

# Performance Analysis of Canny and DGW-Canny in Biometrics using Discrete Wavelet Transform (DWT)

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**Abstract.** There are many applications of edge detection like in image fusion, text extraction, biometric recognition *etc.* In our previous findings on edge detection, DGW-Canny has provided better results in areas of text recognition and fine grain region. It has intrigued us in testing edge detection on biometric features as granularity plays a major role in biometric recognition. Recent literature shows that there are various techniques for biometric detection but DWT based analysis requires least amount of memory space as it provides a much better compression ratio. A methodology proposed in [5] using DWT is used for testing the application of edge detector in the area of biometrics. This paper also uses coefficient of correlation as a parameter to evaluate the performance of an edge detector. The encouraging results show that DGW-Canny renders better results as compared to Canny, and the performance is enhanced as one moves from lower to higher granularity biometric.

**Keywords:** biometrics, canny, DGW-canny, DWT, edge detector.

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## 1. Introduction

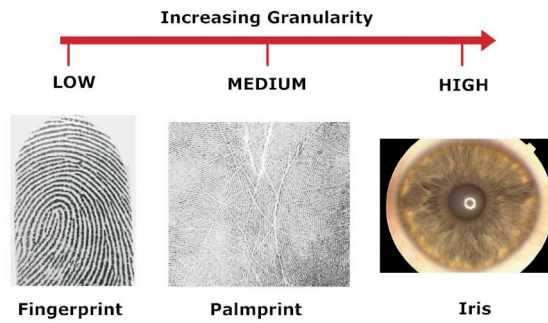
Edge detection is considered to be a vital branch of image processing and signal rendering. In due course of time it has found a vast application in areas ranging from extracting vital information from an image to providing security solutions. Some of its contributions lies in areas like:

- Text Extraction
- Biometric Recognition
- Image Fusion
- Signature Authentication

Newer algorithms and methodology in its application domains and especially in biometric recognition have transformed the way the world around us functions. The kind of security solutions that biometrics provide, are impeccable and nearly impossible to breach. This has intrigued our interest in biometrics and the result is to try to further explore this genre in the present paper.

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**Figure 1.** Categorization of biometrics based on granularity.

### 1.1 Biometrics

There is a long list of biometric traits but pivotally the major ones include fingerprints, palm prints and iris scan. Biometric provides a subtle uniqueness to every individual which distinguishes them from the rest. There is a trait which facilitates this uniqueness and it is present in form of small granules over our skin. The granules provide a unique pattern to every individual. In our previous findings on edge detection [1], DGW-Canny has provided better results in areas of text recognition and fine grain region. This granularity has intrigued us to apply edge detection into biometric recognition. As DGW-canny is sensitive to fine grain regions, a categorization of the three major areas of biometrics i.e iris, palm-print and fingerprint can be made depending upon the nature of granularity of the patterns involved, as shown in Figure 1.

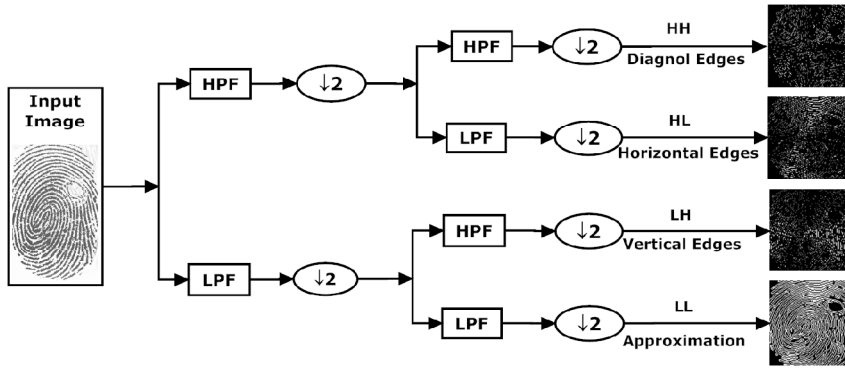
In the present work, two extreme ends of this scale i.e. Iris and Fingerprint have been taken up for study. Recent literature shows that there are various techniques for biometric detection based on pattern recognition, moment based image recognition and DWT. Among them DWT based analysis requires the least amount of memory space, as it considers only wavelet coefficient of an image in matching with preserved coefficient as mentioned in [5].

### 1.2 Discrete wavelet transform

Digitization of biometric cards requires larger storage space, likewise their retrieval and transmission requires longer time as stated in [3]. Therefore, it is often necessary to compress the image while storing the necessary data for subsequent reconstruction as suggested in [2]. There are many image compression techniques available for compressing the images, such as DCT, JPEG, Sub-band Coding, JPEG2000, Wavelet *etc.* [4]. But recent literature [3] shows that wavelet transform like DWT provides much better compression ratio.

DWT is composed of a pair of filters. The way wavelet transform is computed by recursively averaging and differentiating coefficients, is called a filter bank, wherein one is a Low Pass Filter(LPF) and other is a High Pass Filter(HPF). Each of these filters is down sampled by two such filters and their output signals can be further transformed as mentioned in [5] and illustrated in Figure 2.

Successive iterations are performed on the low pass coefficients (approximation) from the previous stage to further reduce the number of low pass coefficients. Since the low pass coefficients



**Figure 2.** Analysis of 2D DWT shows one stage filter.

contain most of the original signal energy, therefore, the iteration process yields better energy compaction as in [3]. Usually, five levels of decompositions are used in the current wavelet based image Compression as stated in [6]. The maximum levels of Decomposition of any image can be determined by using the following formula:

$$\text{Maximum Levels of Decomposition} = \log_2 x_{\max}$$

where  $x_{\max}$  is the maximum size of given image.

