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Current Trends In E-Learning

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E-learning is the buzzword of todayâ€™s era and a large number of e-learning resources are available in online and offline mode. However, to derive useful pattern from this abundant pool of e-learning resources is a very tedious task. Various data mining approach can be used to generate interesting patterns from this enormous repository. The data analytics helps in analyzing the information access pattern of the users. The information access pattern can be helpful in identifying the learning behavior traits of an individual. Moreover, machine learning along with data mining has opened up new avenues. The combination of data analytics and machine learning may be used to generate targeted recommendations.

[View Full Paper] 1-3

Precedent Behavioral Extraction System For Personalization Recommendation

Mahima

Hosting a compilation of billions of videos, YouTube presents one of the leading scale and most precious videos personalization recommendation system in existence. The recommendation system works on to personalized set of videos to users based on their past actions on the website. In this paper, we highlight the some of the major challenges that the system faces and how to address them. To tackle these issues, we have proposed a Precedent Behavioral Extraction Module (PBEM), which also deals with large-scale heterogeneous information to fulfill the requirements of the potential users. PBEM approach especially focus on the remarkable performance enhancements brought by machine learning. PBEM is a new approach as it works on discovering the precise web browsing behavior from uncertain keywords and defines the semantic measurement with user recommendation of keywords within the user query

[View Full Paper] 4-9

Impact Of Wide Variety Feature On Accuracy Of Offline Signature Verification Using Distance Of Mass Centroid

Agung Sediyono, Binti Sholihah, Yani Nur Syamsu, Gatot Budi Santoso

Study on offline signature has been conducted for several years. Skilled forgery verification is difficult to be verified because of the highest similarity between genuine and forgery signature. Based on previous research, it can be concluded that genuine offline signature is never similar, but it still has consistent features. Otherwise, skilled forgery tries to mimic genuine offline signature as similar as possible. It can be hipotized that if skilled forgery signature is matched to genuine signature, it should match on consistent parts (narrow variety) and unmatch on inconsistent features (wide variety). In this reseach, the offline signature verification is conducted by two steps. In first step, the comparison is conducted based on consistant features as most researcher done. In second step, an acceptance result of first verification will be reverification using inconsistant features in order to improve the verification accuracy in case skilled forgery. Based on the experiment, it can be concluded that this proposed method can improve the verification accuracy for certain condition or depend on writer signature characteristic. Therefore, this approach can be applied only if only the conformance characteristic of writer offline signature can be identified before second step of verivication can be done. At least, this result contribute to open mind that wide variety feature can be used in offline signature verification.

[View Full Paper]

Creative Gamification In Kahoot! For Workerâ€™s Health And Safety Learning Assessment

Wegig Murwonugroho, Syaifudin

The Kahoot! game application is used to determine differences in the level of understanding of mining workers, between before and after watching the safety video on the topic of "fatigue". Data shows cognitive improvement between before and after the Occupational Health and Safety (OHS) video was shown. However, the results of increased knowledge of this video material are not accompanied by keeping safety commitments at work. Therefore this research is important to do with the aim of finding indicators of collecting material in the Kahoot! game which can increase workersâ€™ awareness and commitment to safety at work. This research method uses a quasi-experimental method on 60 people who are not mining workers that is analysed using t-test and ANOVA test. The results showed that Kahoot! creative gamefication must fulfill the criteria of preparing questions and answer choices that are capable of: 1) stimulating players to apply their knowledge in the real world; 2) relating aspects of memory, perception, and action; 3) having dramatic, antagonistic, witty, and affective qualities. Implications of this study, the creative gamefication of Kahoot! as an instrument of learning assessment should put more emphasis on the content of OHS guidelines, and further can be applied to the workers that will translate them into practicing safety at work consistently.

[View Full Paper]

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Abstract: Study on offline signature has been conducted for several years. Skilled forgery verification is difficult to be verified because of the highest similarity between genuine and forgery signature. Based on previous research, it can be concluded that genuine offline signature is never similar, but it still has consistent features. Otherwise, skilled forgery tries to mimic genuine offline signature as similar as possible. It can be hipotized that if skilled forgery signature is matched to genuine signature, it should match on consistent parts (narrow variety) and unmatch on inconsistent features (wide variety). In this reseach, the offline signature verification is conducted by two steps. In first step, the comparison is conducted based on consistant features as most researcher done. In second step, an acceptance result of first verification will be reverification using inconsistant features in order to improve the verification accuracy in case skilled forgery. Based on the experiment, it can be concluded that this proposed method can improve the verification accuracy for certain condition or depend on writer signature characteristic. Therefore, this approach can be applied only if only the conformance characteristic of writer offline signature can be identified before second step of verivication can be done. At least, this result contribute to open mind that wide variety feature can be used in offline signature verification.

Indeks Term: mass centroid, narrow variety, offline signature verification, pattern recognition, skilled forgery, verification accuracy, wide variety

1. INTRODUCTION

IN 2012, Indonesia had offline signature forgery as much as 589 cases: 212 cases in PUSLABFOR, 88 cases in LABFORCAB Medan, 88 cases in LABFORCAB Surabaya, 73 cases in LABFORCAB Semarang, 54 cases in LABFORCAB Makasar, 34 cases in LABFORCAB Palembang, and 26 in LABFORCAB Bali. These offline signature forgery cases can be categorized into three categories, such as skilled forgery, moderate forgery, and random forgery. Other interesting case is denial forgery because of his signature different to his own. All cases are offline handwritten signature that be collected from forgery documents [1]. Skilled forgery is the hardest task because it can be mistake even though it was verified by skilled verificator [2]. Therefore, it should be aided by computer application to help for supportive or comparative result in making decision. Research on computer based offline signature verification is conducted by researchers. Based on feature used in decision making, offline signature research can be divided by global and local feature. Global feature cannot be used for skilled forgery verification because the different signature probably has a same global feature. Otherwise, local feature can improve the accuracy of verification for skilled forgery [3]-[15]. The research results proofed that the accuracy of verification was satisfy on either moderate or random forgery, but not for skilled forgery. Nevertheless, there are many important things that should be payed attention, those are: (1) the accuracy of verification can be increased by paying attention on various part of the signatures in same people [11][13][14]; (2) level of variation should pay attention on the time period of the signature [2][15]; (3) level of accuracy depends on the detail of local feature [6][9][10], properly choicing the level of local feature variation and increasing training data [7][8][10]. However, the detail of local feature will be constrained by limited training data [16]. Based on that finding, local feature and level of variation hold important role in improving the accuracy of verification, as long as number of training data cannot be increased because of availability of offline signature in a certain period. Therefore, it needs to be conducted the further research how to increase accuracy of verification that focus on local feature and level of variation of offline signature [17]. Skilled forgery is difficult to be solved by previous methods because: (1) level of variation will be related to the level of easiness of skilled forgery [13], so that the verification of skilled forgery using either variation range or neural network method will be failed because of the signature nearly similar; (2) image matching technique comparing the parts of signature structurally, statistically, and morphologically tend to unsuccess because forger try to create signature as same as the genuine. Moreover, by using cloning tool, offline signature can be created similar to the genuine [2]. Based on the fact that the segment of the offline signature structure of someone is never similar [6][13][15], and the skilled forger tends to creating offline signature as similar as possible [2], and also the level of signature variation related to the easily of forgery [13], skilled forger will be trapped on the signature segments that have wide variation. Otherwise, random and moderate forger will be trapped on narrow variation. Therefore, it can be hypothesized that skilled forgery can be identified by using wide variation segment and random forgery can be identified by using narrow variation segment [17]. This research will proof this hypothesis.

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2 NARROW AND WIDE VARIETY AREAS

On the offline signature verification using local feature, the offline signature will be divided into small parts of signature and the questioned signature will be compared to the genuine signature. Several number of genuine signatures will be used as data training, and it will produce a set of variation area

because the offline signature of someone is never similar [6][13][15]. If the area of offline signature is divided by n, it will produce a set of variation $\{v_1, v_2, v_3, \ldots, v_n\}$. If this member of set is ordered ascendingly, it can be taken a set of narrow variation $\{v_1, v_2, \ldots v_k\}$ and a set of wide variety $\{v_b, \ldots, v_{n-1}, v_n\}$ where k < b are independent variables. In this research, the local features will be resulted from extracting the centroid of mass of the segment of offline signature.

2.1 Centroid of Mass

Centroid of mass (C) is average position of all parts of object representing centered point of object mass. Centroid of mass of an object can be calculated by

$$C(x,y) = \left(\frac{\mu_{1,0}}{\mu_{0,0}}, \frac{\mu_{0,1}}{\mu_{0,0}}\right) \qquad (1)$$

where

$$\mu_{0,0} = \sum_{x=0}^{w} \sum_{y=0}^{h} f(x,y), \quad \mu_{1,0} = \frac{\sum\sum x\, f(x,y)}{\mu_{0,0}},$$

$$\mu_{0,1} = \frac{\sum\sum y\, f(x,y)}{\mu_{0,0}}$$

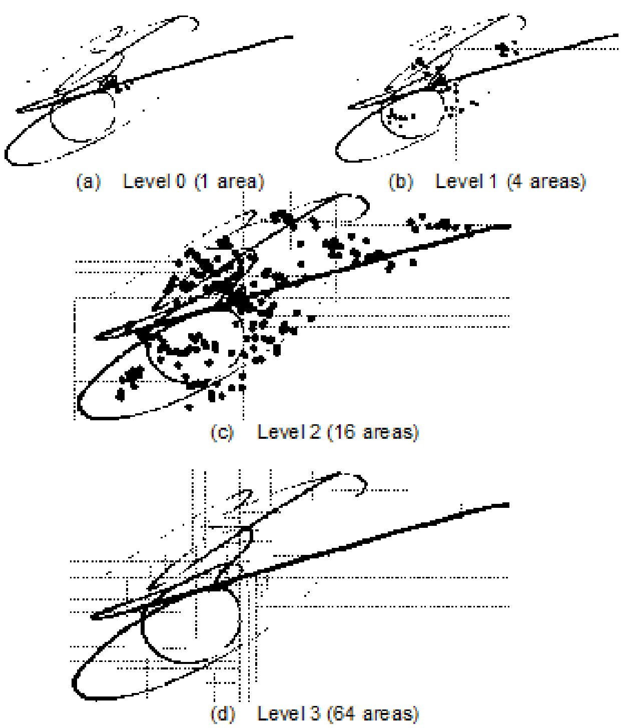
2.2 Distance, Mean, and Variance of the Centroid of Mass

Distance of two centroids of mass can be calculated as a distance of two points, as follow:

$$d_{ij} = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \qquad (2)$$

$$\mu_d = mean(\{d_{ij}\}) \qquad (3)$$

$$\sigma_d = std(\{d_{ij}\}) \qquad (4)$$



(a) Level 0 (1 area) (b) Level 1 (4 areas)

(c) Level 2 (16 areas)

(d) Level 3 (64 areas)

Fig. 1. Example of area of verification

where 1≤ i ≤ n, 1 ≤ j ≤ n, n are number of mass centroids.

