Authentication Using Wavelets

Part II

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Joint Mathematics Meetings, 2010

Outline

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1. Project Beginnings
2. Project Details
3. Summary

Wavelet Workshop

In August 2009, I attended the

Discrete Wavelet Module-Writing Workshop

Workshop Leaders:

- Patrick Van Fleet, University of St. Thomas
- Catherine Beneteau, University of South Florida
- Caroline Haddad, SUNY Geneseo
- David Ruch, Metropolitan State College of Denver.

Supported by: MAA, PREP and NSF

Our Team and Module

Our Team:

- John Merkel
- Jill Guerra
- Caroline Haddad
- Rachel Weir

Our Module: Use wavelets to classify handwriting as forgery or authentic.

Outline

Project Outline

Based primarily on Lyu, Rockmore, Farid: *A digital technique for art authentication*

- Obtain several fingerprint samples for several people
- Convert to digital files (take a picture)
- Apply wavelet transform to picture
- Collect statistical data to form *signature vector* in $\mathbb{R}^{72}$
- Categorize fingerprints based on distance between their signature vectors

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The pictures

Pictures are all 256 $\times$ 256 pixels.

Figure: Gryc1.png

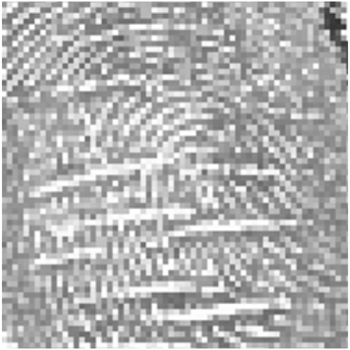


Figure: Gryc2.png

Wavelet Transform

4 Iterations of Daubechies(4)

Figure: Temba1.png

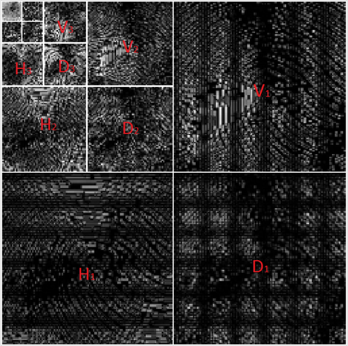
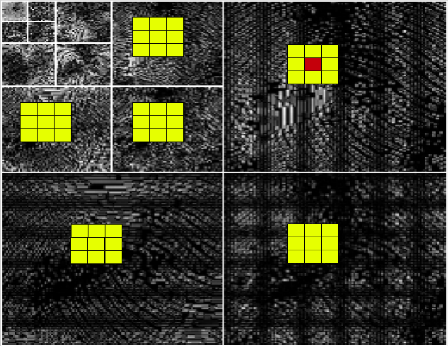


Figure: Transformed Temba1.png

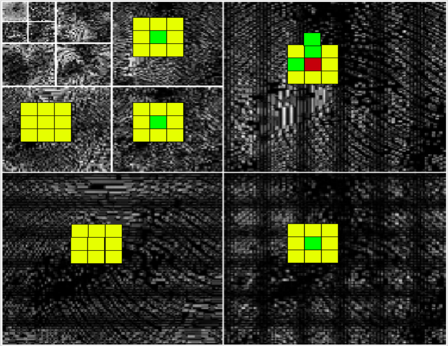
Predictive Neighbors

Which yellow pixels are best at predicting the value of the red pixel?



Predictive Neighbors

Which yellow pixels are best at predicting the value of the red pixel?



Create Linear Predictor

Buccigrossi gives the following as the best neighboring pixels to use for a linear predictor:

$$
\begin{aligned}
L_V^k(r,c) = {} & w_1 V_k(r, c-1) + w_2 V_k(r-1, c) + w_3 V_{k+1}(\lfloor r/2 \rfloor, \lfloor c/2 \rfloor) \\
& + w_4 D_k(r,c) + w_5 V_k(r-2, c) + w_6 D_{k+1}(\lfloor r/2 \rfloor, \lfloor c/2 \rfloor) \\
L_D^k(r,c) = {} & w_1 D_k(r-1, c) + w_2 D_k(r, c-1) + w_3 D_{k+1}(\lfloor r/2 \rfloor, \lfloor c/2 \rfloor) \\
& + w_4 H_k(r,c) + w_5 V_k(r,c) + w_6 D_k(r, c-2) \\
L_H^k(r,c) = {} & w_1 H_k(r, c-1) + w_2 H_k(r-1, c) + w_3 H_{k+1}(\lfloor r/2 \rfloor, \lfloor c/2 \rfloor) \\
& + w_4 D_k(r,c) + w_5 V_k(r, c-2) + w_6 D_{k+1}(\lfloor r/2 \rfloor, \lfloor c/2 \rfloor)
\end{aligned}
$$

But how to find weights?

