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잠재성장모델링을 이용한 미디언 필터링 검출 (Median Filtering Detection using Latent Growth Modeling)

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요 약

최근에 위,변조 영상의 처리이력 복구를 위한 포렌식 툴로서 미디언 필터링 (MF: Median Filtering) 검출기가 크게 고려되고 있다. 미디언 필터링의 분류를 위한 미디언 검출기는 적은 양의 특징 셋과 높은 검출율을 갖도록 설계되어야 한다. 본 논문은 변조된 영상의 미디언 필터링 검출을 위한 새로운 방법을 제안한다. BMP를 미디언 윈도우 사이즈에 의하여 여러 미디언 필터링 영상으로 변환하고, 윈도우 사이즈에 따른 차분포 값을 계산하여 그 값으로 미디언 필터링 윈도우 사이즈와 같은 특징 셋을 만든다. 미디언 필터링 검출기에서, 특징 셋은 잠재성장 모델링 (LFM: Latent Growth Modeling)을 사용하는 모델 특성으로 변환된다. 실험에서, 테스트 영상은 TP (True Positive)와 FN (False Negative) 두 분류로 판별된다. 제안된 알고리즘은 분류 효율성이 TP와 FN의 혼동에서 최소거리 평균이 0.119로서 훌륭한 성능임이 확인 되었다.

Abstract

In recent times, the median filtering (MF) detector as a forensic tool for the recovery of forgery images' processing history has concerned broad interest. For the classification of MF image, MF detector should be designed with smaller feature set and higher detection ratio. This paper presents a novel method for the detection of MF in altered images. It is transformed from BMP to several kinds of MF image by the median window size. The difference distribution values are computed according to the window sizes and then the values construct the feature set same as the MF window size. For the MF detector, the feature set transformed to the model specification which is computed using latent growth modeling (LGM). Through experiments, the test image is classified by the discriminant into two classes: the true positive (TP) and the false negative (FN). It confirms that the proposed algorithm is to be outstanding performance when the minimum distance average is 0.119 in the confusion of TP and FN for the effectivity of classification.

Keywords: Median filter, Median filtering detector, Digital image forensics, Latent growth modeling (LGM), Structural equation modeling (SEM).

I. 서 론

In the image alterations, the content-preserving manipulation is using compression, filtering, averaging, rotate, mosaic editing and scaling and so on, using the forgery method.^[1~2] Median filtering is especially preferred among some forgers because it has characteristics of non-linear filtering based on

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order statistics. Furthermore, median filtering may affect the effectiveness of different steganalysis techniques.^[3~8] Consequently, the median filtering (MF) detector becomes a significant forensic tool for the recovery of the processing history of a forgery image.

To detect MF in forgery images, G. Cao et al.^[6] analyzed the probability that an image's first-order pixel difference is zero in textured regions. In this regard, Ray Liu^[9] account for the scheme which is highly accurate in unaltered or uncompressed images.

In this paper, the author focused on the discrimination of an unaltered or altered image by MF, and the classification of window size, if an image is median filtered. Also, the author attempted to reduce the number of feature set for MF detection. To create a difference distribution from window sizes which are the same as the median filtering window size 3×3 (MF_3), 5×5 (MF_5) and 7×7 (MF_7) respectively in each MF_w , $w \in \{3, 5, 7\}$, and it has different eight level anchor pixel values a_i , where $i \in \{1, 2, \dots, 8\}$.

The proposed algorithm is formed by using structural equation modeling (SEM) to classify MF_w . The SEM in this paper is formed using latent growth modeling (LGM) which assigns the statistical properties to the measurement variables as an exogenous variable in the model.

The rest of the paper is organized as follows. In Section II, it briefly presents a theoretical background of MF operation. In Section III, it describes the construction of the new feature set, and the method to classify the MFw by the formed SEM using LGM for the proposed algorithm. The experimental results of the proposed algorithm are shown in Section IV, the performance estimation is compared with prior arts, and followed by some discussions. Finally, the conclusion is drawn, and the future work is presented in Section V.

