DAFTAR PUSTAKA

[ARD-11] Ardhianto, Eka, Siti Munawaroh, and Agung Prihandono. (2011),"Pengolah Citra Digital untuk Identifikasi Ciri Sidik Jari Berbasis Minutiae." Dinamik-Jurnal Teknologi Informasi 16, no. 1.

[BIC-03] Bicego, M., U. Castellani, and V. Murino, (2003) "Using Hidden Markov Models and wavelets for face recognition." In Image Analysis and Processing, 2003. Proceedings. 12th International Conference on, pp. 52-56. IEEE.

[ELI-08] Elizabeth, (2008), "Pengembangan Sistem Identifikasi Biometrik Wajah Menggunakan Metode *Neural Network* dan *Pattern Matching*", Jurusan Teknik Elektro Universitas Indonesia, Depok.

[GON-02] Gonzales, R.C., Woods, R. E., dan Eddins, S. L., (2002)."Digital Image Processing Second Edition", dalam *Image Sampling and Quantization*, Prentice Hall, hal. 55.

[HUA-12] Huabiao Qin; Jun Liu; Tianyi Hong, (2012), "An eye state identification method based on the Embedded Hidden Markov Model," Vehicular Electronics and Safety (ICVES), IEEE International Conference on , vol., no., pp.255,260, 24-27 July

[JAI-07] Jain, Anil K., Patrick Flynn, Arun A. Ross, (2007),"Handbook of Biometrics", New York : Springer.

[JAM-08] James, (2008), "Identifikasi Plat Nomor Mobil Dengan Skeletonisasi Menggunakan Jaringan Saraf Tiruan", Jurusan Teknik Elektro Universitas Indonesia, Depok.

[KAU-08] Kaur, Manvjeet, Mukhwinder Singh, Akshay Girdhar, and Parvinder S. Sandhu, (2008),"Fingerprint verification system using minutiae extraction technique", World Academy of Science, Engineering and Technology 46, 497-502.

[KRI-11] Krishnasamy Prasanna, Serge Belongie, David Kriegman, (2011),"Wet Fingerprint Recognition : Challenges and

Opportunities", IEEE, International Conference on In Biometrics International Joint Conference, 1-7.

[LEO-08] Leon, J., Sanchez, G., Aguilar, G., Toscano, K., Perez,H., Nakano, M., (2008)," Fingerprint Recongnition Using Espatial Minutae Information", The International Conference on Electronics, Robotics and Automotive Mechanics, 381-386.

[LEK-11] Leksono, Bowo, Achmad Hidayatno, dan R. Rizal Isnanto. (2011), "Aplikasi Metode Template Matching untuk Klasifikasi Sidik Jari." TRANSMISI 13, no. 1: 1-6.

[LEO-09] Leon,J., Sanchez,G ., Aguilar,G ., Toscano,L., Perez,H., Ramirez,J.M., (2009),"Fingerprint verification applying invariant moments", The IEEE International Midwest Symposium on Circuits and Systems, 751-757.

[MAL-03] Maltoni, dkk, (2003),"Handbook of Fingerprint Recognition", New York:Springer.

[MUL-08] Mulyani, dkk, (2008), "Penerapan Hidden Markov Model Dalam Clustering Sequence Protein Globin", Program Studi Ilmu Komputer, FMIPA, Universitas Gadjah mada, Yogyakarta.

[NEU-12] http://www.neurotechnology.com/download.html diakses pada Oktober 2012.

[PAT-05] Patil, P.M.; Suralkar, S.R.; Sheikh, F.B.,(2005),"Rotation invariant thinning algorithm to detect ridge bifurcations for fingerprint identification," Tools with Artificial Intelligence, ICTAI 05. 17th IEEE International Conference on , vol., no., pp.8 pp.,641, 16-16 Nov.

[POR-10] Pornpanomchai Chomtip, Apiradee Phaisitkulwiwat, (2010),"Fingerprint Recognition By Euclidian Distance", IEEE, Second International Conference on Computer and Network Technology, 437-441.

[PRA-11] Prabhakar, Salil, Alexander Ivanisov, and A. K. Jain, (2011),"Biometric recognition: Sensor characteristics and image

quality." Instrumentation & Measurement Magazine, IEEE 14, no. 3, 10-16.

[SEP-12] Sepritahara, (2012), "Sistem Pengenalan Wajah (Face Recognition) Menggunakan Hidden Markov Model (HMM)", Jurusan Teknik Elektro Universitas Indonesia, Depok.

[SER-82] Serra, J, (1982), "Image Analysis and Mathematical Morphology", Academic Press, Inc., London.

