Detecting Image Forgery in Single-Sensor Multispectral Images

Mridul Gupta and Puneet Goyal

Abstract With the advancements in digital technology, multispectral images have found use in fields like forensics, remote sensing due to their ability to perceive things which were otherwise non-existent. They are used to obtain more information about terrains, land cover and in forensics as certain things like blood stains are not visible in visible spectrum. But with newly developed photo-editing softwares, they can be easily manipulated without leaving any visible clue of manipulation, but will destroy the underlying correlation between different bands. Newly developed digital cameras employ a single sensor along with multispectral filter array (MSFA) and then interpolate the data at other locations, hence introducing a correlation between bands. In this paper, we have proposed an algorithm that can identify the lack of correlation at tampered locations in a multispectral image and can thus help in establishing the authenticity of the given multispectral image. We show the efficiency of our approach with respect to the size of tampered regions in images interpolated with one the most common demosaicking algorithm—binary tree-based edge sensing (BTES).

Keywords Multispectral image forgery · Multispectral filter array (MSFA)
MSFA demosaicking · Interpolation · EM algorithm

1 Introduction

Multispectral images since they were brought into use have found use in numerous fields such as military planning, urban planning, forensics. If it becomes possible to forge these images then due to the severity of their uses, it will also become increasingly important to have the methods to authenticate the image. Several algorithms

M. Gupta (✉)
Indian Institute of Technology Roorkee, Roorkee, India
e-mail: mridulgupta9@gmail.com

P. Goyal
Indian Institute of Technology Ropar, Rupnagar, India
e-mail: puneet@iitrpr.ac.in

J. C. Bansal et al. (eds.), *Soft Computing for Problem Solving*,
Advances in Intelligent Systems and Computing 816,
https://doi.org/10.1007/978-981-13-1592-3_67

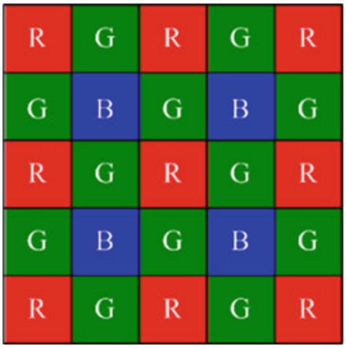

Fig. 1 A typical Bayer pattern

have been proposed for detecting the forged 3-band images [1–8]. Li et al. recently proposed an improved method of image forgery localization via integrating tampering possibility maps [1]. Shen et al. described a novel passive splicing image forgery detection approach using textural features based on the gray-level co-occurrence matrices [2]. Pun et al. proposed a copy-move forgery detection scheme that first integrates both block-based and keypoint-based methods and then performs feature point matching [4]. Ferrarra et al. [5] and Popescu et al. [6] proposed the image forgery detection techniques based on color filter array (CFA) artifacts. These techniques generally assume that although digital forgeries may leave no visual clues of having been tampered with, they may, nevertheless, alter the underlying statistics of an image. A typical digital camera will capture the value of one color at one pixel location, and its value at the rest of the locations will be determined by interpolating the available data. The patterns in which the value of colors at different pixels is recorded are CFA (color filter array) patterns, and the most prominent among them is Bayer pattern as shown in Fig. 1. Missing values at different pixels locations are then interpolated from available data, and this process is called color filter array (CFA) interpolation or demosaicking. Interpolation introduces some correlations between the samples of a color image. Aberrations from these correlations can be quantified to determine whether the image is genuine or not. Our proposed method utilizes an iterative way as inspired by Popescu's and Farid's work [6] to determine the authenticity of a multispectral image. As CFA involves only three colors so the pattern is not complex and it is easier to determine the relationship, but as the number of bands increases, based on the probability of appearance of each band, we get a profusion of possible patterns. These patterns are called multispectral filter array (MSFA). We use BTES [5] demosaicking algorithm to interpolate data from MSFA (4-band and 5-band images), edit them and then implement our algorithm on these images to determine its effectiveness in detecting digital tampering and analyze its accuracy with increase in size of forgeries.