II. Theoretical Background of MF Operation

The median pixel values obtained from overlapping filter windows related to one another since overlapping windows share several pixels in common.^[5]

The median in statistic means the value in the middle of the items or literally halfway down the list of items $\lceil w/2 \rceil$.

$$\tilde{x} \equiv \begin{cases} Y_{(\frac{w+1}{2})} & \text{if } w \text{ is odd} \\ \frac{1}{2}(Y_{(\frac{w}{2})} + Y_{(1+\frac{w}{2})}) & \text{if } w \text{ is even} \end{cases} . \quad (1)$$

where \tilde{x} is the median value of Y , and Y $\{w$ items $\}$.

By using median operation, a noise signal in audio and image can be removed due to its nonlinear nature. Also, median filtering of image is capable of smoothing and denoising a signal while preserving its edges within a content.

Let's consider median filtering of image. The median filter has a non-linear filter based on order statistics. Given an $M \times N$ grayscale image $G_{m,n}$ with $(m,n) \in \{1, 2, \dots, M\} \times \{1, 2, \dots, N\}$, a 2-D median filter is defined as

$$\hat{G}_{m,n} = MF \{ G_{m',n'} : (m',n') \in w(m,n) \}. \quad (2)$$

where $\hat{G}_{m,n}$ is the median filtered image at image coordinates (m,n) . $MF\{\cdot\}$ is the median operator, and $w(m,n)$ is the 2-D filter window centered at the image coordinates (m,n) . The rest of this paper focuses on a filter with $w \times w$ ($w=2r+1$, $r=1,2,3$)

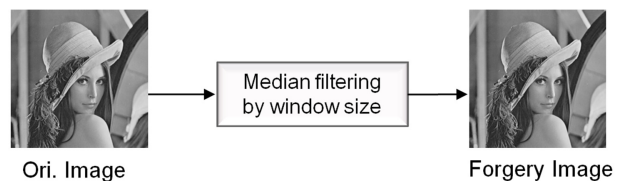


그림 1. 미디언 필터링에 의한 위,변조 영상
Fig. 1. Forgery image produced by median filtering.

square windows as it is the most widely used form of median filtering.^[10]

In the forensics community, median filtering is considerably used. Fig. 1 shows the Lena image altered using MF{·} for a forgery by w .

III. Proposed Algorithm of MF Detection

This paper describes the construction of a new feature set at the different window sizes around an anchor pixel which has eight different level values for consistent MF detection in digital images. Moreover, the methods for both focusing to reduce the number of the feature set and smaller window size than existing techniques is contrived. For the proposed algorithm, a new feature set will be constructed, and SEM will be used to discriminate unaltered images, or median filtering will be formed using LGM in this Section.

And, if it is the median filtered image, which is classified the window size of a median filtering. Thus, for the construction of the feature set, the proposed algorithm in this paper is composed of four functional routines as follows:

- 1) Smaller to reduce the number of feature sets,
- 2) Smaller to window size of MF detector,
- 3) Forming the model specification of SEM, that discriminates an unaltered image and median filtered,
- 4) Classify the window size, if median filtered.

3.1 New Feature Set of MF Detector

In a grayscale image, the pixel value is an integer in the set $\mathcal{P}=\{0, 1, \dots, 255\}$. In Fig. 2, the image pixel values are divided into eight levels (gray color

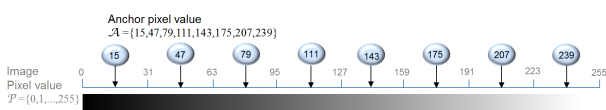


그림 2. \mathcal{A} 의 고정 픽셀
Fig. 2. Anchor pixel values in \mathcal{A} .

