Block Based Copy-Rotate-Move Image Forgery Detection using Aritificial Neural Network

Yeksadiningrat Al Valentino
Computer Engineering Studies
STEI ITB
Bandung, Indonesia
yeksa.ningrat@gmail.com

Rinaldi Munir
Computer Engineering Studies
STEI ITB
Bandung, Indonesia
rinaldi@informatika.org

***Abstract*—Block based detection is the most common method for detecting *copy-move* image forgery. There is a challenge to detect when rotation transformation is added to the forgery part. One of the solution is using the SATS Algorithm for verification part in block based detection's pipeline. For further improvement artificial network is applied to block matching step.**

Keywords— Machine Learning, Artificial Neural Network, Image, Image Forgery, copy-move, copy-rotate-move

I. Introduction

Today image processing is one of the advanced technology that it is very convenient for one to forge an image. One of the most common image forgery is copy-move where there is a region of the image that is copied to another region in the same image. There are several method that have been developed to detect copy-move image forgery including block-based detection.

Block-based copy-move image forgery detection generally adhere to a same steps. When the copied region is additionally rotated, this technique need some rework. One of the solution is using Same Affinie Transformation Selection in validation step. Using For further improve Artifical network is applied to matching step to replace euclidean distance which is most used technique for matching steps of block-based detection.

II. Block Based Copy Move Image Forgery Detection

Block based copy move forgery detection mostly have the same steps as shown in Fig. 1. First image is processed to have optimal value (for instance converting to grayscale) then the image is divided into blocks that can be overlapped in the block-tilling step. The feature will be extracted in each of these blocks that will be used for searching the simillar pair of block. Simillar blocks tend to have similar feature vectors, the similarity of two features can be determined using calculating the euclidian distance between the two feature vector.

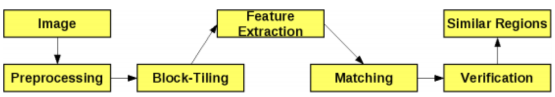

Figure 1: Common CMFD Pipeline

There are three aproaches for verification that have been proposed so far [1]. First one is applying basic filtering, e.g. morphologic operations on a map of matched pairs. The second aproach, a pair of locks is only considered forged when the neighborhoods of both blocks are also similar. Lastly imposing a minimum number of a similar shift vectors between block-pairs. These verification methods are unable to handle rotation, there is a alternative verification step called the *Same Affine Transformation Selections (SATS)* [1] that can handle rotation and scaling.

III. Same Affine Transfomation Selection

SATS is a algorithm proposed by Christlein[1] for rpelacement for the shift vectors. The core idea is to explicitly estimate the rotation and scaling parameters from a few blocks, expressed as an affine transformation matrix.

Consider the i-th matched pair $\vec{f_\iota}$ of feature vectors $\overrightarrow{f_{\iota 1}}, \overrightarrow{f_{\iota 2}}$, $\vec{f_\iota} = (\overrightarrow{f_{\iota 1}}, \overrightarrow{f_{\iota 2}})$. In order to determine the rotation and translation between block pairs, we need to examine the coordinates of the block centers. Let C($\overrightarrow{f_{\iota J}}$) denote the coordinates (in row vector form) of the block center from where $\overrightarrow{f_{\iota J}}$ was extracted. Further, let

$$\vec{p_\iota} = C(\overrightarrow{f_{\iota 1}}), \qquad \vec{q_\iota} = C(\overrightarrow{f_{\iota 2}}) \tag{1}$$

If $\vec{f_\iota}$ stems from a copy-move operation with rotation and scaling, then $\vec{q_\iota}$ is related to $\vec{p_\iota}$ via an affine transformation:

$$\vec{q_\iota} = \vec{p_\iota} \cdot A + \vec{b} \tag{2}$$

Where A is a 2×2 matrix containing rotational and scaling parameters and $\vec{b}$ is a translation vector. This can be satisfied by searching for matched block paris that are spatially close to each oter, *i.e* within a distance t_1. We recover the transformation and treat it as an initial solution to an RS-CMFD region. Then, we search for further matched block pairs that fit this hypothesis, which is iteratively refined. If the number of block pairs that satisfy the hypothesis exceeds a certain limit t2, we consider the transformation a candidate for a copy-moved region. We report the involved blocks as well as the transformation parameters as an RS-CMFD result. SATS follows the same principles as shift vectors for robustness to outliers: clustering of similar results, and required minimum number of similar transformations. Thus, it is expected that SATS be equally robust to this type of noise. The details of the proposed verification method is shown in Algorithm 1.