1.1 MSFA Interpolation Algorithm

There are many algorithms that have been proposed for demosaicking [9–14] a multispectral image, but we primarily focus here on binary tree-based edge sensing (BTES) demosaicking method as it is the most referred work, and unlike many other methods, BTES is a generic algorithm that can handle more diversified MSFA patterns. On the basis of the number of spectral bands and probability of appearance (POA) of each band, BTES suggests an approach to generate an MSFA. To prepare an MSFA for a 5-band image, {A, B, C, D, E} with POA as {1/4, 1/4, 1/4, 1/8, 1/8}, a tree is generated where each leaf node represents a band and its depth represents its POA as shown in Fig. 2a. After generating the tree, checkerboard separation is carried out (Fig. 2b) and the leaf nodes are combined to obtain the final MSFA as in Fig. 2c.

To interpolate the MSFA thus obtained using BTES, a band is selected at random having highest POA (contains more information). To generate complete band D, values at locations of band E are determined using the available data for band D (Fig. 3b), and then the values at locations of band A are computed using newly computed data as shown in Fig. 3c. Final band D is computed using its all available data (Fig. 3d). The method to obtain the value at required location is explained below.

For patterns at odd level (lets say, k) of tree, only down-sampling by $(k-1)$, $k \geq 1$ is sufficient to convert the pattern to basic pattern, and for even levels, it is down-sampled by 2 level/2 $-$ 1, level$>$1 and then rotated by 45° For instance in Fig. 4a, A can be converted to basic pattern just by rotation whereas in Fig. 4b D is down-sampled to get the basic pattern.

Now, for interpolation, weights of four neighboring pixels are calculated. For vertical,

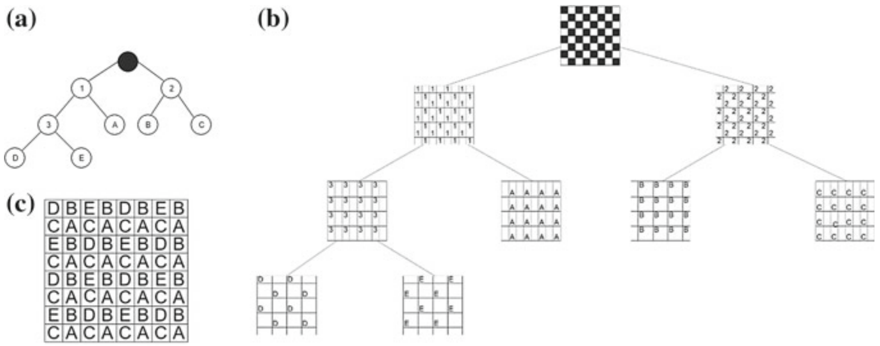

Fig. 2 MSFA generation **a** binary tree, **b** checkerboard separation, **c** 5-band MSFA

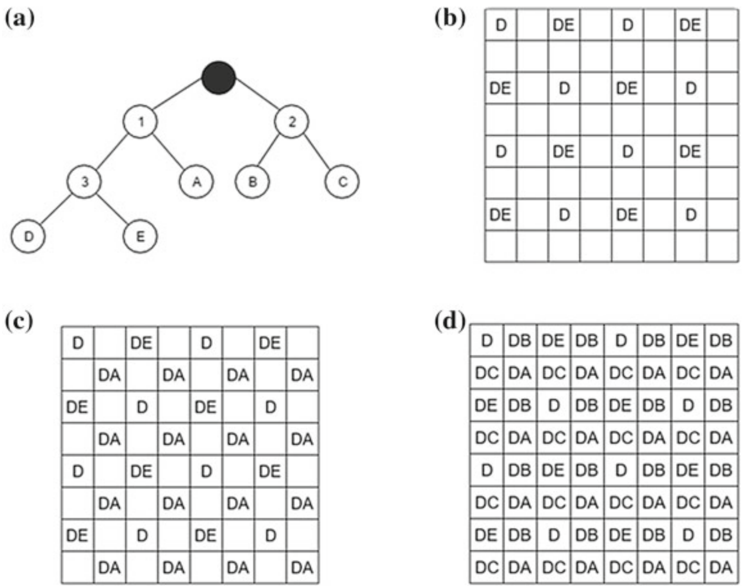

Fig. 3 Demosaicking process **a** binary tree, **b** interpolating D at locations of E, **c** interpolating D at locations of A, **d** interpolating and obtaining D at all locations

$$V : W_{m,n} = \Bigl(1 + \Bigl| R_{m+2,n} - R_{m,n} + \bigl| R_{m-2,n} - R_{m,n} \bigr| + \frac{1}{2} R_{m-1,n-1} - R_{m+1,n-1} + \frac{1}{2} R_{m-1,n+1} - R_{m+1,n+1} \Bigr| \Bigr)^{-1} \tag{1}$$