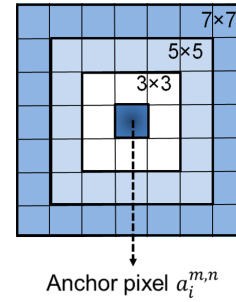


그림 3. 고정 픽셀 주변의 윈도우 사이즈
Fig. 3. Window size around an anchor pixel.

numerals) then the anchor pixel value (numerals in acircle) is set to the center value of each level. Eight anchor pixel value a_i s are in set $\mathcal{A}=\{15, 47, 79, 111, 143, 175, 207, 239\}$, where i -th ($i=1, \dots, 8$).

Let three window types w (3×3 , 5×5 and 7×7) denote the window sizes around each anchor pixel coordinate $a_i^{m,n}$ in Fig. 3, where $w=\{3,5,7\}$ and (m,n) is a coordinate.

The difference distribution values $D_w^{a_i}$ are computed according to w size around $a_i^{m,n}$ by Eq. 3.

$$D_w^{a_i} = \sum_{x=-\lfloor w/2 \rfloor}^{\lfloor w/2 \rfloor} \sum_{y=-\lfloor w/2 \rfloor}^{\lfloor w/2 \rfloor} (D_i^{m,n} - p_{x,y}) \quad (3)$$

where (x,y) and (m,n) ($1, \dots, M$) \times ($1, \dots, N$), and $M \times N$ is the size of an image. As a result, $D_w^{a_i}$ has 24 difference distribution values (three window types \times eight anchor pixels: see Fig. 6 in Section 4). Afterward, an image can have three values for the feature set according to each w then the feature set F_w can be defined as

$$F_w = \sum_{i=1}^8 |D_w^{a_i}|. \quad (4)$$

Thus, the feature set of the image has three values constructed from three widow sizes. Each window size is the same as MF_w respectively.

3.2 Forming SEM for MF Detector

First of all, to form SEM to discriminate an unaltered image or median filtered, a measurement

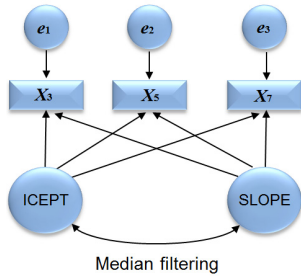


그림 4. 미디어 필터링 영상 분류를 위한 비조건 LGM의 측정 모델
 Fig. 4. The measurement model of an unconditional LGM for the classification of the median filtered image.

model should be presented with an unconditional LGM. For the MF detector, Fig. 4 shows the measurement model measurement variable if it is median filtered, where ICEPT (Initial score), SLOPE (Rate of change), e (Error) and X (Measurement variable by median filtering window size)

F_w in (4) is inputted individually into three X_3 , X_5 and X_7 for repeat measurement analysis. Thus, the

measurement variable X_w is formed as

$$X_w = ICEPT + \left(\frac{w-3}{2}\right) \cdot SLOPE + e \cdot \left(\frac{w-3}{2} + 1\right), \quad (5)$$

where $w = \{3, 5, 7\}$.

3.3 Proposed algorithm

A flow diagram of the proposed algorithm for the MF detector is shown in Fig. 5. The preceding step is to compute the model specifications of SEM S_k (refer in Fig. 7) for the unaltered and median filtered images already known, where ($k=1$: unaltered image BMP, $k=2$: MF₃, $k=3$: MF₅ and $k=4$: MF₇).

In the test step block, when some image is not known at all, $D_w^{a_i}$ and F_w of a test image is computed and then T_{F_w} (test image's F_w) into the estimation step block, which is called T_{F_w} .

Lastly, in the estimation step block, the Euclidean distance and the correlation coefficient between S_k