Algorithm 1 SATS: Rotation and scale invariant verification.

for every matched pair $\vec{f_1} = (\vec{f_{11}}, \vec{f_{12}})$ **do**
  Let the hypothesis-set $H = \{\vec{f_1}\}$;
  for matches $\vec{f_i}$ **do**
    if $\mathrm{d}(C(\vec{f_{11}}), C(\vec{f_{i1}})) < t_1$ and $\mathrm{d}(C(\vec{f_{12}}), C(\vec{f_{i2}})) < t_1$ **then**
      $H = H \cup \vec{f_i}$;
    end if
  end for
  if $|H| < 3$ **then**
    continue; // At least three spatially close block pairs
  end if
  From H, compute A and $\vec{b}$ as described in the text
  for every f_i where $C(f_{i1})$ is close to matched blocks in H **do**
    compute $\vec{q_i} = \vec{p_i} \cdot A + \vec{b}$ as in Eqn. 2
    if $\mathrm{d}(C(\vec{f_{i2}}), \vec{q_i}) < t_1$ **then**
      $H = H \cup \vec{f_i}$
      if $|H| \mod 10 \equiv 0$ **then**
        recompute A and $\vec{b}$ to increase stability of the estimate
      end if
    end if
  end for
  if $|H| > t_2$ **then**
    store A, $\vec{b}$ and mark the blocks in H as copy-moved.
  end if
end for

IV. Proposed Method

The idea of this paper is using ANN for the matching block step. This block matching activity is similliar to image classification which using the feature extracted from a picture and do classification using that feature. Machine learning to our best knowledge is one of the verified method to do image classification. For example feature is extracted from each block in a pair of block and the classification is done using that feature where there is only 2 class : match and not match. Then using the artificial neural network using trained model is viable to applied for the block matching steps. For the rest of the process we will implemented the SATS Algorithm copy-move detection.

The presented method will be following the common CMFD(copy move forgery detection) that shown in Figure 1. Preprocess is not needed in this case and the the image will be divided into 50 x 50 size blocks. Feature extraction will be done in the block. To able to detect copy-rotate-move the feature must be rotation invariant. [1] already conduct an experiment to deterimine which feature has the best result when the block is rotated. We will take feature extraction from [2] and from [3] to be used in this method.

Feature extraction in [2] uses the avareage color information of a circular block as the first three features which is red colour, green colour and blue colour and entropy for the last features. The circular block used is shown at figure 2 .

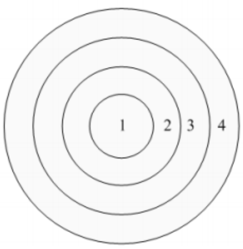

Figure 2 : Circular Block 1

Another feature extraction [3] is also using circular block but with different shapes (figure 4). For each circular block the average intensity is calculated.

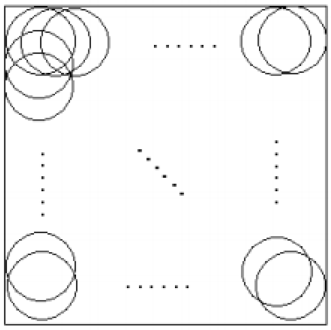

Figure 3 Circular Block 2

V. Artificial Neural Network

Artifical Neural Network(ANN) is a representation of machine learning approach that based on human neural network. ANN is used for classification activity. The structure of an ANN is similar to human brain which become a weighted graph. Usually ANN consist of 2 or more layer which is one input layer, one output layer,and hidden layer is an optional layer that can be composed using more than one layer. A single-layer artificial neural network is called perceptron which is the most simple form of ANN. Perceptron can't handle classification when the data is not linearly separable, to do that ANN must at least consist of one of hidden layer which is called Multilayer Perceptron (Figure).

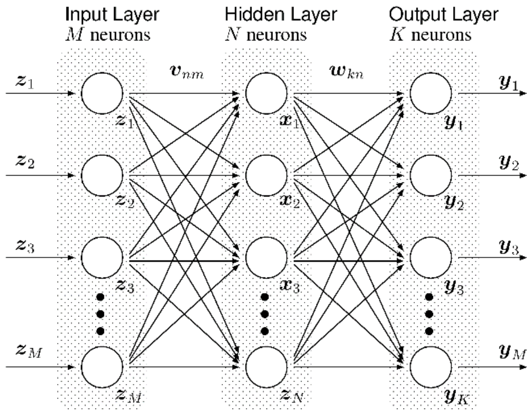

Figure 4: Multilayer Perceptron

The classification process start with calculating *net*, for example calculating *net* for x_1 is done by summing every node value in input layer multiplied by the weight of edges that connecting the node in input layer to node x_1, the value of node x_1 is done by using identity function in this case is using ReLU identity function.

$$o = f(net) = \max(0, net) \quad (3)$$

This process is done until we get all the value of neuron in the output layer. Every neuron in output layer is representing the class for the classification. The class that neuron with the most highest value is the last result of the classification process using ANN.