$m \in \{i-1, i+1\}, n = j.$

For horizontal,

$$H : W_{m,n} = \Bigl(1 + R_{m,n+2} - R_{m,n} + \bigl| R_{m,n-2} - R_{m,n} \bigr| + \frac{1}{2} R_{m+1,n-1} - R_{m+1,n+1} + \frac{1}{2} R_{m-1,n-1} - R_{m-1,n+1} \Bigr)^{-1} \tag{2}$$

where $n \in \{j-1, j+1\}, m = i$.

So, the interpolated value is:

$$\hat{R}_{i,j} = \frac{\sum_{s,t(|s+t|=1)} W_{i+s,j+t} R_{i+s,j+t}}{\sum_{s,t(|s+t|=1)} W_{i+s,j+t}} \tag{3}$$

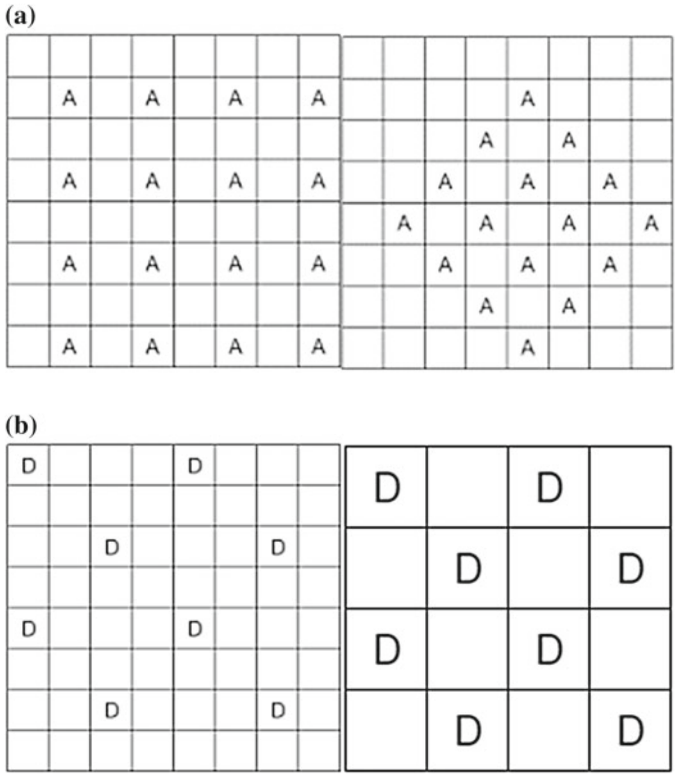

Fig. 4 Transforming the pixels **a** pixels have been rotated by 45° to get a basic pattern, **b** simple down-sampling gives basic pattern

2 Proposed Algorithm

In an MSFA-interpolated image, all pixels of a particular band are likely to have the correlation with each other. If the image is tampered with, it introduces some aberrations in those correlations and identifying them would help us in establishing the originality of an image. We assume that each pixel has a linear relationship with its neighboring pixels as it can reasonably estimate the correlations and is faster.

Inspired by [6], we use the expectation/maximization algorithm to determine the most probable correlation between the pixels, and the pixels that deviate from the expected values more will have higher probability of not belonging to the MSFA.

Let $f(x, y)$ denote a color channel of an MSFA-interpolated image. We begin by assuming that each sample in $f(x, y)$ belongs to one of two models:

(1) M1 if the sample is linearly correlated to its neighbors, satisfying: $f(x, y) = \sum \alpha_{u,v} f(x + u, y + v) + n(x, y)$

Fig. 5 MSFA for 5-band images (using BTES [6])

D	B	E	B	D	B	E	B
C	A	C	A	C	A	C	A
E	B	D	B	E	B	D	B
C	A	C	A	C	A	C	A
D	B	E	B	D	B	E	B
C	A	C	A	C	A	C	A
E	B	D	B	E	B	D	B
C	A	C	A	C	A	C	A

$\alpha_{0,0} = 0$ and $n(x, y)$ denotes random samples drawn from a Gaussian distribution with zero mean and unknown variance.

(2) M2 if the sample is not correlated to its neighbors.

