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Hierarchical Gaussian Scale-Space on Androgenic Hair Pattern Recognition

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Abstract

Androgenic hair pattern stated to be the new biometric trait since 2014. The research to improve the performance of androgenic hair pattern recognition system has begun to be developed due to the problems that occurred when other apparent biometric trait such as face is hidden from sight. The recognition system was built with hierarchical Gaussian scale-space using 4 octaves and 3 levels in each octave. The system also implemented the equalization process to adjust image's intensity by using histogram equalization. We analyzed 400 images of androgenic hair in the database that were analyzed using 2-fold and 10-fold cross validation and Euclidean distance to classify it. The experimental results showed that our proposed method gave better performance compared to previous work that used Haar wavelet transformation and principal component analysis as the main method. The best recognition precision was 94.23 % obtained from the base octave with the third level using histogram equalization and 10-fold cross validation.

***Keywords**: androgenic hair pattern, biometric identification, hierarchical Gaussian scale-space, histogram equalization, pattern recognition*

1. Introduction

Androgenic hair pattern research had arisen in the community of pattern analysis and computer vision since 2014. The main idea behind this new biometric trait is that we can identify a person with his/her apparent biometric traits are covered. The case that needs this kind of biometric identification usually criminal case where the perpetrator hides the face and other distinguish features. In Indonesia only, the cases of child sexual abuse grew higher annually since 2011 and in child pornography and cyber-crime section, the cases already reached total of 1593 cases [1]. When the perpetrator records and distributes the video of child sexual abuse, there are possibilities he/she covers the face, with the only visible parts of the body are hands and legs. On the hands and legs of an adult human, there is androgenic hair that grows on them. Androgenic hair is the hair that grows on a human body since she/he has reached puberty age and it grows because of the influence from androgens hormone [2].

Derived from this issue, the authors in [3] developed this androgenic hair pattern recognition system to identify criminal. This first publication applied Gabor orientation histogram as the main method. Other researches [4-5] developed various techniques to improve the performance of androgenic hair pattern recognition system and they also applied the usage of hair follicle pattern [6] as the input for the system. In 2016, we began the journey to find the best method to improve the performance of androgenic hair pattern recognition system. We applied Haar wavelet transform [7] and extracted features with principal component analysis method [8] for the recognition system.

In this paper, we did a different way to analyze the images of androgenic hair. We analyzed the images in multiresolution that were obtained by building the hierarchical Gaussian scale-space. The reason behind this choice of method is the problem in the database that has variations in lighting conditions, illuminations, and the size of objects that vary in images in the database. Before building the hierarchical Gaussian scale-space for androgenic hair pattern recognition, the system equalized the intensity of images in the database using histogram equalization. The classification was done by cross validation and nearest neighbour with

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Euclidean distance. The rest of this paper is explained as follow: section 2 describes proposed research method. In section 3, we discuss the experimental results and in section 4 the conclusion is made.

2. Research Method

The proposed research method for this paper centres on three methods, which were histogram equalization, hierarchical Gaussian scale-space and classification. The flowchart of proposed research method can be found in Figure 1. At first, the histogram of input image needed to be equalized. We also compared the performance of the recognition system that didn't use the histogram equalization process. Then, we built the hierarchical scale-space by using Gaussian function as the kernel for filtering for *U* octaves and *V* levels. We set $U = 4$ and $V = 3$ in this paper. Each image output from the scale-space results was grouped into training and testing sets according to their scales. By using the rules of 2-fold and 10-fold cross validations and also calculating the Euclidean distance for searching the nearest neighbour, the images were classified.

