file type of each cluster in the scan area of files. Subsequently, a combination of three feature extraction methods (Entropy, Byte Frequency Distribution (BFD) and Rate of Change (RoC)) are used to extract fingerprints for each cluster dataset. The combinations produce seven choices of features selection to be investigated. The ELM algorithm is applied to DFRWS (2006) forensic challenge dataset. Meanwhile, an Extreme Learning Machine (ELM) is deployed as a content-based file type classification method. The ELM classifies JPEG and Non-JPEG files of file clusters and some of which have missing system information. With the aid of the ELM characteristics, the combination of three methods manifests the capabilities of high accuracy of 93.46%. This result promotes this work to be adopted in real scenarios. The lowest accuracy is recorded when using the entropy method alone which is 72.62%. This work is intended to be used in the carving process for fragmented JPEG files recovery.

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