We have conduct an experiment to make the most appropriate model for block matching in this paper. One factor at a time approach is applied. This approach means to make an optimal result of a factor at a time then move to another factor until we get optimal results of all factors which is momentum, learning rate and number of layer in hidden layer.

First factor that we will optimize is number of layer in hidden layer. The result of the experiment can be seen in the Table 1. The number of node of each layer is the same which is the mean of number of node in input layer and in the output

The next factor is the learning rate. Learning rate affect the pace of the weight change that also important to get optimal result. The result of the experiment can be sene in the Table 2, the most optimal is using learning rate 0.01.

Learning Rate	**Acc(train data)**	**Acc(test data)**
0.01	94.78%	94.85%
0.015	94.18%	94.43%
0.005	94.41%	94.5%

Table 2 : MLP's Accuration based on Learning Rate

The last factor is momentum. Momentum is very useful to prevent the model is stuck at the *local maximum*. . The result of the experiment can be sene in the Table 3, the most optimal is using momentum 0.1.

Momentum	**Acc(train data)**	**Acc (test data)**
0.1	94.78	94.85
0.2	94.4	94.332
0.05	94.46	94.69

Table 3 MLP's Accuration based on Momentum

VI. TEST RESULT

The Purpose of this experiment is to determine if using ANN neural network is able to improve the matching blocks step compared to euclid distance calculation. Feature extraction done by Bravo-Solorio[2] and Junwen[3] is used for the euclid distance calculation separately.

The test will be conduct using 7160 of labeled pair of blocks. As we can see ANN is able to improve from 82% to 97%, the most notable is the false positive value of ANN is only 89 much lower compared to Bravo-Solorio 974 and Junwen is 946.

Tech	Accuration	*True Positive*	*True Negative*	*False Positive*	*False Negative*
Bravo-Solorio	82.34	1235	4661	974	285
Junwen	82.75	1231	4694	946	289
ANN	97.23	1411	5551	89	109

Then we also conduct the developed method to test detecting copy-rotate-move image forgery detection. We

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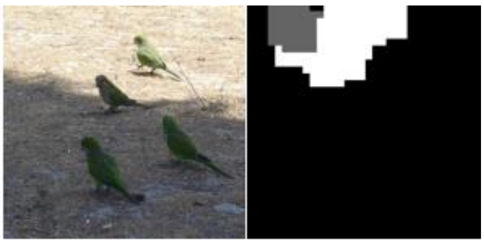

Figure 6 Sample of False Detection

layer. We get 3 hidden layer is the most optimal for match blocking.

Number of Layer	**Acc(Train Data)**	**Acc(Test Data)**
1	94.18%	94.5%
2	94.76%	94.83%
3	94.78%	94.85%

Table 1 : MLP's Accuration based on Number of Layer in Hidden Layer

used 24 forged data with 2 forged images per rotation multiples of 30 and we used 10 non-forged data.

The main focus of the ttesting is to detect the forgery in the image that forgery is happen in rotation with multiples of 30. So the data test we used will be including every rotation in multiple of 30.

The result is in 24 forged images the program is able to detect 18 forged images correctly, 2 is detected but with false detection region and 2 is not detected as forgery. As for the 10 non forged images the software is able to detect 7 of them as non forgery and 3 is detected as forged image.The result is not as satisfied as we hope to be because at the block matching the results is showing improvement. The first analysis is the block size we used is too large. The testing image data is about 500x500 image and block size that we use is 50x50 is too large. The picture in figure 3 show that the detected shows that the detected area is not entirely correct only roughly correct. This also caused by the block size that too large.

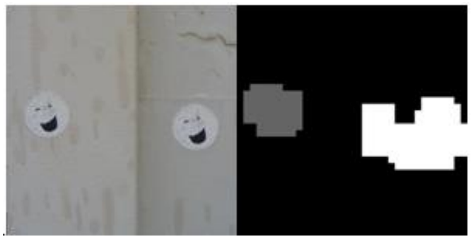

Figure 5 : Sample Detection

Figure 4 shows one of the false positive result on the detection. The detected forgery is the background sand, for this proposed method there is a minimum entropy for the block to be matched with other block. Because sand has high texture it also will have high entrophy, backgrounds blocks is tend to be consider as in the block matching because of the similar feature

VII. CONCLUSION AND FURTHER WORK

This paper presented an extension to CMFD algorithm to use ANN is viable for matching block. This implementation is done using SATS in verification block but without doing any sorting before matching that can be done to improve speed time and maybe accuracy.

Model of the machine learning is trained only using 50x50 size block, it is considered too large so this method can be improved by training using smaller blocks. Rotation transformation in the data train is only at mulriplier of 30, it can be improved to detect more variant rotation.

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