[SRI-10] Sri Huning Anwariningsih, Agus Zainal Arifin, Anny Yuniarti, (2010), "Metode Shape Descriptor Berbasis Shape Matrix Untuk Estimasi Bentuk Structuring Element", Tesis, Program Magister Teknik Informatika, Jurusan Teknik Informatika, FakultasTeknologiInformasi, Institut Teknologi Sepuluh Nopember, Surabaya.

[SUN-10] Sun Zhipeng, JinGuang Sun, (2010),"Face Recognition Based on Fractal and Hidden Markov Model", IEEE, Third International Symposium on Electronic Commerce and Security, 293-297.

[WEI-12] Wei Chen; Lichun Sui; Zhengchao Xu; Yu Lang, (2012),"Improved Zhang-Suen thinning algorithm in binary line drawing applications," Systems and Informatics (ICSAI), International Conference on , vol., no., pp.1947,1950, 19-20 May

[WIB-12] Wibowo, A., & Fathurrahman, F, (2012), "Implementasi Algoritma Breadth First Search Dan Obstacle Detection Dalam Penelusuran Labirin Dinamis Menggunakan Robot Lego". *Jurnal Ilmu Komputer dan Informasi*, *4*(1), 15.

[YUL-08] Yulianti S., Maria, (2008),"Pengenalan Retina Dengan Hidden Markov Model", Jurusan Teknik Elektro Universitas Indonesia, Depok.

[ZHA-12] Zhao Weizhou, Hui Zhang, (2012), "Secure Fingerprint Recognition Based on Frobenius Norm", IEEE, International Conference on Computer Science and Electronics Engineering, Vol. 1, 388-391.

LAMPIRAN

Lampiran 1. Hasil perhitungan Binerisasi Metode otsu

nilai piksel citra	jumlah piksel	jumlah piksel total	Pi	i.Pi	Mean	Zerothcm	Firstcm	variance akhir	cek
53	1		0,006493506	0,344155844		0,006493506	0,344155844	8,982292917	8
55	1		0,006493506	0,357142857		0,006493506	0,357142857	8,039249033	8
59	1		0,006493506	0,383116883		0,006493506	0,383116883	6,31002401	8
62	2		0,012987013	0,805194805		0,012987013	0,805194805	10,36848818	10
63	2		0,012987013	0,818181818		0,012987013	0,818181818	9,642924275	10
69	1		0,006493506	0,448051948		0,006493506	0,448051948	2,901994131	10
70	1		0,006493506	0,454545455		0,006493506	0,454545455	2,633086568	10
71	2		0,012987013	0,922077922		0,012987013	0,922077922	4,785781418	10
72	2		0,012987013	0,935064935		0,012987013	0,935064935	4,297059613	10
73	1		0,006493506	0,474025974		0,006493506	0,474025974	1,904795251	10
74	1	154	0,006493506	0,480519481	90,07142857	0,006493506	0,480519481	1,68817527	10
75	2		0,012987013	0,974025974		0,012987013	0,974025974	2,988788937	10
76	1		0,006493506	0,493506494		0,006493506	0,493506494	1,294150994	10
77	1		0,006493506	0,5		0,006493506	0,5	1,116746699	10
.	.		.	.		.	.	.	.
.	.		.	.		.	.	.	.
.	.		.	.		.	.	.	.
248	1		0,006493506	1,61038961		0,006493506	1,61038961	163,0159064	163
249	1		0,006493506	1,616883117		0,006493506	1,616883117	165,0868681	165
255	39		0,253246753	64,57792208		0,253246753	64,57792208	9224,834028	165

Lampiran 2. Nilai parameter HMM awal

Tabel 1. Matriks inisial

	0
0	1

Tabel 2. Matriks emisi / observasi

	0	1	2	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	23
0	0,041667	0,041667	0,041667	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	0,041667

Tabel 3. Matriks transisi

	0
0	1

Lampiran 3. Hasil algoritma *forward*

Tabel 1. Hasil Inisialisasi algoritma *forward*

I	i < states	fwd(0,i)		c[0]!=0	i < states	c[0]	fwd[0,i]
0	TRUE	0,041667		TRUE	TRUE	0,041667	1
1	FALSE	-		-	-		-

Tabel 2. Hasil induksi algoritma *forward*

t	i	J	t < T	i < states	j < states	t-1	J	i	fwd[t-1,j]	A[i,j]	fwd[t-1,j] * A[i,j]	sum	fwd[t,i]	c[t]	c[t] != 0	i < states	fwd[t,i]
1	0	0	TRUE	TRUE	TRUE	0	0	0	1	1	1	1	0,041667	0,041667	TRUE	TRUE	1
2	1	1	TRUE	FALSE	FALSE	1	0	0	1	1	1	1	0,041667	0,041667	TRUE	TRUE	1
3	2	2	TRUE	FALSE	FALSE	2	0	0	1	1	1	1	0,041667	0,0416667	TRUE	TRUE	1
4	3	3	TRUE	FALSE	FALSE	3	0	0	1	1	1	1	0,041667	0,0416667	TRUE	TRUE	1
5	4	4	TRUE	FALSE	FALSE	4	0	0	1	1	1	1	0,041667	0,0416667	TRUE	TRUE	1
6	5	5	FALSE	FALSE	FALSE												