Here, u, v are the distances of the pixels from central pixel which were considered during interpolation; e.g., Assuming five bands: A, B, C, D, E, with probabilities 1/4, 1/4, 1/4, 1/4, we generate an MSFA as depicted in Fig. 5.

To find the contributing neighbors for band A at locations of band B, the nearest location where A is known is identified. In Fig. 5, immediate vertical neighbors of B hold known values of A so $(u, v) = \{(-1, 0), (+1, 0), (0, -1), (0, +1)\}$. To accomplish this task, a grid of 8×8 size is taken and 1 is stored at locations of band A, 2 at locations of band B, and so on. To solve for band A at location of other bands, nearest occurrence of "1" is searched for and its distance from central pixel is stored as (x, y). From these values, (u, v) are obtained as either $\{(-x, x), (x, x), (x, -x), (-x, -x)\}$ for diagonal nearest neighbor or $\{(x, 0), (-x, 0), (0, x), (0, -x)\}$ for the other case.

From Fig. 5, interpolation of band A at location of band D and E requires the four corner neighbors so $(u, v) = \{(-1, -1), (-1, +1), (+1, -1), (+1, +1)\}$. Interpolation of band D at location of B and E requires values of band D available at locations next to immediate neighbors in horizontal and vertical direction, so $(u, v) = \{(-2, 0), (+2, 0), (0, -2), (0, +2)\}$. The term α represents the relationship between central pixel and its neighbors, so alpha and probability maps for all the cases are calculated separately to ensure higher accuracy and better probability maps.

The EM algorithm is a two-step iterative algorithm: First, we calculate the probability of each sample belonging to each model, and then in the second step, the value of α is estimated, i.e., the correlation. The probability of $f(x, y)$ belonging to M_1 is calculated using Bayes' rule:

$$A = \Pr\{f(x, y) | f(x, y) \in M_1\} \Pr\{f(x, y) \in M_1\}$$

$$\Pr\{f(x, y) \in M_1\} \text{ and } \Pr\{f(x, y) \in M_2\} = 1/2$$

The probability of observing a sample $f(x, y)$ generated from model M1 is given by (probability map):

$$\Pr\{f(x,y)|f(x,y) \in M_1\} = \frac{1}{\sigma\sqrt{2\pi}}\exp\left[-\frac{1}{2\sigma^2}\left(f(x,y) - \sum_{u,v=-N}^{N}\alpha_{u,v}f(x+u, y=v)\right)^2\right] \tag{4}$$

Since first step requires value of α, it is randomly initialized. A new α is obtained by minimizing the squared error function:

$$E(\overrightarrow{\alpha}) = \sum_{x,y} w(x,y)\left(f(x,y) - \sum_{u,v=-N}^{N}\alpha_{u,v}f(x+u, y+v)\right)^2 \tag{5}$$

Differentiating it and putting it equal to zero yields:

$$\sum_{u,v=-N}^{N}\alpha_{u,v}\left(\sum_{x,y} w(x,y)f(x+s, y+t)f(x+u, y+v)\right) = \sum_{x,y} w(x,y)f(x+s, y+t)f(x,y) \tag{6}$$

This is comparatively easier and faster way to get the result.

Detailed Algorithm:

/*initialize*/
Solving for band A
Choose { $\alpha^0_{u,v}$ } randomly
Choose σ_0
Set p_0 as 1 over the size of range of possible values of f(x,y).
for each possible MSFA
    n=0
    /*expectation step*/
    for every other band than A(say B)
        //(x, y) represents locations of band B
        //(x_a, y_a) represents locations of band A
        Calculate u,v:-
            grid=zeros(8,8)
            grid(x_a,y_a)=1
            grid(x,y)=2
            neigh=nearest(grid,1,2)
            //neigh=(x,x) for nearest neighbor at distance x in
                        //diagonal direction

```
        if neigh(0)~=neigh(1)
            (u,v)={(-x,0),(x,0),(0,-x),(0,x)}
        else
            (u,v)={(-x,-x),(x,x),(x,-x),(-x,x)}
    end
    for each location of band B in current MSFA
```

$$R(x,y) = f(x,y) - \sum_{u,v=-N}^{N} \alpha_{u,v} f(x+u, y+v)$$

```
    end
    for each location of band B in current MSFA
```

$$P(x,y) = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{R(x,y)^2}{2\sigma^2}\right]$$

$$W(x,y) = \frac{P(x,y)}{P(x,y)+P_0}$$

```
    end
end
/* maximization step*/
```

Compute $\alpha_{u,v}^{n+1}$ by solving linear equation.

$$\sigma_{n+1} = \left(\frac{\sum_{x,y} W(x,y)\, R^2(x,y)}{\sum_{x,y} W(x,y)}\right)^{1/2}$$

n=n+1

Until $(\alpha_{u,v}^{n+1} - \alpha_{u,v}^{n} < \epsilon)$

end

A probability map ($P(x, y)$) is generated by running this algorithm which helps in determining if the image is genuine.