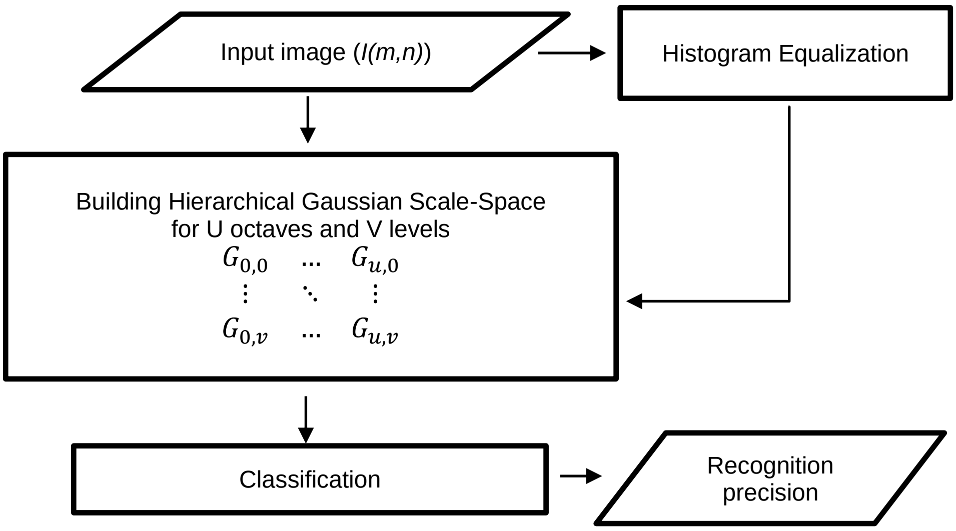

Figure 1. Flowchart of Proposed Research Method

We used androgenic hair database which was created by us in our previous publication [7-8]. We analyzed the system performance by using 400 images which were obtained from 25 people (all male) and 16 images from each person from the database. To simplify the process of the system, we converted the images into gray-scale images and resized into 704 *x* 406 pixel. Each of the method is described briefly.

2.1. Histogram Equalization

To make two images easier to compare we need to adjust their intensity distributions so they are similar to each other [9]. One of several ways to do this is to equalize the image's histogram. The purpose of histogram equalization is to find the operation so that the outcome of this process is modified image that has the histogram approximates uniform distribution [10].

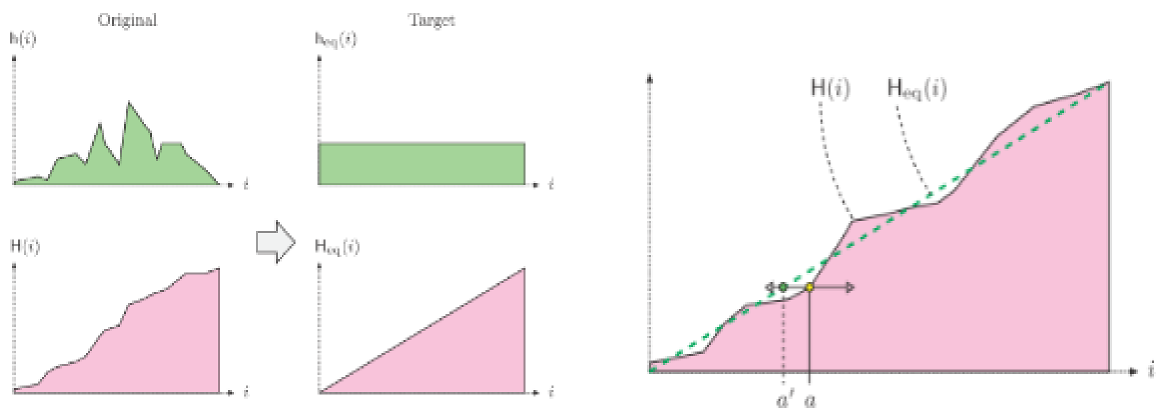

Figure 2. Before and After Histogram Equalization of Two Different Histogram of Images (left) and Finding a Point of Operation f_{eq} to Shift Histogram Line and Create Cumulative Histogram H_{eq} is approximates linear (right) [9].

Equation (1) [9] shows us the process of point of operation (f_{eq}) that shifts each original position of line in histogram from position *a* to *a'* that is shown as the process in Figure 2 (right).

$$f_{eq}(a) = H(a).\frac{k-1}{m.n} \tag{1}$$

With *H* is the cumulative histogram of original image, *m* and *n* is the size of original image and $a \in [0, k-1]$. The goal of using the histogram equalization in the recognition process is to make the images in the testing set much easier to compare to training set and the process also enhances the contrast of an image so it can reveal the detail that previously hidden before the process. Histogram equalization is used in this paper as the pre-processing method in the recognition system so that the recognition precision will be achieved as high as possible.