Determining Weights - Definitions

Define the *weight vector* by $\mathbf{w} = (w_1, \cdots, w_6)^T$.
Let $\mathbf{v}$ =flatten(V_1).
Let Q be the matrix with 6 columns of neighboring pixel values.
Then we can write our linear predictor for V_1 as

$$L_V^1 = Q\mathbf{w}.$$

Define the *error vector* by $\mathbf{e} = \mathbf{v} - L_V^1 = \mathbf{v} - Q\mathbf{w}$.

Determining Weights - Formula

Weights for the linear predictor that minimize the *error function*

$$E(\mathbf{w}) = \mathbf{e} \cdot \mathbf{e} = (\mathbf{v} - L_V^1)^2 = (\mathbf{v} - Q\mathbf{w})^2$$

are given by

$$\mathbf{w} = (Q^T Q)^{-1} Q^T \mathbf{v}.$$

Repeat process for 9 subbands $V_1, V_2, V_3, H_1, H_2, H_3, D_1, D_2, D_3$

Collecting Stats for Signature Vector

For each of the 9 subbands calculate

1. Mean of weights
2. Variance of weights
3. Skewness of weights
4. Kurtosis of weights
5. Mean of **e**
6. Variance of **e**
7. Skewness of **e**
8. Kurtosis of **e**

Each fingerprint has 72 statistical parameters. These form the signature vector in $\mathbb{R}^{72}$

Mutual Distance Table

		Chancelor			Green			Gryc			Mathews			Merkel			Temba		
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Chancelor	1	0.00	3.82	6.43	13.82	14.15	14.39	12.41	12.41	12.13	14.43	12.87	13.23	11.63	12.76	12.36	15.35	13.70	17.60
	2	3.82	0.00	6.77	13.26	13.36	13.59	12.29	11.93	11.76	13.59	12.03	12.65	11.64	12.00	11.99	14.41	12.69	17.81
	3	6.43	6.77	0.00	13.37	14.28	14.62	13.45	12.62	13.32	14.44	12.77	14.13	13.48	13.42	13.35	15.57	13.68	18.73
Green	4	13.82	13.26	13.37	0.00	7.14	7.99	10.67	10.79	10.78	9.57	8.50	9.67	11.33	9.69	10.14	8.84	7.64	16.06
	5	14.15	13.36	14.28	7.14	0.00	5.05	10.58	10.00	9.64	9.64	9.41	9.21	10.52	9.82	9.14	7.55	8.40	15.92
	6	14.39	13.59	14.62	7.99	5.05	0.00	11.11	11.40	10.29	10.07	10.22	10.44	11.46	10.82	10.51	7.98	9.18	16.54
Gryc	7	12.41	12.29	13.45	10.67	10.58	11.11	0.00	11.82	10.62	11.73	11.18	10.76	12.34	12.56	10.85	11.57	11.51	13.48
	8	12.41	11.93	12.62	10.79	10.00	11.40	11.82	0.00	10.16	12.99	11.16	12.45	9.41	8.82	10.13	12.47	10.29	18.48
	9	12.13	11.76	13.32	10.78	9.64	10.29	10.62	10.16	0.00	11.67	11.75	9.77	9.48	11.11	8.12	11.43	11.86	16.72
Mathews	10	14.43	13.59	14.44	9.57	9.64	10.07	11.73	12.99	11.67	0.00	6.29	5.64	12.80	11.88	10.29	9.54	11.01	16.90
	11	12.87	12.03	12.77	8.50	9.41	10.22	11.18	11.16	11.75	6.29	0.00	8.02	11.71	9.70	10.39	10.64	8.53	17.67
	12	13.23	12.65	14.13	9.67	9.21	10.44	10.76	12.45	9.77	5.64	8.02	0.00	11.64	12.01	9.02	9.87	10.81	16.39
Merkel	13	11.63	11.64	13.48	11.33	10.52	11.46	12.34	9.41	9.48	12.80	11.71	11.64	0.00	7.06	9.53	13.40	11.80	18.19
	14	12.76	12.00	13.42	9.69	9.82	10.82	12.56	8.82	11.11	11.88	9.70	12.01	7.06	0.00	9.97	12.15	8.99	18.21
	15	12.36	11.99	13.35	10.14	9.14	10.51	10.85	10.13	8.12	10.29	10.39	9.02	9.53	9.97	0.00	11.14	10.70	15.84
Temba	16	15.35	14.41	15.57	8.84	7.55	7.98	11.57	12.47	11.43	9.54	10.64	9.87	13.40	12.15	11.14	0.00	8.95	15.69
	17	13.70	12.69	13.68	7.64	8.40	9.18	11.51	10.29	11.86	11.01	8.53	10.81	11.80	8.99	10.70	8.95	0.00	16.93
	18	17.60	17.81	18.73	16.06	15.92	16.54	13.48	18.48	16.72	16.90	17.67	16.39	18.19	18.21	15.84	15.69	16.93	0.00

