DETECTING OFF-LINE SIGNATURE MODEL USING WIDE AND NARROW VARIETY CLASS OF LOCAL FEATURE

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ABSTRACT. There are so many questioned document cases in Indonesia, mostly related to disputed signatures, both are forgery and denial of the offline signature. The Indonesian forensic document examiners have been examining the signatures manually and they have not been implementing the computer in signatures identification optimally yet. Therefore, it needs help of computer based detection to speed up and support decision making in examining signature forgery. Many research in this field was done, but it still an open research especially in detection accuracy. Usually every detection method only dictates for certain class of forgery and uses only one phase detection. Otherwise, this research proposes two phase detection that has capability for detecting all classes of forgery. This approaches based on hypothesize that the detection of skilled signatures forgery can be identified using a wide variety of segments and random to moderate signature forgery can be identified using a narrow variation of segments. Otherwise, the skilled forgery will be detected using wide variety of local features. For future work, it has to be selected the appropriate segmentation technique to determine the narrow and wide variety area of signature and formula to calculate the distance among signatures.

Keywords: offline signature, detection, local features, two phase detection

INTRODUCTION

In Indonesia the institution which responsible in examining of disputed documents (mostly signatures cases) is the Centre of Forensic Laboratory (PUSLABFOR) of Indonesian National Police which has six branches around Indonesia. During the year 2012, in Indonesia there has been as many as 589 cases of forgery of the signature of the details: 212 cases in PUSLABFOR, 88 cases in LABFORCAB (Laboratorium Forensik Cabang) Medan, Surabaya LABFORCAB 88 cases, 73 cases in LABFORCAB Semarang, Makassar LABFORCAB 54 cases, 34 in Palembang LABFORCAB, and 26 in LABFORCAB Bali (Syamsu, 2012).

The degree of complexity of Questioned Signature examination can be classified into three such as (very) difficult, moderate, and easy. Fortunately, the most part (more than 80 %) of questioned signature cases which encountered in Indonesia can be categorized as moderate and easy cases. However, because of the uniqueness of signature cases and the dangerous effects of wrong signature examination conclusion, the signature examiners have to keep on nurturing his competency especially in facing a very difficult signature case. The (very) difficult cases mostly related to disguised signature, a genuine signature that is denied by the owner. In term of forgery, the (very) difficult cases related to a skilled forger. All cases handled by a static signature (off-line handwritten signature) are taken from the documents that were forged. (Syamsu, 2012). Examination of skilled forgery category is a difficult task because it may cause errors especially by an inexperienced examiner (Syamsu, 2011).

Therefore, to speed up the examination process, it needs to be assisted bycomputer-based signature examination.

Research of the computer-based signature detection has been carried out offline. Based on features are used as decision-making, research can be divided into two, namely global and local features. Global feature may have asimilar general properties for different signature author, so we cannot use it to sharpen the differentiation factor. Otherwise, the local features have proven to increase the accuracy of the examination especially on signature skilled forgery categories (Nagel & Rosenfeld, 1977; Watanabe et al, 1993; Sabourin, et al, 1994; Sabourin & Genest, 1994; Guo, Doermann, & Rosenfelt, 1997; Zimmer & Ling, 2003; Fang et al, 2003; Jena et al, 2008; Piekarczyk, 2010; Napoles & Zanchettin, 2012). The results showed that the accuracy of inspection has been satisfactory in cases of random to moderate forgery, but has not been satisfactory in cases of skilled forgery. Nevertheless there are some important things to note are (1) accuracy of detection can be further enhanced by taking into account the variation of the signatures on the same author (Justino et al, 2002; Pirlo & Plamondon, 2012; Souborin & Preteux, 1997); (2) the level of these variations must also consider the time frame signature (Alonso-Fernandes et al, 2009; Syamsu 2011), (3) the level of accuracy depends on the detailed examination of the local feature (Sabourin & Genest, 1994; Fang et al, 2003; Jena et al, 2008), and appropriate level of variation and the amount of training data (Guo, Doermann & Rosenfelt, 1997; Zimmer & Ling, 2003; Jena et al, 2008), but details of local features will be constrained by the limited amount of training data (Jain et al, 2000). Under these conditions, the local features and the level of variation play an important role in improving the accuracy of the examination, as long as the amount of training data available due to the limited number of signatures in a specified period. Therefore it is necessary to conduct further research in order to improve the accuracy of the examination signatures by focusing on local features and the level of a person's signature variations.