2.2. Hierarchical Gaussian Scale-Space

The main method that was developed in this paper was hierarchical Gaussian scale-space. The basic process of this method is to represent the original data in multiresolution and filtering it with Gaussian kernel. In real world, the position of camera and the object maybe not is static and it has so many variations at different scales as the distance between camera and object move closer or farther. Motivated by this real situation, we represented the digital image data by a wide range of scale-space. The concept of scale-space that was developed in [11] was used as the first step among many in the popular method of Scale-Invariant Feature Transform (SIFT) that was developed by David Lowe in 1999-2004 [12-13].

In this paper, to represent the input image in the several resolutions, we built the hierarchical scale-space and we chose the Gaussian function because it is the one with the maximum entropy as the probability density function. It has the same properties as the Fourier transform when it acts for kernel in smoothing function. For the diffusion equation, the Gaussian acts as the Green's function [14] and the only one that has the criteria as monotonic condition on first-order maxima increase when the bandwidth of filter is increased and the first-order minima decrease when the bandwidth of filter is increased [15].

The hierarchical Gaussian scale-space can be obtained by filtering the original image*I* (*m*,*n*) with Gaussian kernel $H^{G,\widehat{\sigma}_v}$ as it can be seen in (2) until (8) [16].

$$\mathrm{G(m,n,u=0,v=0) = (I * H^{G,\widehat{\sigma_0}})(m,n)} \tag{2}$$

$$\mathrm{G(m,n,u,v) = (G_{u,0} * H^{G,\widehat{\sigma_v}})(m,n)} \tag{3}$$

$$\widehat{\sigma_0} = \sqrt{\sigma_0^2 - \sigma_s^2} \tag{4}$$

$$\widehat{\sigma_v} = \sigma_0.\sqrt{2^{2v/V} - 1} \quad (5)$$

where σ is the width of the Gaussian filter and we set the $\sigma_0 = 1.6$ and $\sigma_s = 0.5$ [13]. In (2) and (3), (*m,n*) shows the location of pixel (vertical and horizontal) within the image. We call the hierarchical Gaussian scale-space of *U* octaves as

$$G = (G_0, G_1, \dots, G_{U-1}) \quad (6)$$

and in each octave has *V+1* levels of scale $G_{u,v}$

$$G_u = (G_{u,0}, G_{u,1}, \dots, G_{u,v}) \quad (7)$$

where $u \in [0, U-1]$ indicates octave index and $v \in [0, V]$ indicate level index in the same octave. In this paper, we set the value of *U* =4 and *V* =3.

The flow of the hierarchical Gaussian scale-space process is explained in Figure 3. The process starts by pre-filtering the matrix of input image with the Gaussian with the width of $\sigma_s = 0.5$ and set the basic scale in each octave to $\sigma_0 = 1.6$ [13]. This step creates the base level for base octave ($G_{0,0}$).