2.3 Variety of the Centroid of Mass

Variety of the Centroid of Mass represented by the mean of distance set of centroid of mass can be calculated by:

$$v_j = \sqrt{mean(\{(x_{ij} - x_{cj})^2 + (y_{ij} - y_{cj})^2\})} \qquad (5)$$

where x_{ij}, y_{ij} is the point coodinate of mass of area j of signature i, and x_{cj} is *mean* of $\{x_{ij}\}$, y_{cj} is mean of $\{y_{ij}\}$ area j and signature i in signature collecton. Therefore, v_j represent the average of center point of circle x_{cj}, y_{cj}. Value of v_j represent the level of spreading of mass centroids set.

3 METHODOLOGY

This research uses experiment methodology, as follow:

3.1 Dataset

Dataset of experiment is taken from SigComp2011 [23], where the composition of dataset as in Table 1.

TABLE 1.

COMPOSITION OF OFFLINE SIGNATURE DATASET

Item	Training	Testing	
	Genuine	Genuine	Questioned
Number of respondence	53	53	53
Number of signatures per respondence	12	12	3
Number of signatures	636	636	636

3.2 Normalization of Offline Signature Image

For the best result of signature verification, offline signature images should be normalized dan cleaned from noise. Image normalization is sized by either enlarging or shrinking the image proportionally so that all images have same dimension. In this research, the first image is selected to be an image reference and then the rest images will be sized to the size of reference image.

3.3 Signature Areas Division

Every area of signature is divided by four where the center of division is centroid of mass of the area [10]. In this research the depth of division is only four level, so that it has a number of areas per level as in Table 2

TABLE 2.

NUMBER OF AREAS PER LEVEL

Level	Number of Areas
0	1
1	4
2	16
3	64
4	256

Figure 1. show the areas as defined in Table 2, except for level 4 is not visualized because of its complexity.

3.4 Evaluation Criteria

There are two evaluation criteria's, those are (1) evaluation criteria for assessing the performance of verification system; (2) evaluation criteria for determining whether the signature is

genuine or not. Evaluation criteria of verification system measure the accuracy of system verification namely (ACC), false acceptance rate (FAR), and false rejected rate (FRR). ACC is calculated from number of false verifications divided by number of verifications. FAR is a number of false acceptances divided by number of signature verification. FRR is a number of false rejected verification divided by a number of signature verification. To determine whether the questioned signature is genuine or not, this research uses features matching technique between questioned signature and set of genuine signatures. This method uses two steps verification, those are (1) verification using narrow variation features, and then (2) verification using wide variation features will be conducted if only if the result of first verification is a genuine signature. The second step only to make sure that the skilled forgery will be recognized.

1) **Narrow Variation:** Questioned signature (Q) is stated forgery if the distance (dQR) between Q and set of genuine signatures (R) below the determined threshold (A_{vs}), and can be formulated as follow:

$$Q = \begin{cases} genuine, if\ dQR\ \leq A_{vs} \\ forgery, if\ dQR\ > A_{vs} \end{cases} \quad (6)$$

2) **Wide Variation:** Questioned signature (Q) is stated forgery if the distance (d) Q and set of genuine signatures (R) below the determined threshold (A_{vl}), and it can be formulated as follow:

$$Q = \begin{cases} forgery, if\ dQR\ \leq A_{vl} \\ genuine, if\ dQR\ > A_{vl} \end{cases} \quad (7)$$

3) **Narrow Wide Variation:** is a verification process that merge between (1) and (2) sequentially, and can be formulated as follow:

$$Q = \begin{cases} dQR \leq A_{vs} \begin{cases} forgery, if\ dminQR\ \leq A_{vl} \\ genuine, if\ dminQR\ > A_{vl} \end{cases} \\ \qquad forgery, if\ dQR\ > A_{vs} \end{cases} \quad (8)$$

Reference Feature Extraction (R)

A number of M genuine signatures of each R are extracted by dividing the signature area by N and a number of L levels, so that each area can be calculated the level of variation v, average distance, and its deviation standard using formula (5), (2), (3) and (4), as follow:

$$V = \{V_1,\ V_2, \dots, V_P\}$$
$$V_p = \begin{Bmatrix} \{v_{01}, v_{02}, \dots, v_{0,N}\}, \{v_{11}, v_{12}, \dots, v_{1,N}\}, \\ \dots, \{v_{L1}, v_{L2}, \dots, v_{L,N}\} \end{Bmatrix} \quad (9)$$

where

$$v_{ln} = \sqrt{mean(\{(x_{lnm} - x_{ln})^2 +\ (y_{lnm} - y_{ln})^2\})}$$

x_{lnm} is the x coordinate on the lth level, the nth area, and the mth signature, y_{lnm} is the y coordinate at the lth level, the nth area, and the mth signature, x_{ln} is the average of x coordinate at level l and area n.

$$Dmean = \{Dmean_1, Dmean_2\ , \dots, Dmean_P\}$$
$$Dmean_p = \begin{Bmatrix} \{dm_{01}, dm_{02}, \dots, dm_{0N}\}, \{dm_{11}, dm_{12}, \dots, dm_{1N}\}, \\ \dots, \{dm_{L1}, dm_{L2}, \dots, dm_{LN}\} \end{Bmatrix}$$
(10)

where $dm_{ln} = mean\left\{\sqrt{\{x_{lni} - x_{lnj}\}^2 + \{y_{lni} - y_{lnj}\}^2}\right\}$

and $1 \leq i \leq M, 1 \leq j \leq M, and\ i\ \neq j$

Feature Extraction of Questioned Signature (Q)

Feature extraction of Q is conducted using same procedure and methods as for R.

Verification of Questioned Signature (Q)

To verify Q, it should be calculated: (1) the distance between the period Q (dQR) in the area corresponding to the area in R, this quantity will be used to measure the level of difference between Q and R; (2) the minimum distance between the centroid of mass of Q and the set of centroid of mass of R (dminQR) in the corresponding area Q and R, this quantity will be used to determine the level of similarity between Q and R; (3) the cumulative distance of dQR and dminQRc for a number of inspection points (dQRc and dminQRc) that will be compared with the threshold A_{vs} and A_{vl} in formula (6), (7), and (8) to decide whether Q is genuine or not.

1) Distance Between Q and R

The distance between the area in Q and the area in the corresponding R can be calculated using a two-point distance formula that is:

$$dQR_{lij} = \sqrt{\left(x_{qli} - x_{rli}\right)^2 - \left(y_{qli} - y_{rli}\right)^2} \quad (9)$$

where x_{qli}, y_{qli} is the value of x, y coordinates the point of the ladder area and the i area of the signature checked (Q) and x_{rli}, y_{rli} is the value of x, y the average coordinate point of the l area and the i area of the reference signature (R).

2) Minimum Distance between Q and R

The minimum distance between Q and R is required for checking wide variations. The minimum distance $dminQR$ can be calculated using the following formula:

$$dminQR = \min(\left\{\sqrt{\left(x_{qli} - x_{rmli}\right)^2 - (y_{rli} - y_{rmli})^2}\right\}) \quad (10)$$

where x_{qli}, y_{qli} is the value of x, y coordinates the point of the l area and the i area of the signature checked (Q) and x_{rmli}, y_{rmli} is the value of x, y coordinates the centroid of mass for area in level l and i of m reference signature (R).

3) Cumulative Distance dQRc and Threshold A_{vs}

In verifying signature Q, it uses a narrow variation required k area of comparison with R selected based on the ascending radius sequence of v where $k\ is\ 1 \leq k \leq K$. The threshold A_{vs} can be calculated using following formula;

$$A_{vs,k} = \sqrt{\sum_{i=1}^{i=K} dm_k^2} \quad (11)$$

So that cumulative distance between Q and R can be calculated using:

$$dQRc_k = \sqrt{\sum_{i=1}^{i=K} dQR_i^2} \quad (12)$$

where $1 \leq i \leq K,$ K is dependent variable.

4 RESULT AND ANALYSIS

The experiment is conducted in two steps, those are (1) verification using narrow variety; (2) verification using narrow and wide variety.

4.1 Narrow Variety

For this experiment, it uses three difference threshold of A_{vs}, such as (1) Dmean, average distance between centroid of mass; (2) Radius, variation level of a set of centroid of mass; and (3) Dmean+DStd, average distance between centroid of mass plus its deviation standard. The value of three threshold fulfill condition Dmean < Radius < Dmean+Dstd.
Based on Figure 2,3,4 it can be concluded that:

1. The more inspection points (1 until 10), the more accurate results (ACC) and FAR, but FRR gets worse.
2. The best accuracy is achieved in condition where A_{vs} = Dmean, where FRR and FAR almost equal (see Figure. 1). This is an optimal point where the accuracy of verification is highest. This highest accuracy around 70% is conformance to research result of [24] in case of geometry features.
3. The addition of further inspection points tends to produce small system performance changes, from 256 points of variation (level 4) only required no more than 10 check points.