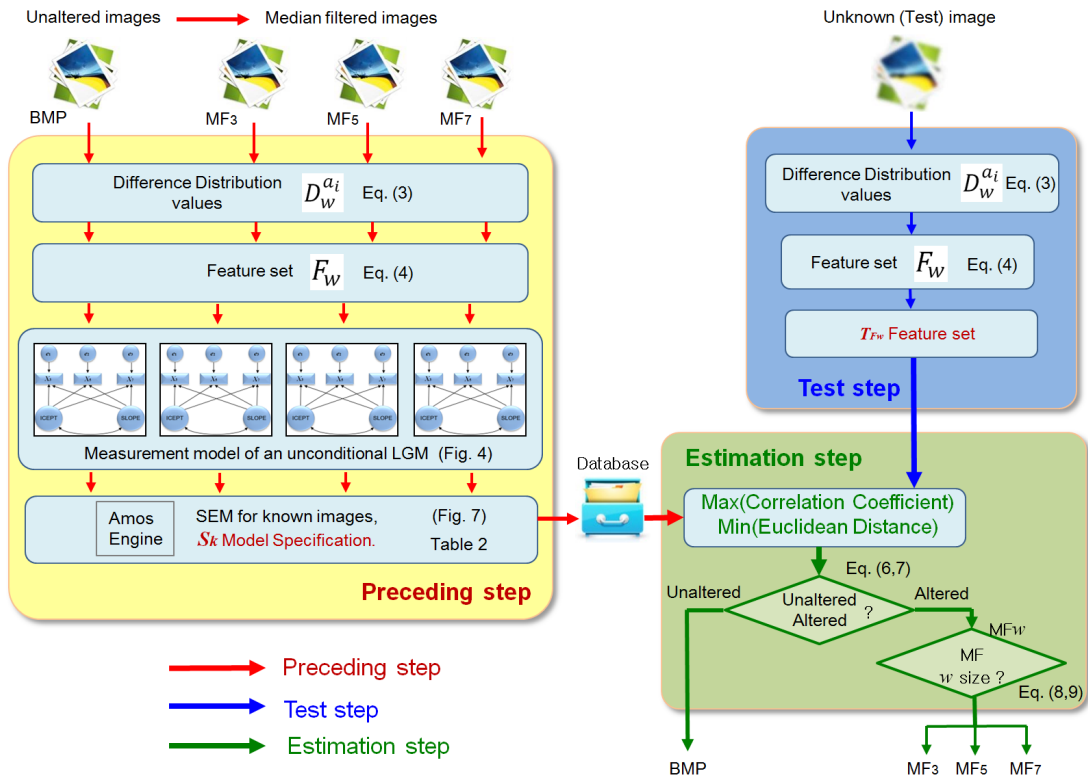


그림 5. 미디어 필터링 검출의 제안된 알고리즘
 Fig. 5. The proposed algorithm for MF detection.

and T_{F_w} are computed by (6) and (7) considering the maximum correlation coefficient and the minimum Euclidean distance for the discrimination of the test image T . True positive (TP) means that the discrimination is accomplished and false negative (FN) means that it failed respectively.

If T is median filtered, according to k , median filtering window size is classified by (8).

$$\begin{aligned} TP &= \max(\text{Corrcoef}(S_k, T_{F_w})) \\ &\cup \min(\text{Euclidean}(k, T_{F_w})) \\ \text{if } k=1 \text{ both } T &= \text{BMP} \\ \text{if } 2 \geq k \text{ both } T &= \text{MF}w, \end{aligned} \quad (6)$$

$$\begin{aligned} FN &= \max(\text{Corrcoef}(S_k, T_{F_w})) \\ &\cap \min(\text{Euclidean}(k, T_{F_w})) \\ \text{if } k=1 \text{ both } T &= \text{BMP} \\ \text{if } 2 \geq k \text{ both } T &= \text{MF}w. \end{aligned} \quad (7)$$

From Eq. (5)-(7) and the coefficients of ICEPT and SLOPE in Fig. 4, a new discriminant is derived as Eq. (8) and (9) for classifying k and w of MF images.

$$k_w = \text{ICEPT} + \left(\frac{w-3}{2}\right) \cdot \text{SLOPE} + e \cdot \left(\frac{w-3}{2} + 1\right) \quad (8)$$

$$\text{MF}Detector(k) = \begin{cases} \text{MF}_3, & \text{if } k = 2 \\ \text{MF}_5, & \text{if } k = 3 \\ \text{MF}_7, & \text{if } k = 4 \end{cases} \quad (9)$$