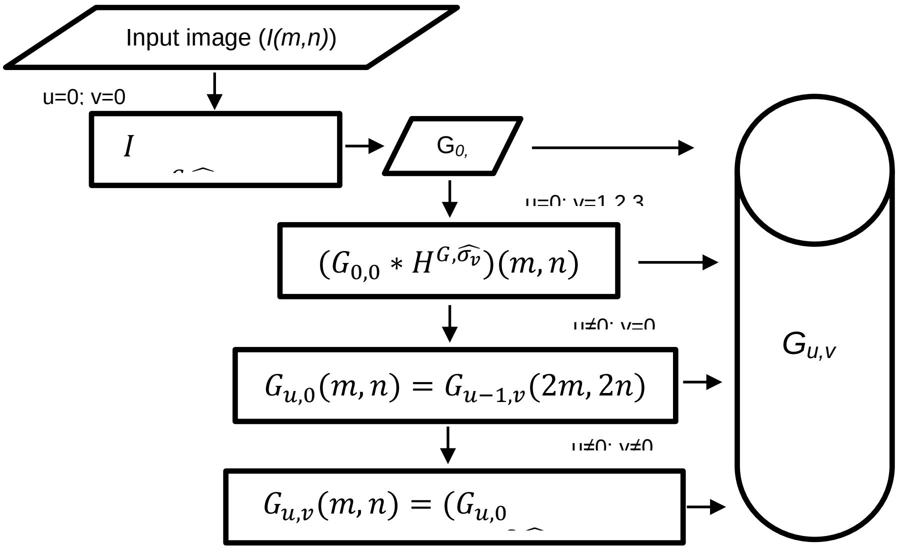

Figure 3. Flowchart of Hierarchical Gaussian Scale-Space for *U* octaves and *V* Levels

The next level in the same octave (base octave) is obtained from filtering the base level with the Gaussian with the width of $\widehat{\sigma_v}$. As we can see in (5), the $\widehat{\sigma_v}$ can be used in every octave because the independency characteristic of this kernel from octave index *u*. When *v* reaches the last level, which is 3 ($G_{u,3}$), we continue it to the next octave ($G_{u+1,0}$) by decimating the last octave in the highest level and sub-sampling by the factor of 2 as described in (8).

$$G_{u,0}(m,n) = G_{u-1,q}(2m,2n) \quad (8)$$

In the level 0 in each octave, we don't filter it with the Gaussian anymore; it is obtained only from the decimating process from the previous octave. We start to filter it again with the Gaussian in the level 1 at each octave. This process continues to run until desired octave and level are reached. In Figure 4, we see the illustration building the scale-space from original image until $G_{1,0}$. When the level in each octave reached the highest level that was set earlier, the process did the decimation process (sub-sampling 2:1) and the result of this decimation was the base level (*v*=0) for the next octave. From the highest level in the previous octave and the base level in the next octave, we did not need to do the Gaussian filtering at all and the filtering process started again from the base level ($G_{u,0}$) to the first level ($G_{u,1}$) in each octave.

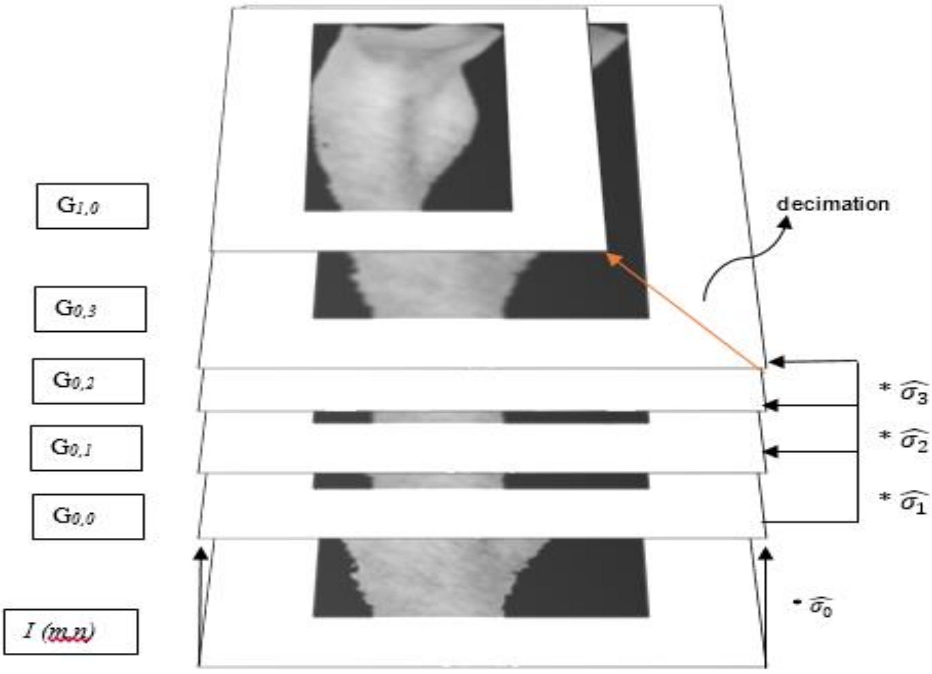

Figure 4. Hierarchical Gaussian Scale-Space from Original Image until $G_{1,0}$

2.3. Classification

We compared two different rules for setting the training and testing groups in this paper. By using the 2-fold and 10-fold cross validations, we analyzed the performance of system recognition.