In general, it can be concluded that a few number of comparison is suficien to make decision so that the time of verification can be decreased. In opposite, previouse methods [4][5][6][7][10] should compare the features for the whole signature. The system performance measurement shown in Fig. 1, 2, 3 is the performance for the whole respondent. Therefor it is necessary to know the examination performance of each respondent to see its stability.

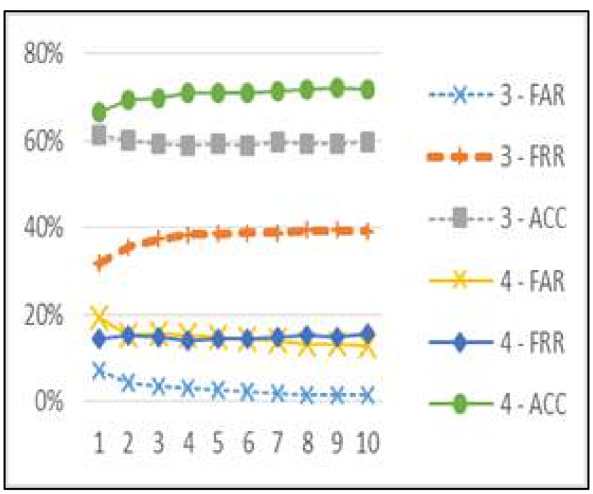


Fig. 2 *Performance of verification system of Dmean threshold, level 3 and 4, and number of point verification k=b=1 until 10 points.*

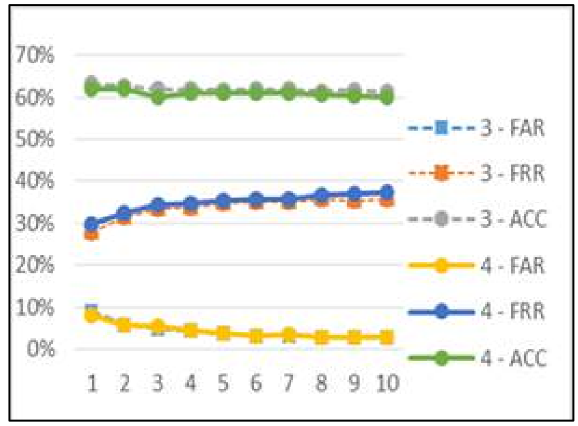


Fig. 3 *Performance of verification system of Radius threshold, level 3 and 4, and number of point verification k=b=1 until 10 points.*

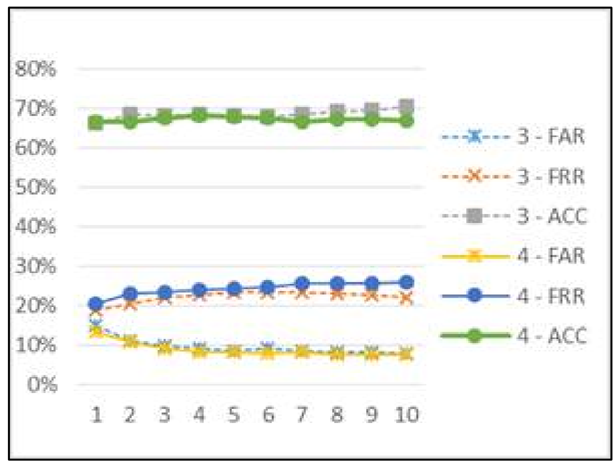


Fig. 4 *Performance of verification system of Dmean+Dstd threshold, level 3 and 4, and number of point verification k=b=1 until 10 points.*

4.2 Stability of the Performance of Verification System

In this research, it used a collection of signatures from 53 respondents. The results of the inspection performance of each respondent can be described as in Fig. 5. Based on Fig. 5 It can be seen that the accuracy of the verification ACC, FAR, and FRR varies between the signature collections, so it can be concluded that the verification performance depends on the signature data. The highest examination accuracy (ACC) in collection number 065 reached 94% at FAR value of 4.5% and FRR of 1.5%, and the lowest in collection number 051 which reached 36.5% at FAR value of 58.5% and FRR of 5%.

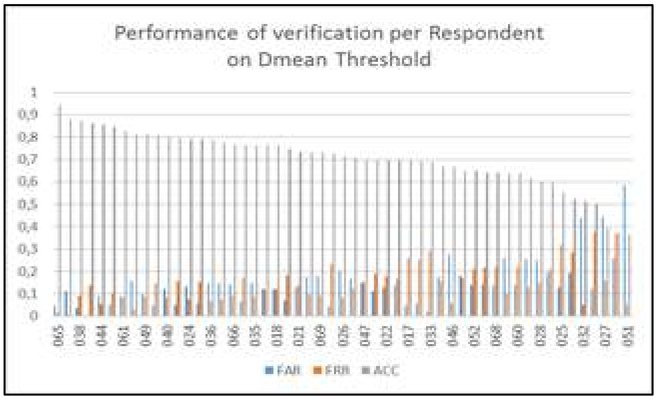


Fig. 5 *The stability of the verification system performance with the Dmean threshold, Level 4, and the number of check points k = b = 10 points to improve the accuracy of the inspection of each signature collection.*

4.3 Narrow and Wide Variety

This experiment tried to proof the argue of [17] that a skilled forgery is trapped by wide variety areas. Verification uses wide variations on the results of a narrow variation examination with genuine output intended to identify fake (Q) trained signatures (skilled forgery). The impact of applying the wide variation in verification is presented in Fig. 6 and 7. Based on Fig. 6 and 7 it can be concluded that the application of verification using Wide Variations has a beneficial and adverse effect. Some signatures show an improvement in checking accuracy (ACC) with repair values reaching 40% (see Fig. 6), other offline signature decrease in ACC value. In other words, the application of Wide Variations can improve the accuracy of checks on some signatures. For example, a collection of signatures 051 on a check with Narrow Variations shows the poorest audit performance, but after applying Wide Variety feature there is a performance improvement of 40%. Therefore, it is necessary to look for signature characteristics such as what can and cannot be applied by Width Variety so that the results of the examination are optimal. Examination of unregularity characteristic can be conducted either using sparse representation technique as in [25], or interval variability as used in [26], or Feature Dissimilarity Measure (FDM) as used in [27].

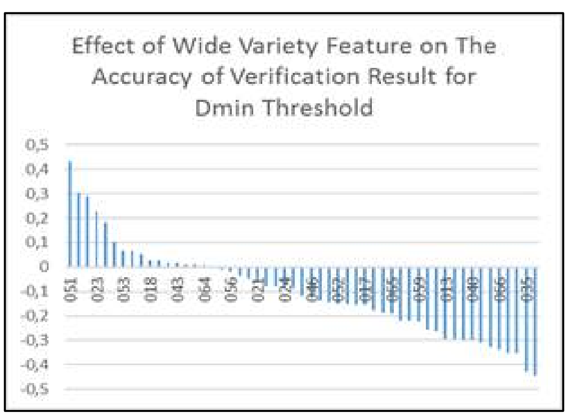


Fig. 6 *The impact of the implementation of the Width Variation on the accuracy of the verification with the threshold Dmin, Level 4, and the number of check points k = b = 10 points on the improvement of accuracy of verification of each signature.*

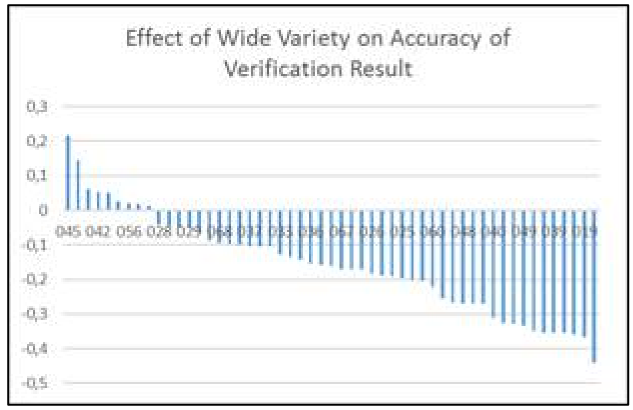


Fig. 7 *The impact of the implementation of the Width Variation verification on the accuracy of the verification with the threshold (Dmean-Dstd)> Dmin, Level 4, and the number of check points k = b = 10 points towards the improvement of accuracy of examination of each signature.*

In general, it can be conclude that the wide variety can improve the accuracy of verification for certain condition. This condition should be defined clearly before to be a wide variety feature can be applied.

5 CONCLUSION

Based on the results of the experiment and analysis of the results it can be concluded that:

1. The more inspection points the more accurate the results of the examination (see ACC values in Fig. 2, 3, and 4)
2. The addition of inspection points tends to lead to the inspection performance limit line so that all the points are not examined. In this study of 256 inspection points (level 4), no more than 10 check points were needed.
3. Use of Wide Variation feature can improve verification performance for some signature collections (see Fig. 6 and 7 in collections with a value of positive accuracy improvement)

6 FURTHER RESEARCH

Based on the conclusions obtained, the verification performance improvement can be done through:

1. Looking for an estimation of values that can be used for decision making, whether or not Wide Variation feature should be applied so that the verification performance improvement is maximized.
2. Need to be retested using more precise features and retest on different datasets to see the level of system performance stability in different datasets.