IV. Experimental Results

4.1. Developing the model specification for the MF detector.

The effectiveness of the proposed MF detection algorithm is extensively evaluated using the BOW2 original image database of 10,000^[11], and its median filtered 30,000 (MF3, MF5 and MF7 artificial

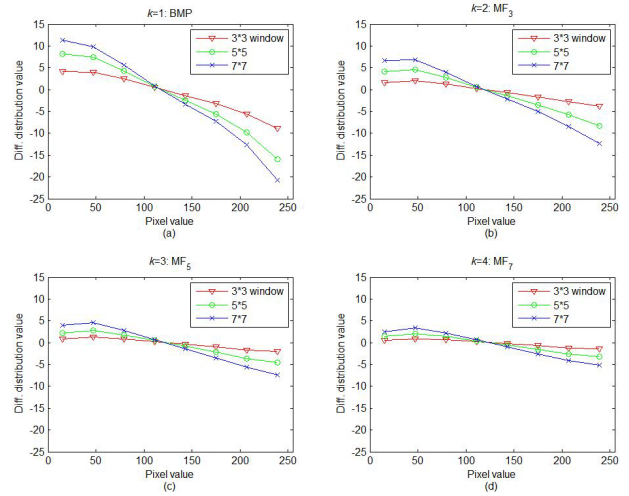


그림 6. k 의 각 고정 픽셀 값의 차분포
Fig. 6. The difference distribution of each anchor pixel values of k respectively.

tampered images) produced with w (3, 5 and 7), for a total of 40,000 images.

The experiment is progressed as follows:

[Step 1] Each k (in Section 3.3) has 10,000 images and the difference distribution $D_w^{a_i}$ of all images is computed by (6) at each a_i in \mathcal{A} (Fig. 2). Around anchor pixel coordinate, window size w is 3×3, 5×5 and 7×7 in Fig. 3, the feature set F_w of each k is constructed by (4). The average difference distribution of each k is shown in Fig. 6.

[Step 2] For the reliability of the feature set, the Z-score of each image at $k=1$ (BMP: univariate normality) is computed from the average pixel value of an image. If the Z-score is $|1.96|$ @ Significance level 0.05, it can not be used in the sample image. The number of available test images is 8,815 excepted 1,185 outlier images due to normality.

[Step 3] F_w (each w of k) is respectively inputted as the measurement variables X_w in Fig. 4. The paths between SLOPE (Rate of change) and the measurement variables ($w_3 \rightarrow w_5 \rightarrow w_7$) are regarded as the latent growth. So, it assigns the factor loading of SLOPE paths to the measurement variables are fixed

with 0, 1 and 2 under an assumed positive linear. This step is executed on Amos 21 (IBM® SPSS®).

Table 1 illustrates the test of goodness-of-fit in [Step 3]. Through the results of sample images, the goodness of fit is satisfaction.

표 1. 적합도의 테스트 결과

Table 1. The results of the test of goodness-of-fit.

Model		BMP	MF ₃	MF ₅	MF ₇
Hair <i>et al.</i> AVE	ICEPT	0.58	0.45	0.39	0.40
	SLOPE	0.20	0.19	0.17	0.17