Lampiran 4. Hasil algoritma *backward*

Tabel 1. Hasil inisialisasi algoritma *backward*

I	i < states	bwd[T-1,i]
0	TRUE	24
1	FALSE	

Tabel 2. Hasil induksi algoritma *backward*

t	I	J	t >= 0	i< states	j < states	T	i	j	A[i,j] * B[j,observations[t+1]] * bwd[t+1,j]	sum	sum / c[t]	bwd[t,i]
4	0	0	TRUE	TRUE	TRUE	4	0	0	1	1	24	24
3	1	1	TRUE	FALSE	FALSE	3	0	0	1	1	24	24
2			TRUE			2	0	0	1	1	24	24
1			TRUE			1	0	0	1	1	24	24
0			TRUE			0	0	0	1	1	24	24

Lampiran 5. Hasil perhitungan matriks *gamma*

t	k	t < T	k < states	T	K	gamma[i][t,k]	s	gamma[i][t,k]
0	0	TRUE	TRUE	0	0	24	24	1
1	1	TRUE	FALSE	1	0	24	24	1
2	2	TRUE	FALSE	2	0	24	24	1
3	3	TRUE	FALSE	3	0	24	24	1
4	4	TRUE	FALSE	4	0	24	24	1
5	5	TRUE	FALSE	5	0	24	24	1
6	6	FALSE	FALSE					

Lampiran 6. Hasil perhitungan matriks *epsilon*

t	k	l	t < T-1	k < states	i < states	t	k	l	epsilon[i][t,k,l]	s+	epsilon[i][t,k,l]
0	0	0	TRUE	TRUE	TRUE	0	0	0	1	1	1
1	1	1	TRUE	FALSE	FALSE	1	0	0	1	1	1
2	2	2	TRUE	FALSE	FALSE	2	0	0	1	1	1
3	3	3	TRUE	FALSE	FALSE	3	0	0	1	1	1
4	4	4	TRUE	FALSE	FALSE	4	0	0	1	1	1
5	5	5	FALSE	FALSE	FALSE						
6	6	6	FALSE	FALSE	FALSE						

Lampiran 7. Hasil perhitungan *likelihood*

t	t<scaling.length	log10	newlikelihood +
0	TRUE	-1,38021	-8,28127
1	TRUE	-1,38021	
2	TRUE	-1,38021	
3	TRUE	-1,38021	
4	TRUE	-1,38021	
5	TRUE	-1,38021	
6	FALSE		

Lampiran 8. Re-estimasi parameter HMM dan perhitungan algoritma *forward, backward,* matriks *gamma, epsilon, likelihood* baru dan evaluasi hasil setelah parameter HMM terestimasi kembali

Tabel 1. Re-estimasi matriks inisial

k	i	k < states	i < N	K	i	gamma[i][0,k]	sum +=	pi[k]
0	0	TRUE	TRUE	0	0	1	1	1
1	1	FALSE	FALSE					

Tabel 2. Matriks inisial yang terestimasi kembali

pi	0
0	1

Tabel 3. Re-estimasi matriks transisi

i	j	K	l	i < states	j < states	k < N	l < T-1	k	l	i	j	epsilon[k][l,i,j]	num	gamma[k][l,i]	den	A[i,j]
0	0	0	0	TRUE	TRUE	TRUE	TRUE	0	0	0	0	1	5	1	5	1
1	1	1	1	FALSE	FALSE	FALSE	TRUE	0	1	0	0	1		1		
2	2	2	2	FALSE	FALSE	FALSE	TRUE	0	2	0	0	1		1		
3	3	3	3	FALSE	FALSE	FALSE	TRUE	0	3	0	0	1		1		
4	4	4	4	FALSE	FALSE	FALSE	TRUE	0	4	0	0	1		1		
5	5	5	5	FALSE	FALSE	FALSE	FALSE									
6	6	6	6	FALSE	FALSE	FALSE	FALSE									

Tabel 4. Matriks transisi yang terestimasi kembali

A	0
0	1

Tabel 5. Re-estimasi matriks emisi

k	l	i	k < N	l < T	i < states	k	L	i	den+
0	0	0	TRUE	TRUE	TRUE	0	0	0	5
1	1	1	FALSE	TRUE	FALSE	0	1	0	
2	2	2	FALSE	TRUE	FALSE	0	2	0	
3	3	3	FALSE	TRUE	FALSE	0	3	0	
4	4	4	FALSE	TRUE	FALSE	0	4	0	
5	5	5	FALSE	TRUE	FALSE	0	5	0	
6	6	6	FALSE	FALSE	FALSE				