Mutual Distance Averages

AVERAGES		Chancelor			Green			Gryc			Mathews			Merkel			Temba		
Chancelor			5.67		13.48	13.93	14.20	12.72	12.32	12.40	14.15	12.56	13.34	12.25	12.73	12.57	15.11	13.36	18.05
Green		14.12	13.40	14.09		6.73		10.79	10.73	10.24	9.76	9.38	9.77	11.10	10.11	9.93	8.12	8.41	16.18
Gryc		12.32	11.99	13.13	10.75	10.07	10.93		10.87		12.13	11.36	11.00	10.41	10.83	9.70	11.82	11.22	16.22
Mathews		13.51	12.76	13.78	9.25	9.42	10.24	11.22	12.20	11.07		6.65		12.05	11.20	9.90	10.02	10.12	16.98
Merkel		12.25	11.88	13.42	10.39	9.83	10.93	11.92	9.45	9.57	11.66	10.60	10.89		8.85		12.23	10.50	17.41
Temba		15.55	14.97	15.99	10.85	10.63	11.24	12.19	13.74	13.33	12.48	12.28	12.36	14.47	13.12	12.56		13.86	

Out of Sample Prints

	Chancelor	Green	Gryc	Mathews	Merkel	Temba
Chancelor	4.77	13.75	12.99	13.48	12.42	13.49
	3.43	13.49	12.61	13.02	11.91	12.41
	6.06	14.27	13.29	13.99	12.80	12.91
Green	13.09	6.90	12.49	13.10	10.42	6.63
	13.38	7.42	10.53	13.75	10.32	6.32
	13.73	9.28	11.53	13.88	11.11	7.14
Gryc	12.40	10.67	12.86	13.29	12.31	11.08
	12.04	11.05	7.25	14.58	9.14	11.02
	12.21	10.58	11.72	13.68	10.78	11.47
Mathews	13.82	9.68	13.79	14.36	12.13	9.98
	11.92	8.87	12.77	13.23	9.99	8.39
	12.93	9.26	13.17	13.91	12.05	10.13
Merkel	11.95	11.16	10.40	14.11	6.57	11.67
	12.22	9.99	10.50	12.08	4.44	9.54
	12.71	9.26	10.74	14.07	9.85	10.74
Temba	14.52	9.95	14.07	14.41	12.60	6.89
	12.77	8.75	11.63	12.36	9.13	6.35
	17.63	15.24	19.23	15.88	18.45	16.54

AVERAGES	Chancelor	Green	Gryc	Mathews	Merkel	Temba
Chancelor	4.75	13.84	12.96	13.49	12.37	12.93
Green	13.40	7.87	11.52	13.58	10.62	6.70
Gryc	12.22	10.76	10.61	13.85	10.74	11.19
Mathews	12.89	9.27	13.24	13.83	11.39	9.50
Merkel	12.29	10.14	10.55	13.42	6.95	10.65
Temba	14.97	11.31	14.98	14.22	13.39	9.93

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- The project shows promise as a “proof of concept"
- All pictures need to be processed identically!
- This technique could be used in other settings

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