BMP Sem.AStructure (Model specifications) ("BMP_w3=(1.00)ICEPT+(.00)SLOPE+(1)e1") ("BMP_w5=(1.00)ICEPT+(1.00)SLOPE+(1)e2") ("BMP_w7=(1.00)ICEPT+(2.00)SLOPE+(1)e3") ("SLOPE <--> ICEPT (146.72)") ("ICEPT (20.90, 784.38)") ("SLOPE (14.62, 341.76)") ("e1 (0, -223.73)") ("e2 (0, 199.10)") ("e3 (0, -441.20)")
MF₃ Sem.AStructure (Model specifications) ("MF3_w3=(1.00)ICEPT+(.00)SLOPE+(1)e1") ("MF3_w5=(1.00)ICEPT+(1.00)SLOPE+(1)e2") ("MF3_w7=(1.00)ICEPT+(2.00)SLOPE+(1)e3") ("SLOPE <--> ICEPT (59.71)") ("ICEPT (15.89, 105.28)") ("SLOPE (16.28, 99.17)") ("e1 (0, -17.48)") ("e2 (0, 18.45)") ("e3 (0, -35.88)")
MF₅ Sem.AStructure (Model specifications) ("MF5_w3=(1.00)ICEPT+(.00)SLOPE+(1)e1") ("MF5_w5=(1.00)ICEPT+(1.00)SLOPE+(1)e2") ("MF5_w7=(1.00)ICEPT+(2.00)SLOPE+(1)e3") ("SLOPE <--> ICEPT (27.09)") ("ICEPT (10.60, 38.50)") ("SLOPE (11.35, 41.13)") ("e1 (0, -1.63)") ("e2 (0, 1.95)") ("e3 (0, 5.46)")
MF₇ Sem.AStructure (Model specifications) ("MF7_w3=(1.00)ICEPT+(.00)SLOPE+(1)e1") ("MF7_w5=(1.00)ICEPT+(1.00)SLOPE+(1)e2") ("MF7_w7=(1.00)ICEPT+(2.00)SLOPE+(1)e3") ("SLOPE <--> ICEPT (15.43)") ("ICEPT (7.79, 25.87)") ("SLOPE (8.34, 24.12)") ("e1 (0, -1.79)") ("e2 (0, 2.00)") ("e3 (0, 3.53)")

그림 7. Amos에서 미디언 필터링 검출의 구조방정식 모델링의 모델특성

Fig. 7. The model specifications of SEM for MF detection on Amos.

where Hair *et al.* AVE (convergent validity): OK 0.5 higher (BMP is the initial basis of the several tampered images) on Amos.

The proposed MF detection algorithm is executed on the measurement model of an unconditional LGM for the model specifications, which are like the path coefficient, the variance and covariance of the latent variable, and the structural equation for SEM. These model specifications on Amos are presented in Fig. 7. LGM of BMP, MF₃, MF₅ and MF₇ is drawn, and the structural equation with its coefficients and the error values of the measurement variables are presented respectively.

Until here, it is the preceding step of the proposed algorithm in Fig. 5.

4.2. Estimation of MF detector

In the estimation step block in Fig. 5, by Eq. (6) and (7), BMP and MF images are discriminated with S_k and T_{Fw} both according to k . Moreover, considering $k \geq 2$ again in Eq. (8) and (9), if median filtered, which classify the window size of median filtering as shown in Table 2.

In order to relieve the proposed algorithm, the k 's combinational table is suggested in Table 3, and the results of Table 2 is estimated for the performance with the confusion matrix (TP and FN), ROC (Receiver Operating Characteristic curve) and Pe (Minimum average decision). If so, what types of image are classified well? Which could be proven with a lower value by Pe as

표 2. 미디언 필터에서 윈도우 사이즈 분류

Table 2. Classification of window size, if median filtered.

k	Image type	Number of images	Classified images	Classification ratio (%)
1	BMP	10,000	9,250	92.50
2	MF ₃	10,000	6,540	65.40
3	MF ₅	10,000	8,641	86.41
4	MF ₇	10,000	9,405	94.05
Total		40,000	33,836	84.57

표 3. k 의 조합테이블에 포함된 혼동 매트릭스, ROC 그리고 Pe .

AUROC는 0.948로서, 0.9 이상은 'Excellent'로 평가

Table 3. The k 's combinational table involves the confusion matrix, ROC and Pe .