Tabel 6. Matriks emisi yang terestimasi kembali

B	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	0,2	1,00E-10	1,00E-10	0,2	…	…	…	…	…	…	0,2	…	…	…	…	0,2	…	0,2	…	…	0,2	…	…	1,00E-10

Tabel 7. Hasil inisialisasi algoritma *forward* setelah parameter HMM terestimasi kembali

I	i < states	fwd(0,i)		c[0]!=0	i < states	c[0]	fwd[0,i]
0	TRUE	0,2		TRUE	TRUE	0,2	1
1	FALSE	-		-	-		-

Tabel 8. Hasil induksi algoritma *forward* setelah parameter HMM terestimasi kembali

t	i	J	t < T	i < states	j < states	t-1	j	I	fwd[t-1,j]	A[i,j]	fwd[t-1,j] * A[i,j]	sum	fwd[t,i]	c[t]	c[t] != 0	i < states	fwd[t,i]
1	0	0	TRUE	TRUE	TRUE	0	0	0	1	1	1	1	0,2	0,2	TRUE	TRUE	1
2	1	1	TRUE	FALSE	FALSE	1	0	0	1	1	1	1	0,2	0,2	TRUE	TRUE	1
3	2	2	TRUE	FALSE	FALSE	2	0	0	1	1	1	1	0,2	0,2	TRUE	TRUE	1
4	3	3	TRUE	FALSE	FALSE	3	0	0	1	1	1	1	0,2	0,2	TRUE	TRUE	1
5	4	4	TRUE	FALSE	FALSE	4	0	0	1	1	1	1	0,2	0,2	TRUE	TRUE	1
6	5	5	FALSE	FALSE	FALSE												

Tabel 9. Hasil inisialisasi algoritma *backward* setelah parameter HMM terestimasi kembali

i	i < states	bwd[T-1,i]
0	TRUE	5
1	FALSE	

Tabel 10. Hasil induksi algoritma *backward* setelah parameter HMM terestimasi kembali

t	i	J	t >= 0	i< states	j < states	t	i	j	A[i,j] * B[j,observations[t+1]] * bwd[t+1,j]	sum	sum / c[t]	bwd[t,i]
4	0	0	TRUE	TRUE	TRUE	4	0	0	1	1	5	5
3	1	1	TRUE	FALSE	FALSE	3	0	0	1	1	5	5
2			TRUE			2	0	0	1	1	5	5
1			TRUE			1	0	0	1	1	5	5
0			TRUE			0	0	0	1	1	5	5

Tabel 11. Hasil perhitungan matriks *gamma* setelah parameter HMM terestimasi kembali

t	k	t < T	k < states	t	k	gamma[i][t,k]	s	gamma[i][t,k]
0	0	TRUE	TRUE	0	0	5	5	1
1	1	TRUE	FALSE	1	0	5	5	1
2	2	TRUE	FALSE	2	0	5	5	1
3	3	TRUE	FALSE	3	0	5	5	1
4	4	TRUE	FALSE	4	0	5	5	1
5	5	TRUE	FALSE	5	0	5	5	1
6	6	FALSE	FALSE					

Tabel 12. Hasil perhitungan matriks *epsilon* setelah parameter HMM terestimasi kembali

t	k	l	t < T-1	k < states	i < states	t	k	l	epsilon[i][t,k,l]	s+	epsilon[i][t,k,l]
0	0	0	TRUE	TRUE	TRUE	0	0	0	1	1	1
1	1	1	TRUE	FALSE	FALSE	1	0	0	1	1	1
2	2	2	TRUE	FALSE	FALSE	2	0	0	1	1	1
3	3	3	TRUE	FALSE	FALSE	3	0	0	1	1	1
4	4	4	TRUE	FALSE	FALSE	4	0	0	1	1	1
5	5	5	FALSE	FALSE	FALSE						
6	6	6	FALSE	FALSE	FALSE						

Tabel 13. Perhitungan *likelihood* baru setelah parameter HMM terestimasi kembali

t	T<scaling.length	log10	newlikelihood +
0	TRUE	-0,69897	-4,19382
1	TRUE	-0,69897	
2	TRUE	-0,69897	
3	TRUE	-0,69897	
4	TRUE	-0,69897	
5	TRUE	-0,69897	
6	FALSE		

Tabel 14. Hasil evaluasi

i	coefficient.length	i < coef..	log10(coeffi..	likelihood +	hasil akhir
0	6	TRUE	-0,69897	-4,19382	0,015089
1		TRUE	-0,69897		
2		TRUE	-0,69897		
3		TRUE	-0,69897		
4		TRUE	-0,69897		
5		TRUE	-0,69897		
6		FALSE			