7 ACKNOWLEDGEMENT

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Impact Of Wide Variety Feature On Accuracy Of Offline Signature Verification Using Distance Of Mass Centroid

Agung Sediyono, Binti Sholihah, Yani Nur Syamsu, Gatot Budi Santoso

Abstract: Study on offline signature has been conducted for several years. Skilled forgery verification is difficult to be verified because of the highest similarity between genuine and forgery signature. Based on previous research, it can be concluded that genuine offline signature is never similar, but it still has consistent features. Otherwise, skilled forgery tries to mimic genuine offline signature as similar as possible. It can be hipotized that if skilled forgery signature is matched to genuine signature, it should match on consistent parts (narrow variety) and unmatch on inconsistent features (wide variety). In this reseach, the offline signature verification is conducted by two steps. In first step, the comparison is conducted based on consistant features as most researcher done. In second step, an acceptance result of first verification will be reverification using inconsistant features in order to improve the verification accuracy in case skilled forgery. Based on the experiment, it can be concluded that this proposed method can improve the verification accuracy for certain condition or depend on writer signature characteristic. Therefore, this approach can be applied only if only the conformance characteristic of writer offline signature can be identified before second step of verivication can be done. At least, this result contribute to open mind that wide variety feature can be used in offline signature verification.

Indeks Term: mass centroid, narrow variety, offline signature verification, pattern recognition, skilled forgery, verification accuracy, wide variety

1. INTRODUCTION

IN 2012, Indonesia had offline signature forgery as much as 589 cases: 212 cases in PUSLABFOR, 88 cases in LABFORCAB Medan, 88 cases in LABFORCAB Surabaya, 73 cases in LABFORCAB Semarang, 54 cases in LABFORCAB Makasar, 34 cases in LABFORCAB Palembang, and 26 in LABFORCAB Bali. These offline signature forgery cases can be categorized into three categories, such as skilled forgery, moderate forgery, and random forgery. Other interesting case is denial forgery because of his signature different to his own. All cases are offline handwritten signature that be collected from forgery documents [1]. Skilled forgery is the hardest task because it can be mistake even though it was verified by skilled verificator [2]. Therefore, it should be aided by computer application to help for supportive or comparative result in making decision. Research on computer based offline signature verification is conducted by researchers. Based on feature used in decision making, offline signature research can be divided by global and local feature. Global feature cannot be used for skilled forgery verification because the different signature probably has a same global feature. Otherwise, local feature can improve the accuracy of verification for skilled forgery [3]-[15]. The research results proofed that the accuracy of verification was satisfy on either moderate or random forgery, but not for skilled forgery. Nevertheless, there are many important things that should be payed attention, those are: (1) the accuracy of verification can be increased by paying attention on various part of the signatures in same people [11][13][14]; (2) level of variation should pay attention on the time period of the signature [2][15]; (3) level of accuracy depends on the detail of local feature [6][9][10], properly choicing the level of local feature variation and increasing training data [7][8][10]. However, the detail of local feature will be constrained by limited training data [16]. Based on that finding, local feature and level of variation hold important role in improving the accuracy of verification, as long as number of training data cannot be increased because of availability of offline signature in a certain period. Therefore, it needs to be conducted the further research how to increase accuracy of verification that focus on local feature and level of variation of offline signature [17]. Skilled forgery is difficult to be solved by previous methods because: (1) level of variation will be related to the level of easiness of skilled forgery [13], so that the verification of skilled forgery using either variation range or neural network method will be failed because of the signature nearly similar; (2) image matching technique comparing the parts of signature structurally, statistically, and morphologically tend to unsuccess because forger try to create signature as same as the genuine. Moreover, by using cloning tool, offline signature can be created similar to the genuine [2]. Based on the fact that the segment of the offline signature structure of someone is never similar [6][13][15], and the skilled forger tends to creating offline signature as similar as possible [2], and also the level of signature variation related to the easily of forgery [13], skilled forger will be trapped on the signature segments that have wide variation. Otherwise, random and moderate forger will be trapped on narrow variation. Therefore, it can be hypothesized that skilled forgery can be identified by using wide variation segment and random forgery can be identified by using narrow variation segment [17]. This research will proof this hypothesis.

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2 NARROW AND WIDE VARIETY AREAS

On the offline signature verification using local feature, the offline signature will be divided into small parts of signature and the questioned signature will be compared to the genuine signature. Several number of genuine signatures will be used as data training, and it will produce a set of variation area

because the offline signature of someone is never similar [6][13][15]. If the area of offline signature is divided by n, it will produce a set of variation $\{v_1, v_2, v_3, \ldots, v_n\}$. If this member of set is ordered ascendingly, it can be taken a set of narrow variation $\{v_1, v_2, \ldots v_k\}$ and a set of wide variety $\{v_b, \ldots, v_{n-1}, v_n\}$ where k < b are independent variables. In this research, the local features will be resulted from extracting the centroid of mass of the segment of offline signature.

2.1 Centroid of Mass

Centroid of mass (C) is average position of all parts of object representing centered point of object mass. Centroid of mass of an object can be calculated by

$$C(x,y) = \left(\frac{\mu_{1,0}}{\mu_{0,0}}, \frac{\mu_{0,1}}{\mu_{0,0}}\right) \quad (1)$$

where

$$\mu_{0,0} = \sum_{x=0}^{w}\sum_{y=0}^{h} f(x,y),\ \mu_{1,0} = \frac{\sum\sum x\, f(x,y)}{\mu_{0,0}},$$

$$\mu_{0,1} = \frac{\sum\sum y\, f(x,y)}{\mu_{0,0}}$$

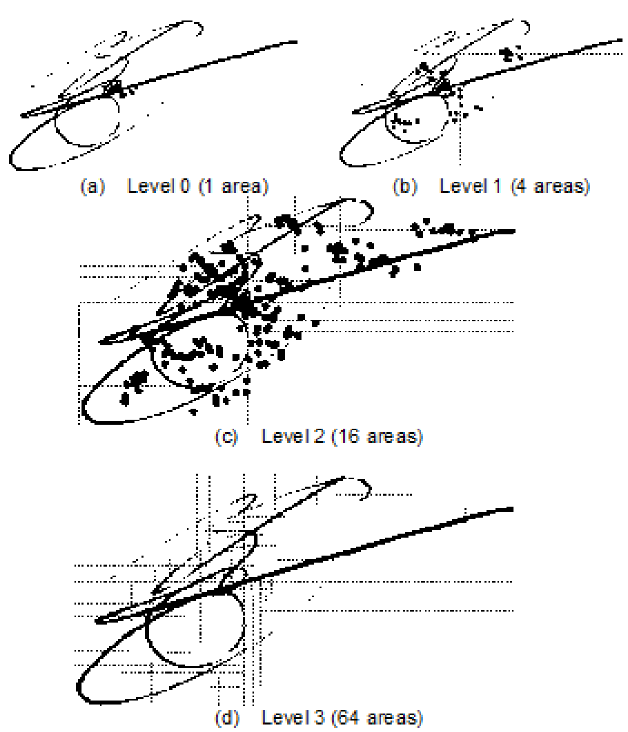
2.2 Distance, Mean, and Variance of the Centroid of Mass

Distance of two centroids of mass can be calculated as a distance of two points, as follow:

$$d_{ij} = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \quad (2)$$

$$\mu_d = mean(\{d_{ij}\}) \quad (3)$$

$$\sigma_d = std(\{d_{ij}\}) \quad (4)$$



(a) Level 0 (1 area) (b) Level 1 (4 areas) (c) Level 2 (16 areas) (d) Level 3 (64 areas)

Fig. 1. Example of area of verification

where 1≤ i ≤ n, 1 ≤ j ≤ n, n are number of mass centroids.

2.3 Variety of the Centroid of Mass

Variety of the Centroid of Mass represented by the mean of distance set of centroid of mass can be calculated by:

$$v_j = \sqrt{mean(\{(x_{ij} - x_{cj})^2 + (y_{ij} - y_{cj})^2\})} \quad (5)$$

where x_{ij}, y_{ij} is the point coodinate of mass of area j of signature i, and x_{cj} is *mean* of $\{x_{ij}\}$, y_{cj} is mean of $\{y_{ij}\}$ area j and signature i in signature collecton. Therefore, v_j represent the average of center point of circle x_{cj}, y_{cj}. Value of v_j represent the level of spreading of mass centroids set.

3 METHODOLOGY

This research uses experiment methodology, as follow:

3.1 Dataset

Dataset of experiment is taken from SigComp2011 [23], where the composition of dataset as in Table 1.

TABLE 1.
COMPOSITION OF OFFLINE SIGNATURE DATASET

Item	Training	Testing	
	Genuine	Genuine	Questioned
Number of respondence	53	53	53
Number of signatures per respondence	12	12	3
Number of signatures	636	636	636

3.2 Normalization of Offline Signature Image

For the best result of signature verification, offline signature images should be normalized dan cleaned from noise. Image normalization is sized by either enlarging or shrinking the image proportionally so that all images have same dimension. In this research, the first image is selected to be an image reference and then the rest images will be sized to the size of reference image.

3.3 Signature Areas Division

Every area of signature is divided by four where the center of division is centroid of mass of the area [10]. In this research the depth of division is only four level, so that it has a number of areas per level as in Table 2

TABLE 2.
NUMBER OF AREAS PER LEVEL

Level	Number of Areas
0	1
1	4
2	16
3	64
4	256

Figure 1. show the areas as defined in Table 2, except for level 4 is not visualized because of its complexity.

3.4 Evaluation Criteria

There are two evaluation criteria's, those are (1) evaluation criteria for assessing the performance of verification system; (2) evaluation criteria for determining whether the signature is

genuine or not. Evaluation criteria of verification system measure the accuracy of system verification namely (ACC), false acceptance rate (FAR), and false rejected rate (FRR). ACC is calculated from number of false verifications divided by number of verifications. FAR is a number of false acceptances divided by number of signature verification. FRR is a number of false rejected verification divided by a number of signature verification. To determine whether the questioned signature is genuine or not, this research uses features matching technique between questioned signature and set of genuine signatures. This method uses two steps verification, those are (1) verification using narrow variation features, and then (2) verification using wide variation features will be conducted if only if the result of first verification is a genuine signature. The second step only to make sure that the skilled forgery will be recognized.