3 Experimental Results

We tested our algorithm on cave dataset of 31 images (512 × 512) [15] provided by Columbia University. We generated 31 4-band and 31 5-band images and stored first 3 bands of 4-band images and 1, 3, 5 bands of the 5-band image. All of these images were edited in varying proportions of 1–16% hence giving five groups of 31 images each.

To quantify the results, we prepared a synthetic map and compared it with the obtained probability maps of original images and (manually tampered) edited images.

Synthetic map:

$$\text{if } (\mathrm{S}(x, y) = \mathrm{r}_{x,y}) \quad \mathrm{S}_r(x, y) = 0 \quad \text{else } \mathrm{S}_r(x, y) = 1$$

where r represents any channel and S represents the MSFA and we already have the probability map p_r obtained from channel r of an image. P_r and S_r represent their respective Fourier transforms.

The measure of similarity M is: $M = \sum|\mathrm{P}_r(x, y)|.|\mathrm{S}_r(x, y)|$

If the value of M is above a specified threshold, then it is assumed that a correlation is present and the image is genuine. When all three channels of an image

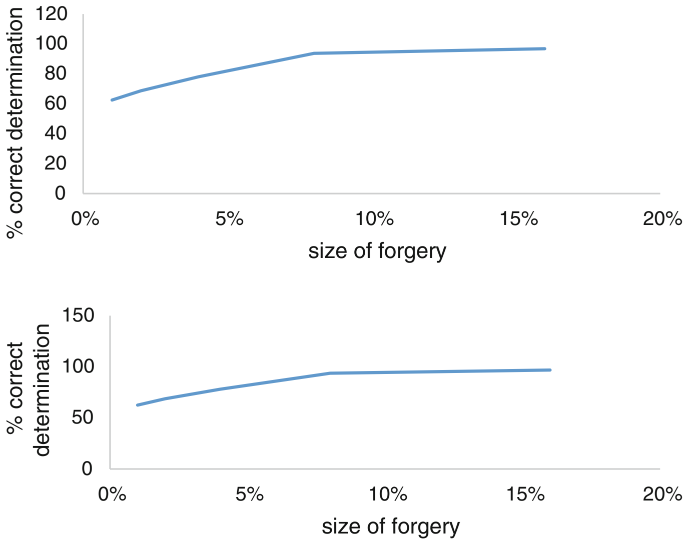

Fig. 6 % correct determination in 4-band images (upper) and 5-band images

for all possible MSFA patterns is below threshold, then the image is considered a forged image. Accuracy of the algorithm was determined on the basis of its correct determination of forged images out of 31 images, and results have been plotted in Fig. 6. The accuracy increased with increase in size of forgeries.

To determine the authenticity of an image with an accuracy of about 80%, image should at least be 7% forged for 4- and 5-band images. Since the algorithm determines originality on the basis of correlations between the pixels produced due to demosaicking, it can be used to determine authenticity of an image with any number of bands(including 3-band images), with the only constraint on their probability of appearances.

We compared the probability maps obtained from our algorithm with the probability maps as described in [6] for five channel images by applying the algorithm on only one channel without any changes. Figure 7 shows the obtained probability maps. The proposed algorithm gives much better results for multispectral images.

The image shown in (Fig. 8a) was reproduced using 4-band BTES (IR, R, G, B) and saved as NIR-G-B image, and the blood stains on the T-shirt were removed using Photoshop as in Fig. 8b. The probability map of image was then prepared using the suggested algorithm, and it clearly demarcates the tampered portion; Fig. 8c.