In the 2-fold cross validation, 400 images in our database were divided into two folds, the first fold used 200 images for training set and 200 images for testing set and the second fold used the same images but they were exchanged: the 200 images from the testing set in the first fold will be used for the training set in the second fold and the 200 images from the training set in the first fold will be used in testing set for the second fold. In the 10-fold cross validation, the same principles were applied, the differences were they divided the fold into 10 folds and there were 40 images for each testing set and remaining 360 images for the training set. Each iteration gave one recognition precision and we set 10 iterations for each type of cross validation so the final recognition precision was obtained from the average of 10 precisions of recognition. The recognition precision is actually a calculation to compare how many times the recognition system detects correctly with the total of trial [17].

To classify the testing image to the closest match in the group of training images, we used nearest neighbour calculation with the Euclidean distance. It classified the closest match by calculating the distance in each pixel.

3. Results and Analysis

The results of the experiment conducted in this paper are presented in Table 1, Table 2 and also Figure 5. We used the parameters $\sigma_0 = 1.6$ and $\sigma_s = 0.5$ as the usual setting in many publications such as in [13]. We also set the scale-space to have 4 octaves (U = 4) and each octave had 3 levels (V = 3). In addition, aside from making the database into several scales (octaves and levels), we also wanted to analyze the performance of histogram equalization. The output from the histogram equalization process became the input in the hierarchical Gaussian scale space as we can see in Figure 1. Each level in each octave ($G_{0,0}$, $G_{0,1}$, …., $G_{3,3}$) was stored in the database as we described before in Figure 3. Each of this scale-space database then was treated as the input for the classification with Euclidean distance and the outcome was the average of recognition precision that was obtained from each iteration in the cross validation. The system of androgenic hair pattern recognition was built by using Matlab.

Table 1 presents the performance results of recognition system with the option of choosing the 2-fold cross validation and 10-fold cross validation without the process of histogram equalization. Table 2 presents the same performance results of the system but with the process of histogram equalization. The results from both tables are showed for each level in each octave. To have a clear view, we also present it in the Figure 5. Figure 5 gives us the graph of overall performance for every system setting that is compared in this paper.

From Table 1 and Figure 5, we see that overall, the best performances of recognition system (highest recognition precision) were obtained from 10-fold cross validation. It happened because the system gave more chances in training images than the 2-fold cross validation. The best result in each type of cross validation came from the first octave (*u*=1) and the first level (for 2-fold cross validation) and the second level (for 10-fold cross validation). In each octave (*u*), the first level was obtained by filtering the base level ($G_{u,0}$) with the Gaussian width of $\widehat{\sigma_1} = 1.23$. This parameter was obtained from (5). The second level in each octave was obtained by filtering $G_{u,0}$ with the Gaussian width of $\widehat{\sigma_2} = 1.97$. Meanwhile, the third level in each octave was obtained by filtering $G_{u,0}$ with the Gaussian width of $\widehat{\sigma_3} = 2.77$. The higher the level in each octave, the wider the Gaussian filters. According to the proof of theory in [16], if we have wider width of a Gaussian filter by the factor of *t* and we transform it to the frequency domain with Fourier transform, it was proven that the corresponding Fourier transform shrinks by the factor of *t*. It means that if we make the Gaussian filter wider by the factor of *t*, it gives result of the decimation of the signal bandwidth by the factor of *t*. In this case, when the system reached higher level and octave in the scale-space, the Gaussian filter removed the sudden changes in the image and it gave result as the image was more blur than before. Furthermore, we decimated the resolution in each octave. The resolution in original image (*I*) was 704*x*408 pixel. These resolutions were applied from original image until $G_{0,3}$. When it reached $G_{1,v}$, it decimated by the factor of 2 and in the first octave became half of the previous resolution (352*x*204 pixel). It did the same decimation by factor of 2 in every next octave, so the next octave besides having more blur version of previous octave it also had half of the resolution from previous octave. From the experiment result, having the image filtered by Gaussian with the width of 1.23 and decimated until the resolution reached 352*x*204, it made the recognition precision better, it happened because all of the not-so-important details and noise are filtered and removed.