1) **Narrow Variation:** Questioned signature (Q) is stated forgery if the distance (dQR) between Q and set of genuine signatures (R) below the determined threshold (A_{vs}), and can be formulated as follow:

$$Q = \begin{cases} genuine, if\ dQR \le A_{vs} \\ forgery, if\ dQR > A_{vs} \end{cases} \quad (6)$$

2) **Wide Variation:** Questioned signature (Q) is stated forgery if the distance (d) Q and set of genuine signatures (R) below the determined threshold (A_{vl}), and it can be formulated as follow:

$$Q = \begin{cases} forgery, if\ dQR \le A_{vl} \\ genuine, if\ dQR > A_{vl} \end{cases} \quad (7)$$

3) **Narrow Wide Variation:** is a verification process that merge between (1) and (2) sequentially, and can be formulated as follow:

$$Q = \begin{cases} dQR \le A_{vs} \begin{cases} forgery, if\ dminQR \le A_{vl} \\ genuine, if\ dminQR > A_{vl} \end{cases} \\ \qquad forgery, if\ dQR > A_{vs} \end{cases} \quad (8)$$

Reference Feature Extraction (R)

A number of M genuine signatures of each R are extracted by dividing the signature area by N and a number of L levels, so that each area can be calculated the level of variation v, average distance, and its deviation standard using formula (5), (2), (3) and (4), as follow:

$$V = \{V_1, V_2, \dots, V_P\}$$
$$V_p = \begin{Bmatrix} \{v_{01}, v_{02}, \dots, v_{0,N}\}, \{v_{11}, v_{12}, \dots, v_{1,N}\}, \\ \dots, \{v_{L1}, v_{L2}, \dots, v_{L,N}\} \end{Bmatrix} \quad (9)$$

where

$$v_{ln} = \sqrt{mean(\{(x_{lnm} - x_{ln})^2 + (y_{lnm} - y_{ln})^2\})}$$

x_{lnm} is the x coordinate on the lth level, the nth area, and the mth signature, y_{lnm} is the y coordinate at the lth level, the nth area, and the mth signature, x_{ln} is the average of x coordinate at level l and area n.

$$Dmean = \{Dmean_1, Dmean_2, \dots, Dmean_P\}$$
$$Dmean_p = \begin{Bmatrix} \{dm_{01}, dm_{02}, \dots, dm_{0N}\}, \{dm_{11}, dm_{12}, \dots, dm_{1N}\}, \\ \dots, \{dm_{L1}, dm_{L2}, \dots, dm_{LN}\} \end{Bmatrix}$$
(10)

where $dm_{ln} = mean\left\{\sqrt{\{x_{lni} - x_{lnj}\}^2 + \{y_{lni} - y_{lnj}\}^2}\right\}$

and $1 \le i \le M, 1 \le j \le M, and\ i \ne j$

Feature Extraction of Questioned Signature (Q)

Feature extraction of Q is conducted using same procedure and methods as for R.

Verification of Questioned Signature (Q)

To verify Q, it should be calculated: (1) the distance between the period Q (dQR) in the area corresponding to the area in R, this quantity will be used to measure the level of difference between Q and R; (2) the minimum distance between the centroid of mass of Q and the set of centroid of mass of R (dminQR) in the corresponding area Q and R, this quantity will be used to determine the level of similarity between Q and R; (3) the cumulative distance of dQR and dminQRc for a number of inspection points (dQRc and dminQRc) that will be compared with the threshold A_{vs} and A_{vl} in formula (6), (7), and (8) to decide whether Q is genuine or not.

1) Distance Between Q and R

The distance between the area in Q and the area in the corresponding R can be calculated using a two-point distance formula that is:

$$dQR_{lij} = \sqrt{(x_{qli} - x_{rli})^2 - (y_{qli} - y_{rli})^2} \quad (9)$$

where x_{qli}, y_{qli} is the value of x, y coordinates the point of the ladder area and the i area of the signature checked (Q) and x_{rli}, y_{rli} is the value of x, y the average coordinate point of the l area and the i area of the reference signature (R).

2) Minimum Distance between Q and R

The minimum distance between Q and R is required for checking wide variations. The minimum distance $dminQR$ can be calculated using the following formula:

$$dminQR = \min(\left\{\sqrt{(x_{qli} - x_{rmli})^2 - (y_{rli} - y_{rmli})^2}\right\}) \quad (10)$$

where x_{qli}, y_{qli} is the value of x, y coordinates the point of the l area and the i area of the signature checked (Q) and x_{rmli}, y_{rmli} is the value of x, y coordinates the centroid of mass for area in level l and i of m reference signature (R).

3) Cumulative Distance dQRc and Threshold A_{vs}

In verifying signature Q, it uses a narrow variation required k area of comparison with R selected based on the ascending radius sequence of v where $k\ is\ 1 \le k \le K$. The threshold A_{vs} can be calculated using following formula;

$$A_{vs,k} = \sqrt{\textstyle\sum_{i=1}^{i=K} dm_k^2} \quad (11)$$

So that cumulative distance between Q and R can be calculated using:

$$dQRc_k = \sqrt{\textstyle\sum_{i=1}^{i=K} dQR_i^2} \quad (12)$$

where $1 \le i \le K$, K is dependent variable.

4 RESULT AND ANALYSIS

The experiment is conducted in two steps, those are (1) verification using narrow variety; (2) verification using narrow and wide variety.

4.1 Narrow Variety

For this experiment, it uses three difference threshold of A_{vs}, such as (1) Dmean, average distance between centroid of mass; (2) Radius, variation level of a set of centroid of mass; and (3) Dmean+DStd, average distance between centroid of mass plus its deviation standard. The value of three threshold fulfill condition Dmean < Radius < Dmean+Dstd.
Based on Figure 2,3,4 it can be concluded that:

1. The more inspection points (1 until 10), the more accurate results (ACC) and FAR, but FRR gets worse.
2. The best accuracy is achieved in condition where A_{vs} = Dmean, where FRR and FAR almost equal (see Figure. 1). This is an optimal point where the accuracy of verification is highest. This highest accuracy around 70% is conformance to research result of [24] in case of geometry features.
3. The addition of further inspection points tends to produce small system performance changes, from 256 points of variation (level 4) only required no more than 10 check points.

In general, it can be concluded that a few number of comparison is suficien to make decision so that the time of verification can be decreased. In opposite, previouse methods [4][5][6][7][10] should compare the features for the whole signature. The system performance measurement shown in Fig. 1, 2, 3 is the performance for the whole respondent. Therefor it is necessary to know the examination performance of each respondent to see its stability.

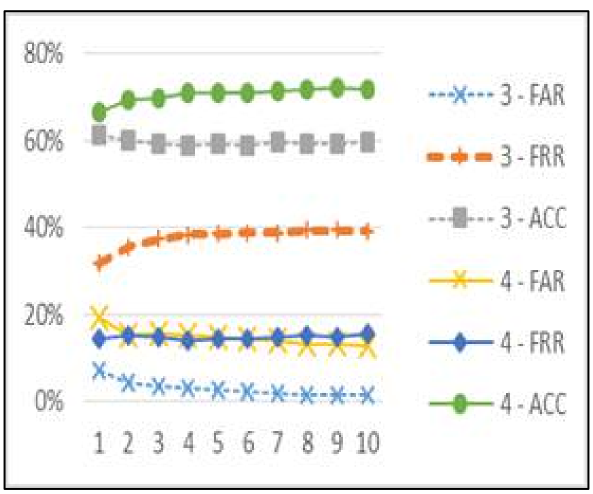


Fig. 2 *Performance of verification system of Dmean threshold, level 3 and 4, and number of point verification k=b=1 until 10 points.*

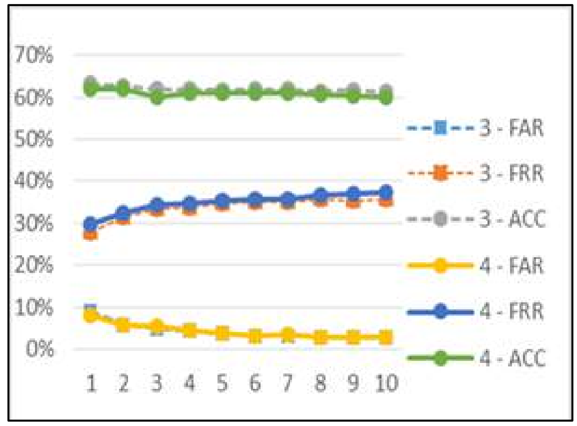


Fig. 3 *Performance of verification system of Radius threshold, level 3 and 4, and number of point verification k=b=1 until 10 points.*

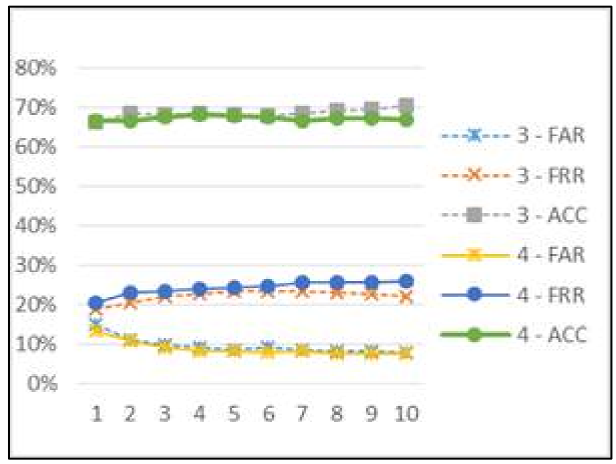


Fig. 4 *Performance of verification system of Dmean+Dstd threshold, level 3 and 4, and number of point verification k=b=1 until 10 points.*

4.2 Stability of the Performance of Verification System

In this research, it used a collection of signatures from 53 respondents. The results of the inspection performance of each respondent can be described as in Fig. 5. Based on Fig. 5 It can be seen that the accuracy of the verification ACC, FAR, and FRR varies between the signature collections, so it can be concluded that the verification performance depends on the signature data. The highest examination accuracy (ACC) in collection number 065 reached 94% at FAR value of 4.5% and FRR of 1.5%, and the lowest in collection number 051 which reached 36.5% at FAR value of 58.5% and FRR of 5%.