PROBLEM STATEMENT

Cases of signature forgeries was difficult to be solved using techniques that have been developed previously, because (1) the degree of variation of the signature is related to the level of ease of skilled signatures forgery (Justino et al, 2002), so that the detection of the signature using weighted range of variation and neural network techniques was not succeed because of the resemblance, (2) the application of image matching techniques that compare the signature of the structural, statistical, and morphological forms, tend to be less successful because the counterfeiters will try to make the signature as closely as possible to the original. Moreover using cloning techniques it can be produceda false signatures that the exactly similar to the genuine signature (Syamsu, 2011). Based on the fact that a segment of the structure of a person's signature varies or is never similar (Preteux & Sabourin, 1997; Justino et al, 2002; Alonso-Fernandes et al, 2009), and behavioral tendencies of skilled signature forger who try to make signature as similar as possible to the genuine signature(Syamsu, 2011), it can be hypothesized that the skilled signature forger can be caught on a wide variety of segments of the signature, meanwhile random to moderate signature forger can get stuck on a narrow variety of segment of the signatures. On the other word, it can be hypothesized that the detection of skilled signatures forgery can be identified using a wide variety of segments and random to moderate signature forgery can be identified using a narrow variation of segments. Therefore, It should be designed the offline signature detection that can detect all class of signature forgery using dual local features those are wide and narrow variety of local features.

LITERATURE REVIEW

Offline signature verification was done in 3 stages: (1) image processing to eliminate background noise, get a normal form that is not affected by the transformation, dilatation, translation, (2) extraction of features used as the feature matching process input; (3) detection process to obtain the decision about originality of signature (Al-Omari & Omar, 2011). Based on the features used, it can be divided into global and local features. Global feature is a feature that describes the overall signature such as width and length, orientation, density, shape envelope, the pixel distribution, while local features are taken from the parts that make up the signature such as thick and thin lines, bends, strokes, place stops and starts , and rhythm (Al-Omari & Omar, 2011; Syamsu, 2011).

In general, each individual action is inevitably influenced by the physical and psychological state of the author as well as the tools used, so if the physical state and psychology author changed the signature generated can vary from small to large accidental due to deliberate. One factor is age-makers signature, where the signature changes from an early age in elementary school to adults and even the elderly (Syamsu, 2011). Age grouping within the range of <25 years, between 25 and 60 years, and over 60 years can help sharpen the results of the signature verification of identity (Costa-abreu & Fairhurst, 2012). Variations of the signature are also influenced by the space provided for the signature (Pirlo & Plamondon, 2012). Alonso-Fernandes et al (2009) concluded that there is no significant error if the genuine signature data is not more than 2 months of the questioned signature. Souborin and Preteux (1997) argued that the orientation and the overall proportion of the genuine signature does not vary significantly in the same person, while the rate of variation of local features can be used as individual characteristics. This was confirmed by Justino et al (2002) which states that due to the variation in the shape and layout of the signature of each person is different, then the range of variation in individual settings can improve the accuracy of detection of the authenticity of the signature. From these studies it can be concluded that the local features, the level of local variation, and grouping the right time of the original collection of signatures can be used as an intrinsic property of the author and are believed to increase inspection accuracy especially in skilled forgery.

Many researches have been done related to the use of local features as an input of decision-making system mainly structural feature segmentation approach. Watanabe, et al (1993) performs feature extraction with the segmentation that is resulted from shadowing signature image, not all segments are used only large segments were compared. Each segment is encoded by the coordinates of gravity, long, curved, and slope of segment. Sabourin, Plamondon, & Beaumier (1994) extract features graphics based on the parts that have the same geometric orientation, and then do the reduction by discarding regions having low pixel density and then resulting in a primitive feature that can present the overall signature. This feature extraction requires a lot of computing, so that Sabourin and Genest (1994) use another approach, namely Extended-shadow-code mapping feature on a flat, vertical, and diagonal of a square. The more square area of the signature will increasingly accurate, this approach produces FRR on 27 square areas of 0.01% -0.88% depending on the classification method used. Although this approach lowers the level of computing, but the accuracy declined as many point features that occupy the same projection. Nagel and Rosenfeld (1997) perform feature extraction using gray scale projection on a flat and upright as a whole to produce a histogram of the number of gray scales. This method produces 12% FRR and 0% FAR (all fraud is detected). Guo, Doermann, and Rosenfelt (1997) took the form of a local feature shapes that are segmented based on the strike of the starting point, the point of intersection, and the end point. The training process is needed to determine the degree of variation of each form pieces and give weight based on the inverse value of the variation, the more the amount of training data will be more accurate. This model can generate 1.57% FRR and FAR of