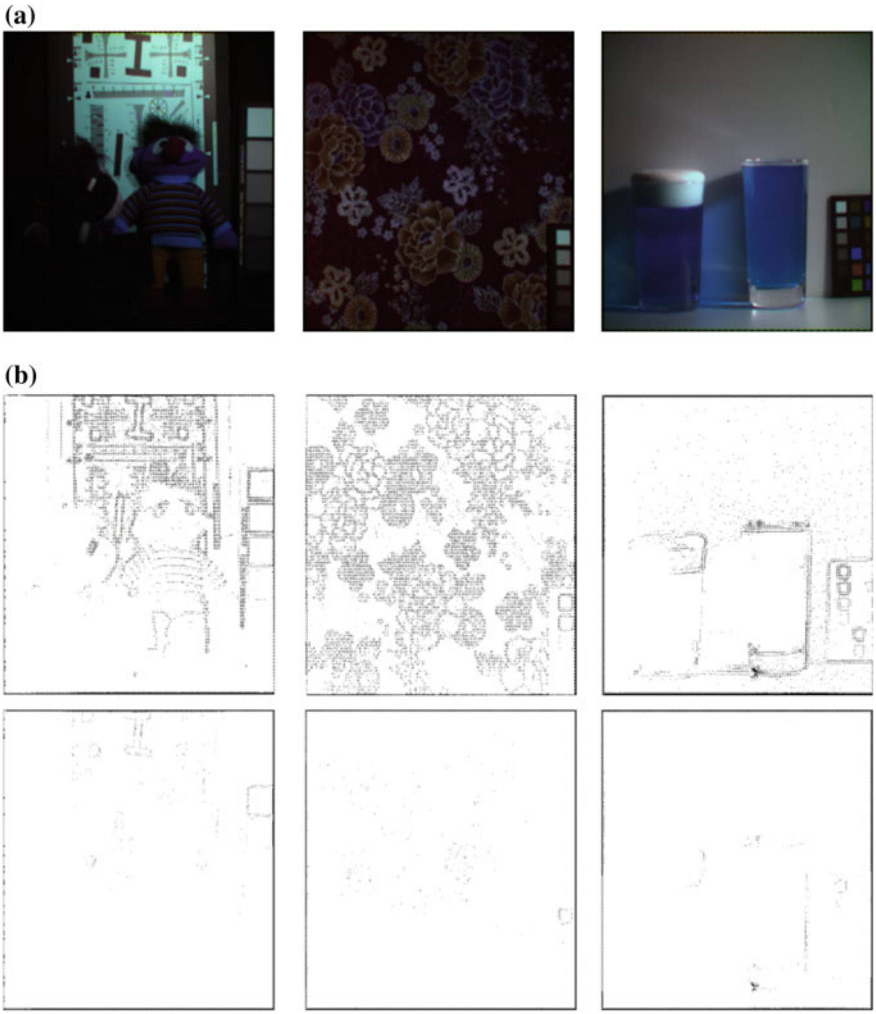

Fig. 7 **a** Shows the test images and **b** their probability maps obtained from the proposed algorithm (down) and Popescu et al. [6]

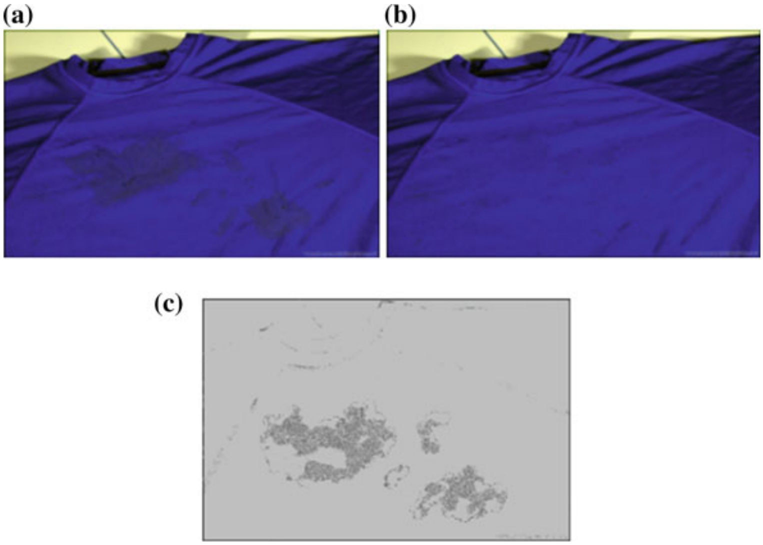

Fig. 8 **a** Blood-stained T-shirt (NIR-G-B), **b** photoshopped T-shirt, **c** probability map of (**b**)