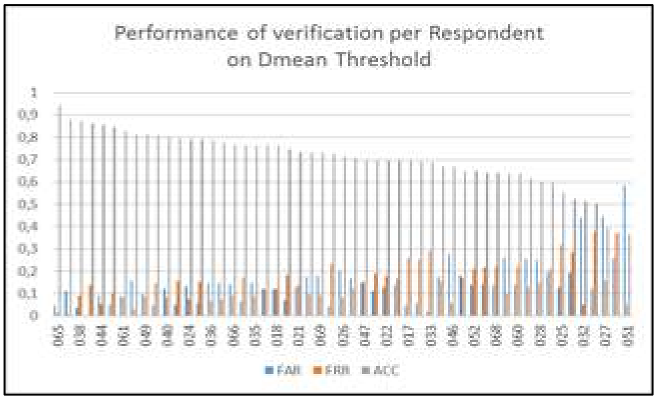


Fig. 5 *The stability of the verification system performance with the Dmean threshold, Level 4, and the number of check points k = b = 10 points to improve the accuracy of the inspection of each signature collection.*

4.3 Narrow and Wide Variety

This experiment tried to proof the argue of [17] that a skilled forgery is trapped by wide variety areas. Verification uses wide variations on the results of a narrow variation examination with genuine output intended to identify fake (Q) trained signatures (skilled forgery). The impact of applying the wide variation in verification is presented in Fig. 6 and 7. Based on Fig. 6 and 7 it can be concluded that the application of verification using Wide Variations has a beneficial and adverse effect. Some signatures show an improvement in checking accuracy (ACC) with repair values reaching 40% (see Fig. 6), other offline signature decrease in ACC value. In other words, the application of Wide Variations can improve the accuracy of checks on some signatures. For example, a collection of signatures 051 on a check with Narrow Variations shows the poorest audit performance, but after applying Wide Variety feature there is a performance improvement of 40%. Therefore, it is necessary to look for signature characteristics such as what can and cannot be applied by Width Variety so that the results of the examination are optimal. Examination of unregularity characteristic can be conducted either using sparse representation technique as in [25], or interval variability as used in [26], or Feature Dissimilarity Measure (FDM) as used in [27].

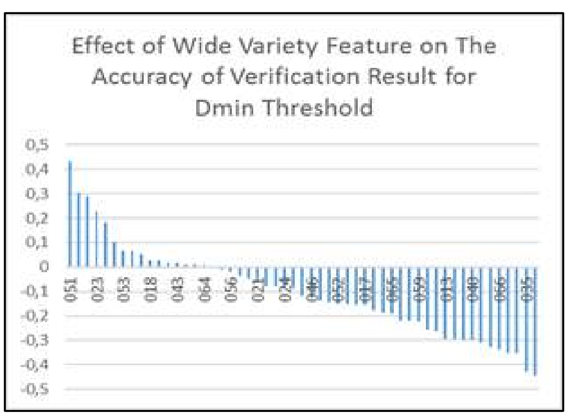


Fig. 6 *The impact of the implementation of the Width Variation on the accuracy of the verification with the threshold Dmin, Level 4, and the number of check points k = b = 10 points on the improvement of accuracy of verification of each signature.*

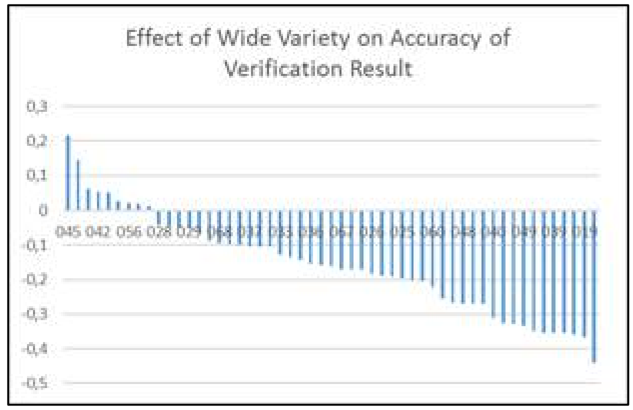


Fig. 7 *The impact of the implementation of the Width Variation verification on the accuracy of the verification with the threshold (Dmean-Dstd)> Dmin, Level 4, and the number of check points k = b = 10 points towards the improvement of accuracy of examination of each signature.*

In general, it can be conclude that the wide variety can improve the accuracy of verification for certain condition. This condition should be defined clearly before to be a wide variety feature can be applied.

5 CONCLUSION

Based on the results of the experiment and analysis of the results it can be concluded that:

1. The more inspection points the more accurate the results of the examination (see ACC values in Fig. 2, 3, and 4)
2. The addition of inspection points tends to lead to the inspection performance limit line so that all the points are not examined. In this study of 256 inspection points (level 4), no more than 10 check points were needed.
3. Use of Wide Variation feature can improve verification performance for some signature collections (see Fig. 6 and 7 in collections with a value of positive accuracy improvement)

6 FURTHER RESEARCH

Based on the conclusions obtained, the verification performance improvement can be done through:

1. Looking for an estimation of values that can be used for decision making, whether or not Wide Variation feature should be applied so that the verification performance improvement is maximized.
2. Need to be retested using more precise features and retest on different datasets to see the level of system performance stability in different datasets.

7 ACKNOWLEDGEMENT

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Impact Of Wide Variety Feature On Accuracy Of Offline Signature Verification Using Distance Of Mass Centroid

Agung Sediyono, Binti Sholihah, Yani Nur Syamsu, Gatot Budi Santoso

Abstract: Study on offline signature has been conducted for several years. Skilled forgery verification is difficult to be verified because of the highest similarity between genuine and forgery signature. Based on previous research, it can be concluded that genuine offline signature is never similar, but it still has consistent features. Otherwise, skilled forgery tries to mimic genuine offline signature as similar as possible. It can be hipotized that if skilled forgery signature is matched to genuine signature, it should match on consistent parts (narrow variety) and unmatch on inconsistent features (wide variety). In this reseach, the offline signature verification is conducted by two steps. In first step, the comparison is conducted based on consistant features as most researcher done. In second step, an acceptance result of first verification will be reverification using inconsistant features in order to improve the verification accuracy in case skilled forgery. Based on the experiment, it can be concluded that this proposed method can improve the verification accuracy for certain condition or depend on writer signature characteristic. Therefore, this approach can be applied only if only the conformance characteristic of writer offline signature can be identified before second step of verivication can be done. At least, this result contribute to open mind that wide variety feature can be used in offline signature verification.

Indeks Term: mass centroid, narrow variety, offline signature verification, pattern recognition, skilled forgery, verification accuracy, wide variety

1. INTRODUCTION

IN 2012, Indonesia had offline signature forgery as much as 589 cases: 212 cases in PUSLABFOR, 88 cases in LABFORCAB Medan, 88 cases in LABFORCAB Surabaya, 73 cases in LABFORCAB Semarang, 54 cases in LABFORCAB Makasar, 34 cases in LABFORCAB Palembang, and 26 in LABFORCAB Bali. These offline signature forgery cases can be categorized into three categories, such as skilled forgery, moderate forgery, and random forgery. Other interesting case is denial forgery because of his signature different to his own. All cases are offline handwritten signature that be collected from forgery documents [1]. Skilled forgery is the hardest task because it can be mistake even though it was verified by skilled verificator [2]. Therefore, it should be aided by computer application to help for supportive or comparative result in making decision. Research on computer based offline signature verification is conducted by researchers. Based on feature used in decision making, offline signature research can be divided by global and local feature. Global feature cannot be used for skilled forgery verification because the different signature probably has a same global feature. Otherwise, local feature can improve the accuracy of verification for skilled forgery [3]-[15]. The research results proofed that the accuracy of verification was satisfy on either moderate or random forgery, but not for skilled forgery. Nevertheless, there are many important things that should be payed attention, those are: (1) the accuracy of verification can be increased by paying attention on various part of the signatures in same people [11][13][14]; (2) level of variation should pay attention on the time period of the signature [2][15]; (3) level of accuracy depends on the detail of local feature [6][9][10], properly choicing the level of local feature variation and increasing training data [7][8][10]. However, the detail of local feature will be constrained by limited training data [16]. Based on that finding, local feature and level of variation hold important role in improving the accuracy of verification, as long as number of training data cannot be increased because of availability of offline signature in a certain period. Therefore, it needs to be conducted the further research how to increase accuracy of verification that focus on local feature and level of variation of offline signature [17]. Skilled forgery is difficult to be solved by previous methods because: (1) level of variation will be related to the level of easiness of skilled forgery [13], so that the verification of skilled forgery using either variation range or neural network method will be failed because of the signature nearly similar; (2) image matching technique comparing the parts of signature structurally, statistically, and morphologically tend to unsuccess because forger try to create signature as same as the genuine. Moreover, by using cloning tool, offline signature can be created similar to the genuine [2]. Based on the fact that the segment of the offline signature structure of someone is never similar [6][13][15], and the skilled forger tends to creating offline signature as similar as possible [2], and also the level of signature variation related to the easily of forgery [13], skilled forger will be trapped on the signature segments that have wide variation. Otherwise, random and moderate forger will be trapped on narrow variation. Therefore, it can be hypothesized that skilled forgery can be identified by using wide variation segment and random forgery can be identified by using narrow variation segment [17]. This research will proof this hypothesis.