** AUROC (Area Under ROC curve): 0.948, and Estimation: 0.9 higher (Excellent).

Label	BMP	MF ₃	MF ₅	MF ₇			ROC		Pe
					Number of TP	Number of FN	Sensitivity (TP rate)	1-Specificity (FP rate)	
A	—	—	—	—	0	2,324	0.768	1	0.384
B	—	—	—	○	3	738	0.693	1	0.347
C	—	—	○	—	1	664	0.627	0.999	0.314
D	—	—	○	○	32	242	0.603	0.998	0.302
E	—	○	—	—	0	462	0.557	0.996	0.280
F	—	○	—	○	7	212	0.536	0.996	0.270
G	—	○	○	—	2	173	0.519	0.996	0.261
H	—	○	○	○	705	61	0.512	0.999	0.258
I	○	—	—	—	254	2,814	0.231	0.925	0.153
J	○	—	—	○	653	863	0.145	0.900	0.123
K	○	—	○	—	164	681	0.077	0.834	0.121
L	○	—	○	○	2,353	217	0.055	0.818	0.119
M	○	○	—	—	86	311	0.024	0.583	0.221
N	○	○	—	○	356	98	0.014	0.574	0.220
O	○	○	○	—	88	95	0.005	0.538	0.233
P	○	○	○	○	5,296	45	0	0.530	0.235
Total					10,000	10,000	1 1		
							AUROC**: 0.948		

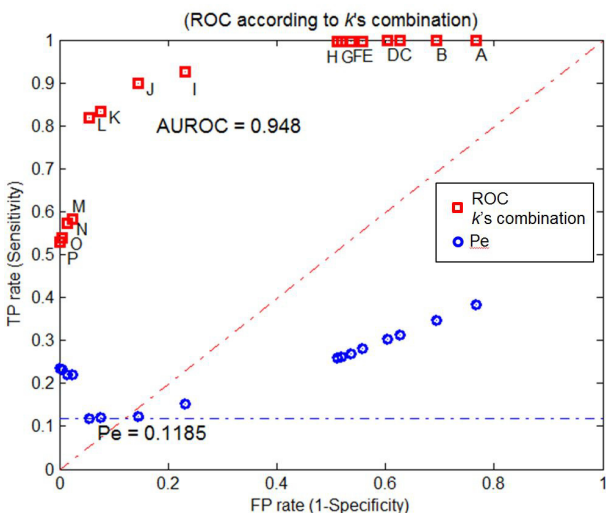


그림 8. 제안된 미디언 필터링 검출기의 ROC 커브와 Pe

Fig. 8. ROC curve and Pe for the proposed MF detector.

표 4. 기존의 AUROC와 제안된 미디언 필터링 검출기의 비교

Table 4. AUROC compared between prior arts and the proposed MF detector.

Schemes	Feature set	AUROC
The proposed MF detector	Difference distribution to feature set.	0.948
[6]	Post-sharpened	0.923
[7]	Post-sharpened	0.525
[8]	Post-sharpened	0.706

$$Pe = \min\left(\frac{P_{FP} + 1 - P_{TP}}{2}\right), \quad (10)$$

where P_{FP} is FP rate, and P_{TP} is TP rate respectively.

According to k , TP and FN, and its ROC curve are shown in Table 3. As a result, at the lowest $Pe=0.119$ (in Label L) the outstanding performance is

carried out.

The ROC curve and the Pe are drawn in Fig. 8 and the compared results between the proposed and prior arts are presented in Table 4.

V. Conclusion

In the classification of the MF image, the typical works have tried to reduce the number of the feature sets and the window size for extracting a feature vector, and yet they increase the MF detection ratio. In the classification of the MF image, the typical works have tried to reduce the number of the feature sets and the window size for extracting a feature vector, and yet they increase the MF detection ratio.

In this paper, the MF detector for the construction of the feature set is proposed, which has smaller window sizes, same as the median filtering sizes. Through a series of experiments, the discriminant is formed with coefficients of the model specification of SEM; using an unconditional LGM. The coefficients are computed using a growth structure of LGM, which is like a window size (3→5→7).

Additionally, the experimental results show that the proposed MF detector can more reliably discriminates between unaltered and median filtering than the existing median filtering forensic techniques. Moreover, its window size is also classified if median filtered is to be outstanding performance when $Pe=0.119$ in the confusion of TP and FN for the effectivity of classification.

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