0.56% on the amount of training as many as 20 signatures. Zimmer and Ling (2003) using a simple form of traction to reduce the amount of traction that will be compared and define the width of the window area depends on the variations that occur during the training process. The more rigorous the training data, this model can produce errors up to 1%. Fang et al. (2003) perform feature extraction on local variations in the genuine signature of each person and calculate the mean of individual variation. Local feature was projected vertically and variables were calculated, position variations are identified and searched into its original position in the signature, resulting in between 18% FRR and 24%, FAR between 19% and 25%. Jena et al (2008) conducted by dividing the extraction area based on gravity point of each area, in this way the distribution segment signature structure will be strongly influenced by the distribution of pixels in the area. The more rigorous the zoning, this model can result in FRR by 20% for skilled forgery. Piekarczyk (2010) developed a model graph formed from local features. Local features were extracted by segmenting the basic forms of stroke and encoded using Zernike moments. Moreover, the local features are related to each other in order according to signature form and the relative position of each feature based on gravity. The research rigor despite the unsatisfactory result that FRR of 21.6% and a FAR of 11.6%, it is due to the fact not accommodate variations each signature, but inspiring model of unification between local and global features. Napoles & Zanchettin (2012) conducted by dividing local extraction area of the same size and combining global proportions. This research resulted in a FRR of 3.42% and 0.4% FAR. Based on this research, accuracy of signature detection was depending on the type and number of features, the level of variation of signature, the method of decision-making, and the number of training data used. Number of training data required was at least 10 times the number of features that will be used as a differentiating factor among the signatures of the individuals (Jain et al, 2000).

Based on previous studies, the detection accuracy of skilled signatures forgery has not been satisfactory. This is due to the similarity between genuine and forged signatures. Justino et al (2002) stated that the rate of variation of the signature was related to the level of ease of skilled forgery. The wider the variation that occurs in a person's signature, the greater the likelihood of failed in detecting skilled forgery or in other words a false signature is accepted as a genuine signature. Furthermore, trained forgers would try to make the signature as closely as possible to the original even with cloning techniques can produce false signatures exactly match the original. In this case, experienced examiner may decide directly that the signature is fake based on the assumption that a person may not make the exact same signature (Syamsu, 2011). This is why earlier studies less rigorous when faced with cases of skilled signature forgery. Sabourin and Preteux (1997) illustrates that there is a level of variation in the signatures segment in the same person. In other words, the degree of variation of local features is not always equal to each other. According to Justino et al (2002) and Syamsu (2011) combined with the fact that was revealed by Sabourin and Preteux (1997), it can be concluded that the level of variation occured in each signature can be used as a distinguishing feature. The degree of variation resulted can be categorized by two extremes of the range area those are the wide variation that is used in skilled forgery detection and narrow variations that is used in the random to moderate forgery. By simply noting areas of extreme then the number of features can be reduced so that the amount of training data can also be reduced in order to meet the rules of the number of training data proposed by Jain et al (2000).

PROPOSED MODEL

This paper proposes a new model in detecting offline signature forgery using two classes of local feature signature variety as in Figure 1. Firstly, system will be trained using set of genuine signature to determine the range of narrow and wide variety of local feature. Questioned signature will be segmented based on area of narrow and wide variety according to area of narrow and wide variety in training phase. In detecting phase, this proposed system implements two phase detection. In first phase, it will be detected random or moderate forgery based on narrow variety of local features. If the distance between questioned signature and template signature is not in the range of narrow variety, the system will label the questioned signature as a false signature. Otherwise, system will label genuine signature. But, it may be a skilled forgery because the questioned signature close to genuine signature. So, we have to detect in second phase. In second phase, system will compare the questioned signature segment that in wide variety areas. If the distance between questioned signature and template signature is below the minimum of wide variety, the system will label the questioned signature as a false signature. Otherwise, system will label genuine signature.