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2 NARROW AND WIDE VARIETY AREAS

On the offline signature verification using local feature, the offline signature will be divided into small parts of signature and the questioned signature will be compared to the genuine signature. Several number of genuine signatures will be used as data training, and it will produce a set of variation area

because the offline signature of someone is never similar [6][13][15]. If the area of offline signature is divided by n, it will produce a set of variation $\{v_1, v_2, v_3, \ldots, v_n\}$. If this member of set is ordered ascendingly, it can be taken a set of narrow variation $\{v_1, v_2, \ldots v_k\}$ and a set of wide variety $\{v_b, \ldots, v_{n-1}, v_n\}$ where k < b are independent variables. In this research, the local features will be resulted from extracting the centroid of mass of the segment of offline signature.

2.1 Centroid of Mass

Centroid of mass (C) is average position of all parts of object representing centered point of object mass. Centroid of mass of an object can be calculated by

$$C(x,y) = \left(\frac{\mu_{1,0}}{\mu_{0,0}}, \frac{\mu_{0,1}}{\mu_{0,0}}\right) \quad (1)$$

where

$$\mu_{0,0} = \sum_{x=0}^{w}\sum_{y=0}^{h} f(x,y),\ \mu_{1,0} = \frac{\sum\sum x\, f(x,y)}{\mu_{0,0}},$$

$$\mu_{0,1} = \frac{\sum\sum y\, f(x,y)}{\mu_{0,0}}$$

2.2 Distance, Mean, and Variance of the Centroid of Mass

Distance of two centroids of mass can be calculated as a distance of two points, as follow:

$$d_{ij} = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \quad (2)$$

$$\mu_d = mean(\{d_{ij}\}) \quad (3)$$

$$\sigma_d = std(\{d_{ij}\}) \quad (4)$$

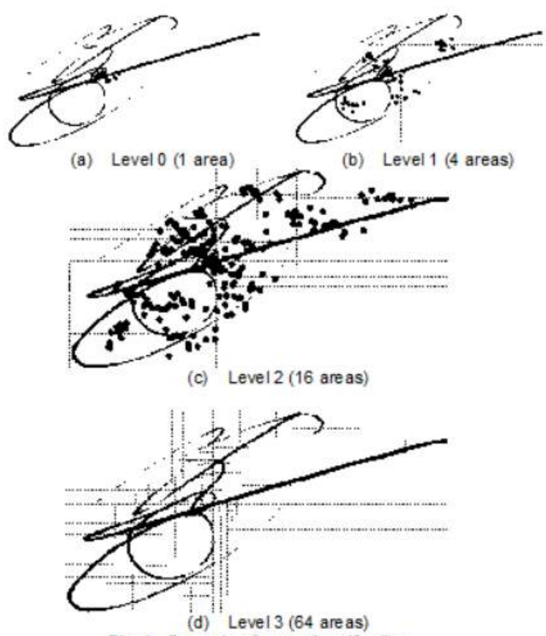

Fig. 1. Example of area of verification

where $1 \le i \le n$, $1 \le j \le n$, n are number of mass centroids.

2.3 Variety of the Centroid of Mass

Variety of the Centroid of Mass represented by the mean of distance set of centroid of mass can be calculated by:

$$v_j = \sqrt{mean(\{(x_{ij} - x_{cj})^2 + (y_{ij} - y_{cj})^2\})} \quad (5)$$

where x_{ij}, y_{ij} is the point coodinate of mass of area j of signature i, and x_{cj} is *mean* of $\{x_{ij}\}$, y_{cj} is mean of $\{y_{ij}\}$ area j and signature i in signature collecton. Therefore, v_j represent the average of center point of circle x_{cj}, y_{cj}. Value of v_j represent the level of spreading of mass centroids set.

3 METHODOLOGY

This research uses experiment methodology, as follow:

3.1 Dataset

Dataset of experiment is taken from SigComp2011 [23], where the composition of dataset as in Table 1.

TABLE 1.
COMPOSITION OF OFFLINE SIGNATURE DATASET

Item	Training	Testing	
	Genuine	Genuine	Questioned
Number of respondence	53	53	53
Number of signatures per respondence	12	12	3
Number of signatures	636	636	636

3.2 Normalization of Offline Signature Image

For the best result of signature verification, offline signature images should be normalized dan cleaned from noise. Image normalization is sized by either enlarging or shrinking the image proportionally so that all images have same dimension. In this research, the first image is selected to be an image reference and then the rest images will be sized to the size of reference image.

3.3 Signature Areas Division

Every area of signature is divided by four where the center of division is centroid of mass of the area [10]. In this research the depth of division is only four level, so that it has a number of areas per level as in Table 2

TABLE 2.
NUMBER OF AREAS PER LEVEL

Level	Number of Areas
0	1
1	4
2	16
3	64
4	256

Figure 1. show the areas as defined in Table 2, except for level 4 is not visualized because of its complexity.

3.4 Evaluation Criteria

There are two evaluation criteria's, those are (1) evaluation criteria for assessing the performance of verification system; (2) evaluation criteria for determining whether the signature is

genuine or not. Evaluation criteria of verification system measure the accuracy of system verification namely (ACC), false acceptance rate (FAR), and false rejected rate (FRR). ACC is calculated from number of false verifications divided by number of verifications. FAR is a number of false acceptances divided by number of signature verification. FRR is a number of false rejected verification divided by a number of signature verification. To determine whether the questioned signature is genuine or not, this research uses features matching technique between questioned signature and set of genuine signatures. This method uses two steps verification, those are (1) verification using narrow variation features, and then (2) verification using wide variation features will be conducted if only if the result of first verification is a genuine signature. The second step only to make sure that the skilled forgery will be recognized.

1) Narrow Variation: Questioned signature (Q) is stated forgery if the distance (dQR) between Q and set of genuine signatures (R) below the determined threshold (A_{vs}), and can be formulated as follow:

$$Q = \begin{cases} genuine, if\ dQR \le A_{vs} \\ forgery, if\ dQR > A_{vs} \end{cases} \quad (6)$$

2) Wide Variation: Questioned signature (Q) is stated forgery if the distance (d) Q and set of genuine signatures (R) below the determined threshold (A_{vl}), and it can be formulated as follow:

$$Q = \begin{cases} forgery, if\ dQR \le A_{vl} \\ genuine, if\ dQR > A_{vl} \end{cases} \quad (7)$$

3) Narrow Wide Variation: is a verification process that merge between (1) and (2) sequentially, and can be formulated as follow:

$$Q = \begin{cases} dQR \le A_{vs} \begin{cases} forgery, if\ dminQR \le A_{vl} \\ genuine, if\ dminQR > A_{vl} \end{cases} \\ \qquad forgery, if\ dQR > A_{vs} \end{cases} \quad (8)$$

Reference Feature Extraction (R)

A number of M genuine signatures of each R are extracted by dividing the signature area by N and a number of L levels, so that each area can be calculated the level of variation v, average distance, and its deviation standard using formula (5), (2), (3) and (4), as follow:

$$V = \{V_1,\ V_2, \dots, V_P\}$$
$$V_p = \begin{Bmatrix} \{v_{01}, v_{02}, \dots, v_{0,N}\}, \{v_{11}, v_{12}, \dots, v_{1,N}\}, \\ \dots, \{v_{L1}, v_{L2}, \dots, v_{L,N}\} \end{Bmatrix} \quad (9)$$

where

$$v_{ln} = \sqrt{mean(\{(x_{lnm} - x_{ln})^2 + \ (y_{lnm} - y_{ln})^2\})}$$

x_{lnm} is the x coordinate on the lth level, the nth area, and the mth signature, y_{lnm} is the y coordinate at the lth level, the nth area, and the mth signature, x_{ln} is the average of x coordinate at level l and area n.

$$Dmean = \{Dmean_1, Dmean_2, \dots, Dmean_P\}$$
$$Dmean_p = \begin{Bmatrix} \{dm_{01}, dm_{02}, \dots, dm_{0N}\}, \{dm_{11}, dm_{12}, \dots, dm_{1N}\}, \\ \dots, \{dm_{L1}, dm_{L2}, \dots, dm_{LN}\} \end{Bmatrix}$$
(10)

where $dm_{ln} = mean\left\{\sqrt{\{x_{lni} - x_{lnj}\}^2 + \{y_{lni} - y_{lnj}\}^2}\right\}$

and $1 \le i \le M, 1 \le j \le M, and\ i \ne j$

Feature Extraction of Questioned Signature (Q)

Feature extraction of Q is conducted using same procedure and methods as for R.

Verification of Questioned Signature (Q)

To verify Q, it should be calculated: (1) the distance between the period Q (dQR) in the area corresponding to the area in R, this quantity will be used to measure the level of difference between Q and R; (2) the minimum distance between the centroid of mass of Q and the set of centroid of mass of R (dminQR) in the corresponding area Q and R, this quantity will be used to determine the level of similarity between Q and R; (3) the cumulative distance of dQR and dminQRc for a number of inspection points (dQRc and dminQRc) that will be compared with the threshold A_{vs} and A_{vl} in formula (6), (7), and (8) to decide whether Q is genuine or not.

1) Distance Between Q and R

The distance between the area in Q and the area in the corresponding R can be calculated using a two-point distance formula that is:

$$dQR_{lij} = \sqrt{(x_{qli} - x_{rli})^2 - (y_{qli} - y_{rli})^2} \quad (9)$$

where x_{qli}, y_{qli} is the value of x, y coordinates the point of the ladder area and the i area of the signature checked (Q) and x_{rli}, y_{rli} is the value of x, y the average coordinate point of the l area and the i area of the reference signature (R).

2) Minimum Distance between Q and R

The minimum distance between Q and R is required for checking wide variations. The minimum distance $dminQR$ can be calculated using the following formula:

$$dminQR = \min(\left\{\sqrt{(x_{qli} - x_{rmli})^2 - (y_{rli} - y_{rmli})^2}\right\}) \quad (10)$$

where x_{qli}, y_{qli} is the value of x, y coordinates the point of the l area and the i area of the signature checked (Q) and x_{rmli}, y_{rmli} is the value of x, y coordinates the centroid of mass for area in level l and i of m reference signature (R).