Table 1. Performance Results: Average Recognition precision with Hierarchical Gaussian Scale-Space for Androgenic Hair Pattern

hierarchical Gaussian scale-space	Average Recognition precision (%)							
	2-fold cross validation				10-fold cross validation			
	v = 0	*v* = 1	*v* = 2	*v* = 3	*v* = 0	*v* = 1	*v* = 2	*v* = 3
u = 0	71.03	72.45	70.88	72.05	83.18	82.95	83.08	83.58
u = 1		**72.93**	71.25	70.9		83.43	**84.08**	83.2
u = 2		71.45	69.58	70.88		83.4	82.83	81.63
u = 3		70.33	68.05	67.5		81.25	81.13	80.9

Table 2. Performance Results: Average Recognition precision with Hierarchical Gaussian Scale-Space with Histogram Equalization for Androgenic Hair Pattern

hierarchical Gaussian scale-space with histogram equalization	Average Recognition precision (%)							
	2-fold cross validation				10-fold cross validation			
	v = 0	*v* = 1	*v* = 2	*v* = 3	*v* = 0	*v* = 1	*v* = 2	*v* = 3
u = 0	86.3	86.78	86.53	86.9	93.83	93.83	93.73	**94.23**
u = 1		**88.7**	87.4	87.43		93.88	94.03	94.08
u = 2		87.85	87.75	87.93		93.83	94.2	93.83
u = 3		87.98	87.7	87.1		94.03	93.8	93.38

From Table 2, we see that the system that used the equalization process in their images' histogram gave better recognition precision compare the system that did not use it

(Table 1). Histogram equalization made the comparison between testing images and training images easier and their intensities were adjusted so they were more similar to each other in the terms of illumination. In other research of biometric identification, the histogram equalization process made the performance of hand gesture recognition system worse [18] and also face recognition better [8]. The histogram equalization method in Contrast-Limited Adaptive Histogram Equalization (CLAHE) also used in other biometric trait such as teeth identification system as pre-processing method [19]. And in [20], histogram equalization also used as pre-processing step in the system of face recognition that had variations with illumination in their objects. In this paper, the histogram equalization process improved the performance of the system by 10-15%. The database of the androgenic hair has different variations in illumination and lighting conditions that were why this equalization in intensity gray-level values made the performance of the system better because it was easier to compare between two images. The best result was obtained from the first level and first octave in 2-fold cross validation and in the third level and base octave for 10-fold cross validation.

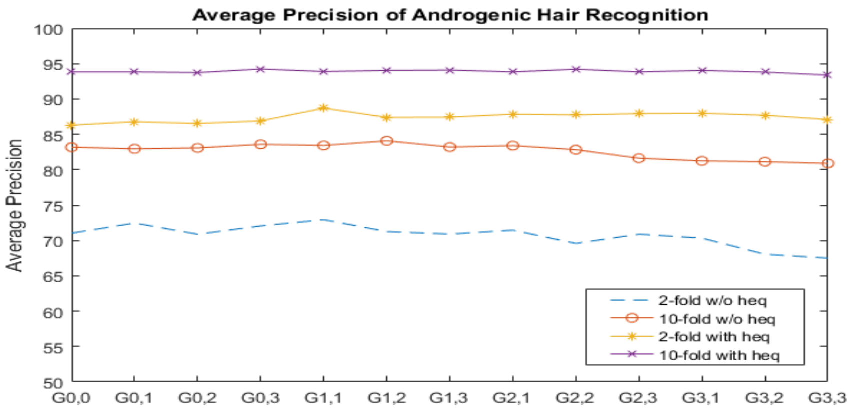

Figure 5. The Graph of Average Precision of Androgenic Hair Recognition for Every System Setting