4 Conclusion

In this paper, we studied the potential of expectation/maximization algorithm in determining the authenticity of a single-sensor multispectral image reconstructed using some demosaicking method. We discussed in relation to the binary tree-driven demosaicking method BTES, but approach seems applicable to other demosaicking methods in general. The demosaicking methods lead to correlations which would get affected if the original multispectral image is tampered. By using the expectation/maximization algorithm, these correlations can be estimated and it can then be used to determine whether the image is forged or not. With the use of multispectral images increasing with time, it was imperative that an algorithm to determine an image's authenticity be developed. This algorithm also highlights the importance of using an MSFA. It not only reduces the cost of capturing these high-content images but also provides the means to detect digital manipulations/any tampering in the multispectral images.

References

1. Li, H., Luo, W., Qiu, X., Huang, J.: Image forgery localization via integrating tampering possibility maps. IEEE Trans. Inf. Forensics Secur. **12**(5), 1240–1252 (2017). https://doi.org/10.1109/TIFS.2017.2656823
2. Shen, X., Shi, Z., Chen, H.: Splicing image forgery detection using textural features based on the grey level co-occurrence matrices. IET Image Process. **11**(1), 44–53 (2017). https://doi.org/10.1049/iet-ipr.2016.0238

3. Farid, H.: How to Detect Faked Photos. Am. Sci. (2017)
4. Pun, C.M., Yuan, X.C., Bi, X.L.: Image forgery detection using adaptive over-segmentation and feature point matching. IEEE Trans. Inf. Forensics Secur. **10**(8), 1705–1716 (2015). https://doi.org/10.1109/TIFS.2015.2423261
5. Ferrara, P., Bianchi, T., Rosa, A.D., Piva, A.: Image forgery localization via fine-grained analysis of CFA artifacts. IEEE Trans. Inf. Forensics Secur. **7**(5), 1566–1577 (2012). https://doi.org/10.1109/TIFS.2012.2202227
6. Popescu, A.C., Farid, H.: Exposing digital forgeries in color filter array interpolated images. IEEE Trans. Signal Processing **53**(10), 3948–3959 (2005)
7. Cao, H., Kot, A.C.: Accurate Detection of demosaicing regularity for digital image forensics. IEEE Trans. Inf. Forensics Secur. **4**(4), 899–910 (2009)
8. Farid, H.: A Survey of image forgery detection. IEEE Sig. Process. Mag. **26**(2), 16–25 (2009)
9. Miao, L., Qi, H., Ramanath, R., Snyder, W.E.: Binary tree-based generic demosaicking algorithm for multispectral filter arrays. IEEE Trans. Image Process. **15**(11), 3550–3558 (2006)
10. Miao, L., Qi, H.: The design and evaluation of a generic method for generating mosaicked multispectral filter arrays. IEEE Trans. Image Process. **15**(9), 2780–2791 (2006)
11. Jaiswal, S.P., Fang, L., Jakhetiya, V., Pang, J., Mueller, K., Au, O.C.: Adaptive multispectral demosaicking based on frequency-domain analysis of spectral correlation. IEEE Trans. Image Process. **26**, 953–968 (2017)
12. Aggarwal, H.K., Majumdar, A., Ward, R.: A reconstruction al-gorithm for multi-spectral image demosaicing. In: Proceedings of the IASTED International Conference on Signal and Image, Banff, AL, Canada, vol. 1719 (2013)
13. Monno, Y., Kikuchi, S., Tanaka, M., Okutomi, M.: A practical one shot multispectral imaging system using a single image sensor. IEEE Trans. Image Process. **24**(10), 3048–3059 (2015)
14. Mihoubi, S., Losson, O., Mathon, B., Macaire, L.: Multispectral demosaicing using pseudo-panchromatic image. IEEE Trans. Comput. Imaging **3**(4), 982–995 (2017). https://doi.org/10.1109/TCI.2017.2691553
15. Yasuma, F., Mitsunaga, T., Iso, D., Nayar, S.K.: Generalized assorted pixel camera: post-capture control of resolution, dynamic range and spectrum. IEEE Trans. Image Process. **19**(9), 2241–2253 (2010). http://www.cs.columbia.edu/CAVE/projects/gap_camera/