3) Cumulative Distance dQRc and Threshold A_{vs}

In verifying signature Q, it uses a narrow variation required k area of comparison with R selected based on the ascending radius sequence of v where $k\ is\ 1 \le k \le K$. The threshold A_{vs} can be calculated using following formula;

$$A_{vs,k} = \sqrt{\textstyle\sum_{i=1}^{i=K} dm_k^2} \quad (11)$$

So that cumulative distance between Q and R can be calculated using:

$$dQRc_k = \sqrt{\textstyle\sum_{i=1}^{i=K} dQR_i^2} \quad (12)$$

where $1 \le i \le K$, K is dependent variable.

4 RESULT AND ANALYSIS

The experiment is conducted in two steps, those are (1) verification using narrow variety; (2) verification using narrow and wide variety.

4.1 Narrow Variety

For this experiment, it uses three difference threshold of A_{vs}, such as (1) Dmean, average distance between centroid of mass; (2) Radius, variation level of a set of centroid of mass; and (3) Dmean+DStd, average distance between centroid of mass plus its deviation standard. The value of three threshold fulfill condition Dmean < Radius < Dmean+Dstd.
Based on Figure 2,3,4 it can be concluded that:

1. The more inspection points (1 until 10), the more accurate results (ACC) and FAR, but FRR gets worse.
2. The best accuracy is achieved in condition where A_{vs} = Dmean, where FRR and FAR almost equal (see Figure. 1). This is an optimal point where the accuracy of verification is highest. This highest accuracy around 70% is conformance to research result of [24] in case of geometry features.
3. The addition of further inspection points tends to produce small system performance changes, from 256 points of variation (level 4) only required no more than 10 check points.

In general, it can be concluded that a few number of comparison is suficien to make decision so that the time of verification can be decreased. In opposite, previouse methods [4][5][6][7][10] should compare the features for the whole signature. The system performance measurement shown in Fig. 1, 2, 3 is the performance for the whole respondent. Therefor it is necessary to know the examination performance of each respondent to see its stability.

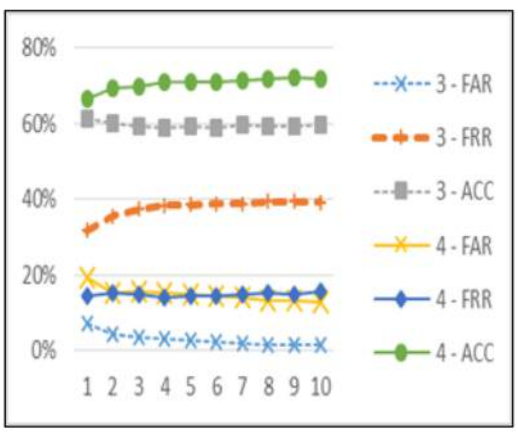

Fig. 2 *Performance of verification system of Dmean threshold, level 3 and 4, and number of point verification k=b=1 until 10 points.*

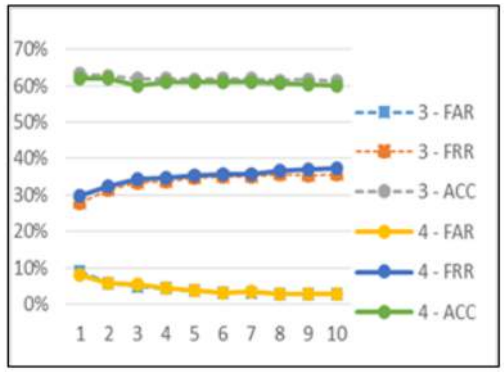

Fig. 3 *Performance of verification system of Radius threshold, level 3 and 4, and number of point verification k=b=1 until 10 points.*

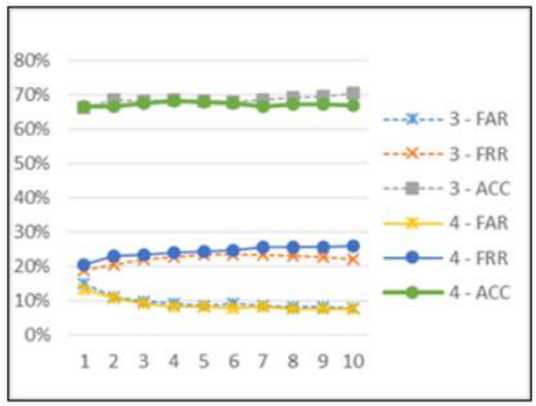

Fig. 4 *Performance of verification system of Dmean+Dstd threshold, level 3 and 4, and number of point verification k=b=1 until 10 points.*

4.2 Stability of the Performance of Verification System

In this research, it used a collection of signatures from 53 respondents. The results of the inspection performance of each respondent can be described as in Fig. 5. Based on Fig. 5 It can be seen that the accuracy of the verification ACC, FAR, and FRR varies between the signature collections, so it can be concluded that the verification performance depends on the signature data. The highest examination accuracy (ACC) in collection number 065 reached 94% at FAR value of 4.5% and FRR of 1.5%, and the lowest in collection number 051 which reached 36.5% at FAR value of 58.5% and FRR of 5%.

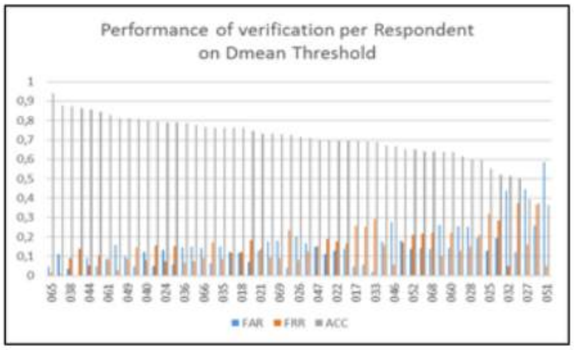

***Fig. 5** The stability of the verification system performance with the Dmean threshold, Level 4, and the number of check points k = b = 10 points to improve the accuracy of the inspection of each signature collection.*

4.3 Narrow and Wide Variety

This experiment tried to proof the argue of [17] that a skilled forgery is trapped by wide variety areas. Verification uses wide variations on the results of a narrow variation examination with genuine output intended to identify fake (Q) trained signatures (skilled forgery). The impact of applying the wide variation in verification is presented in Fig. 6 and 7. Based on Fig. 6 and 7 it can be concluded that the application of verification using Wide Variations has a beneficial and adverse effect. Some signatures show an improvement in checking accuracy (ACC) with repair values reaching 40% (see Fig. 6), other offline signature decrease in ACC value. In other words, the application of Wide Variations can improve the accuracy of checks on some signatures. For example, a collection of signatures 051 on a check with Narrow Variations shows the poorest audit performance, but after applying Wide Variety feature there is a performance improvement of 40%. Therefore, it is necessary to look for signature characteristics such as what can and cannot be applied by Width Variety so that the results of the examination are optimal. Examination of unregularity characteristic can be conducted either using sparse representation technique as in [25], or interval variability as used in [26], or Feature Dissimilarity Measure (FDM) as used in [27].

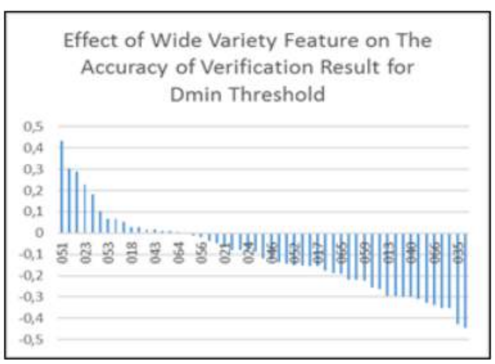

***Fig. 6** The impact of the implementation of the Width Variation on the accuracy of the verification with the threshold Dmin, Level 4, and the number of check points k = b = 10 points on the improvement of accuracy of verification of each signature.*

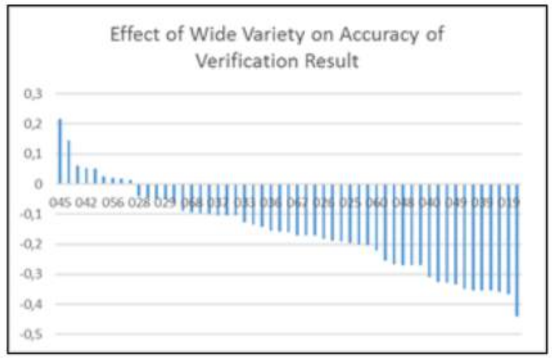

***Fig. 7** The impact of the implementation of the Width Variation verification on the accuracy of the verification with the threshold (Dmean-Dstd)> Dmin, Level 4, and the number of check points k = b = 10 points towards the improvement of accuracy of examination of each signature.*

In general, it can be conclude that the wide variety can improve the accuracy of verification for certain condition. This condition should be defined clearly before to be a wide variety feature can be applied.

5 CONCLUSION

Based on the results of the experiment and analysis of the results it can be concluded that:

1. The more inspection points the more accurate the results of the examination (see ACC values in Fig. 2, 3, and 4)
2. The addition of inspection points tends to lead to the inspection performance limit line so that all the points are not examined. In this study of 256 inspection points (level 4), no more than 10 check points were needed.
3. Use of Wide Variation feature can improve verification performance for some signature collections (see Fig. 6 and 7 in collections with a value of positive accuracy improvement)

6 FURTHER RESEARCH

Based on the conclusions obtained, the verification performance improvement can be done through:

1. Looking for an estimation of values that can be used for decision making, whether or not Wide Variation feature should be applied so that the verification performance improvement is maximized.
2. Need to be retested using more precise features and retest on different datasets to see the level of system performance stability in different datasets.

7 ACKNOWLEDGEMENT

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