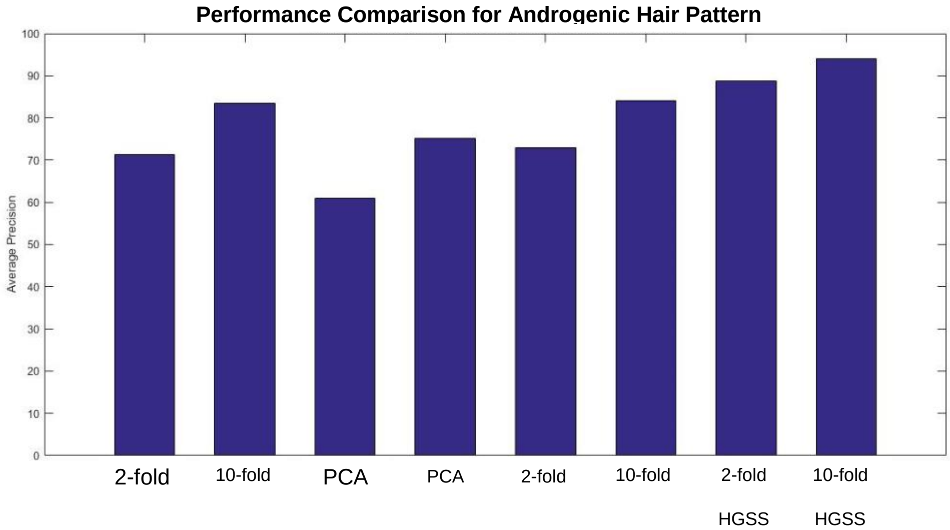

Figure 6. Performance Comparison for Androgenic Hair Pattern Researches: 2-fold cross validation with Haar wavelet (2-fold Haar) [7], 10-fold cross validation with Haar wavelet (10-fold Haar) [7], Principal Component Analysis method for feature extraction (PCA) [8], PCA with histogram equalization (PCA with heq) [8] and the performance of the system in this paper: 2-fold cross validation and 10-fold cross validation with (-heq) or without histogram equalization using hierarchical Gaussian scale-space (HGSS)

We also compared our research result in this paper with other results of androgenic hair pattern research for this past year. Figure 6 shows the comparison from three publications. The first publication from [7] optimized Haar wavelet transform as the feature extraction method in 2-fold (2f-Haar) and 10-fold cross validation (10f-Haar). The research showed that the 10-fold cross validation also gave better performance (83.43 %) compared to 2-fold cross validation (71.28 %). The second publication from [8] utilized the Principal Component Analysis (PCA) as the main feature extraction method and the research gave around 60.9 % for the system that didn't use histogram equalization and gave better precision around 75.19 % for the system that used histogram equalization (PCA-heq). The third publication came from this paper that made use of hierarchical Gaussian scale-space that combined the usage of histogram equalization and with the choice of 2-fold (2f-HGSS/2f-HGSS-heq) and 10-fold cross validation (10f-HGSS/10f-HGSS-heq). From Figure 6, we can see that from three publications the best performance (94.23 %) came from our research in this paper that optimized histogram equalization with the choice if 10-fold cross validation for hierarchical Gaussian scale-space with the parameter from the base octave (u=0) and third level (v=3).

4. Conclusion

We already established the androgenic hair pattern recognition by building the hierarchical Gaussian scale-space with 4 octaves and 3 levels in each octave. The recognition system also applied equalization of intensity in each image's gray-level value using histogram equalization. The experimental results showed that the proposed method gave better performance compared to other previous research. The best recognition precision was 94.23 % and it was obtained by using histogram equalization and 10-fold cross validation and derived from base octave in the third level of the hierarchical Gaussian scale-space. We believe that the equalization of the histogram of images made the images in the database more similar to one another and it became easier to be classified. Meanwhile the option to use the 10-fold cross validation made the system had more chances to do the training set than the testing set. The hierarchical Gaussian scale-space was built so that the system had the features of androgenic hair images in several different image scales.

We plan to do further studies based on the results that were obtained in this paper. We will develop the scale-space and implement it in the SIFT method (Scale-Invariant Feature Transform) so we can achieve better system performance.