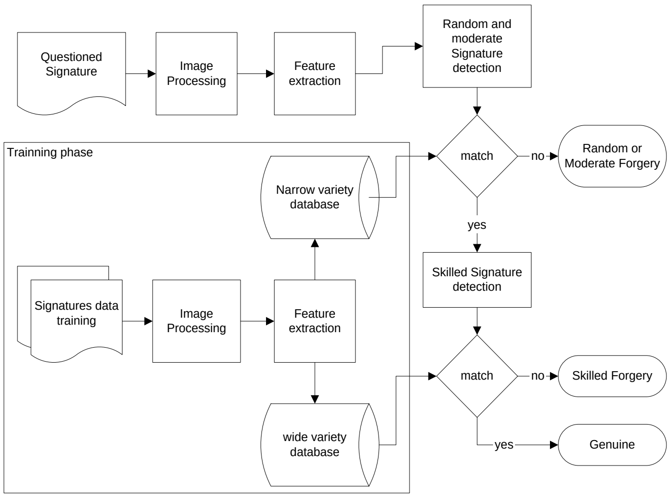

Figure 1. Proposed model for detecting offline signature forgery

CONCLUSION

This paper proposes a new model in detecting offline signature forgery using two classes of local features. Those are narrow and wide variety of local features. This approaches based on not only the fact of segment variety of signatures in the same author, but also the fact that forger make arbitrary signature on random forgery or make nearly similar signature on moderate forgery or try to make similar signature on skilled forgery. In first and second forgery types, signature forgery will be detected using narrow variety of local features. Otherwise, the skilled forgery will be detected using wide variety of local features. For future work, it has to be selected the appropriate segmentation technique to determine the narrow and wide variety area of signature and formula to calculate the distance among signatures.

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REFERENCES

Al-Omari, Y., Abdullah, S.S. & Omar, K. (2011). State-of-the-art in offline signature verification system. *Proceedings of The International Conference on Pattern Analysis and Intelligent Robotics*, 59-64.

Alonso-Fernandez, F., Fierrez, J., Gilperez, A. & Ortega-Garcia, J. (2009). Impact of time variability in off-line writer identification and verification. *Proceedings of the 6th International Symposium on Image and Signal Processing and Analysis*, 540-545.

Costa-Abreu, M.D. & Fairhurst, M. (2012). Improving handwritten signature-based identity prediction through the integration of fuzzy soft-biometric data. *Proceedings of The International Conference on Frontiers in Handwriting Recognition*, 793-798.

Fang, B., Leung, C., Tang, Y., Tse, K.W., Kwok, P., & Wong, Y.K. (2003). Off-line signature verification by the tracking of feature and stroke positions. *Pattern Recognition*, 36(1), 91-101.

Guo, J. K., Doermann, D., & Rosenfeld, A. (1997). Local Correspondence for Detecting Random Forgeries. *Proceedings of the 4th International Conference on Document Analysis and Recognition*, 319-323.

Impedovo, D., Pirlo, G. & Plamondon, R. (2012). Handwritten signature verification: new advancements and open issues. *Proceedings of The International Conference on Frontiers in Handwriting Recognition,* 365-370.

Jain, A.K., Duin, R., & Mao, J. (2000). Statistical pattern recognition: a review. *IEEE Transactions On Pattern Analysis And Machine Intelligence*, 22(1), 4-37.

Jena, D., Majhi, B., Panigrahy, K.S. & Jena, K.S. (2008). Improved offline signature verification scheme using feature point extraction method. *Proceeding of The 7th IEEE International Conference on Cognitive Informatics,* 475-480.

Justino, J.E., Bortolozzi, F. & Souborin, R. (2002). The interpersonal and intrapersonal variability influences on off-line signature verification using HMM. *Proceedings of The IEEE International Conference on Computer Graphics and Image Processing,* 197-202.

Leoncio de Medeiros Napoles, S.H., & Zanchettin, C. (2012). Offline handwritten signature verification through network radial basis functions optimized by differential evolution. *Proceedings of the 2012 International Joint Conference on Neural Networks***,** 1-5.

Piekarczyk, M. (2010). Hierarchical random graph model for off-line handwritten signatures recognition. *Proceeding of The International Conference on Complex, Intelligent and Software Intensive Systems*, 860-865.

Rosenfeld, A., & Nagel, N. R. (1997). Computer detection of freehand forgeries. *IEEE Transactions On Computers, C-26(9),* 895-905.

Rueda, S., Udupab, J. K., & Bai, L. (2008). Local curvature scale: a new concept of shape description. *Proceeding of SPIE 6914, Medical Imaging 2008: Image Processing 69144Q.*

Souborin, R., & Preteux, F. (1997). Off-line signature verification by local granulometric size distribution. *IEEE Transaction on Pattern Analysis and Machine Intelligence, 19(9),* 976-988.

Souborin, R., Plamondon, R., & Beaumier, L. (1994). Structural interpretation of handwritter signature images. *International Journal of Pattern Recognition and Artificial Intellegence, 8(3),* 79-108.

Syamsu, Y.N. (2011). Grafonomi Sistem Sibarani dan Sistem Huber, Bali, Indonesia.

Syamsu, Y.N. (2012). Data Kasus Pemalsuan Tandatangan di Indonesia, Bali, Indonesia.