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References

[1] Komisi Perlindungan Anak Indonesia. *Kasus Pengaduan Anak Berdasarkan Klaster Perlindungan Anak Tahun 2011-2016*. KPAI. 2016.
[2] Palastanga N, Soames R, Anatomy and Human Movement: Structure and Function. Sixth Edition. Elsevier Churchill Livingstone. 2012: 541.
[3] Su H, Kong AWK. A Study on Low Resolution Androgenic Hair Patterns for Criminal and Victim Identification. *IEEE Transactions on Information Forensics and Security*. 2014; Vol. 9(4): 666-680.
[4] Islam MR, Chan FKS, Kong AWK. *A Preliminary Study of Lower Leg Geometry as a Soft Biometric Trait for Forensic Investigation*. 22nd International Conference on Pattern Recognition. Stockholm. 2014: 427-431.
[5] Chan FKS, Kong AWK. *Using Leg Geometry to Align Androgenic Hair Patterns in Low Resolution Images for Criminal and Victim Identification*. 22nd International Conference on Pattern Recognition. Stockholm. 2014: 495-500.
[6] Chan FKS, Kong AWK. *Using Hair Follicles with Leg Geometry to Align Androgenic Hair Patterns*. Intelligence and Security Informatics Conference. Manchester. 2015: 137-140.
[7] Lionnie R, Alaydrus M. *An Analysis of Haar Wavelet Transform for Androgenic Hair Pattern Recognition*. Proceedings of the First International Conference on Informatics and Computing. Lombok. 2016.

[8] Lionnie R. Alaydrus M. *Biometric Identification System based on Principal Component Analysis*. Proceedings of the 12th IMT-GT International Conference on Mathematics, Statistics and Their Applications. Banda Aceh: 2016.
[9] Burger W, Burge MJ. Principles of Digital Image Processing: Fundamental Techniques. London: Springer-Verlag. 2009: 63-66.
[10] Gonzales RC, Woods RE, Digital Image Processing. Third Edition. New Jersey: Pearson Prentice Hall. 2008: 122-128.
[11] Lindeberg T. Feature Detection with Automatic Scale Selection. *International Journal of Computer Vision*. 1998; 30(2): 77-116.
[12] Lowe DG. *Object Recognition from Local Scale-Invariant Features*. Proceedings of the 7th IEEE International Conference on Computer Vision. Kerkyra. 1999; 2: 1150-1157.
[13] Lowe DG. Distinctive Image Features from Scale-Invariant Keypoints. *International Journal of Computer Vision*. 2004; 60(2): 91-110.
[14] Lindeberg T. Scale-Space Theory in Computer Vision. Kluwer Academic Publishers. 1994: 48.
[15] Babaud J, Witkin AP, Baudin M, Duda RO. Uniqueness of the Gaussian Kernel for Scale-Space Filtering. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 1986; 8(1): 26-33.
[16] Burger W, Burge MJ. Principles of Digital Image Processing: Advanced Methods. London: Springer-Verlag. 2013: 229-296.
[17] Sundaram M, Mani A. Face Recognition: Demystification of Multifarious Aspect in Evaluation Metrics. In: Ramakrishnan S. *Editor*. Face Recognition – Semisupervised Classification, Subspace Projection and Evaluation Methods. Intech. 2016.
[18] Lionnie R, Timotius IK, Setyawan I. *An analysis of edge detection as a feature extractor in a hand gesture recognition system based on nearest neighbour*. International Conference on Electrical Engineering and Informatics. Bandung. 2011: 1-4.
[19] Yuniarti A, Nugroho AS, Amaliah B, Arifin AZ. Classification and Numbering of Dental Radiographs for an Automated Human Identification System. *Telecommunication Computing Electronics and Control (Telkomnika)*. 2012; 10(1): 137-146.
[20] Kusuma H, Wirawan, Soeprijanto A. Gabor-based Face Recognition with Illumination Variation using Subpace-Linear Discriminant Analysis. *Telecommunication Computing Electronics and Control (Telkomnika)*. 2012; 10(1): 119-128.