### 1.3 Organization

To elucidate the framework used, we have organized the paper as follows:

- Section 2 starts with explaining the algorithm used.
- Section 3 elucidates the experiments performed.
- Section 4 juxtaposes the results obtained.

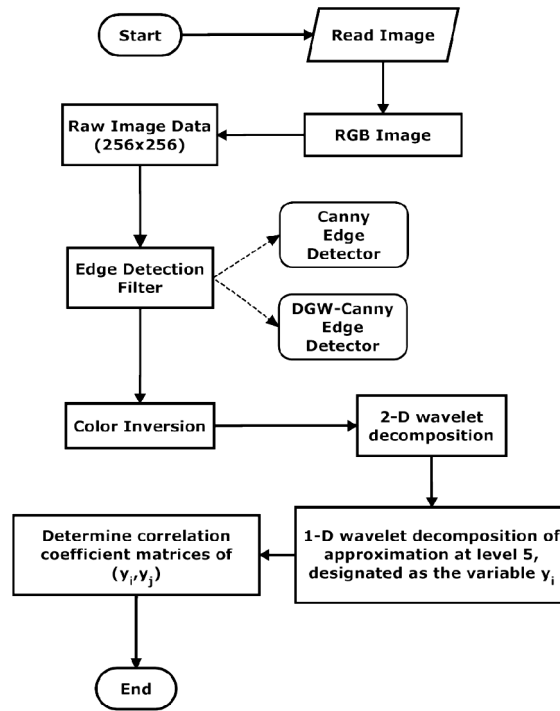
## 2. Methodology

A methodology proposed in [5] using DWT is used for testing the application of DGW-Canny in the area of biometrics.

Figure 3 shows the flow chart of the algorithm.

A set consisting of three images for each biometric are taken as input to the algorithm. Then an RGB Conversion is performed on the images followed by the Edge-Detection filter. Canny and DGW-Canny edge detectors are used separately for edge detection. Then color inversion is performed on the images thus obtained followed by a 2D DWT. Four signals namely approximation, horizontal, vertical and diagonal details which are obtained after 2D DWT are attributed as  $A$ ,  $B$ ,  $C$  and  $D$  respectively. These signals are then transformed to the 5th level 1D DWT, and their approximation vectors ( $A_1, B_1, C_1, D_1$ ) are then stored and concatenated to form a matrix of the form:

$$Y_1 = [A_1 \quad B_1 \quad C_1 \quad D_1]$$



**Figure 3.** Flow chart of the algorithm used.

Similarly  $Y_2$  and  $Y_3$  are obtained for the other two images and these vectors are then convoluted in pairs.

More overlapping behavior of the peaks of the convoluted pairs suggests that they are of the same person whereas non- overlapping peaks affirms the point that they belong to different individuals.

### 3. Experiment

The implementation of the framework is carried out on Sony Vaio PCG-7T1L, Intel(R) Centrino Duo 1.6Ghz, 1 GB RAM, Windows XP Media Center Edition Version 2005 (Service Pack 2) in MATLAB 7.0.

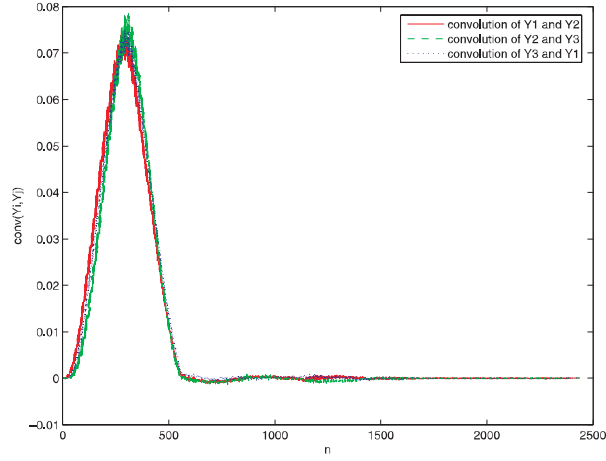
A set consisting of three images for each biometric corresponding to same and different persons is taken in random manner i.e. in terms of rotation and translation.

#### 3.1 Fingerprint simulation

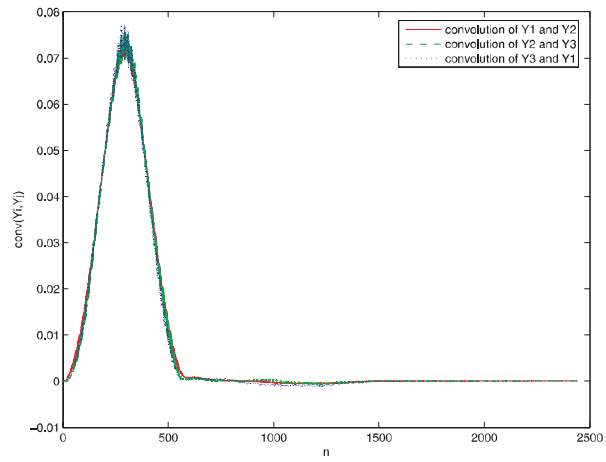
For fingerprint simulation, [7] is used as data-set. Figure 4 shows three fingerprints of the same person. Now, the framework is applied on these three images, using Canny as an edge detector, which in turn provides the vectors  $Y_1$ ,  $Y_2$  and  $Y_3$  according to the algorithm discussed in Section 2. After procuring them, their pair wise convolutions have granted three new vectors  $V_1$ (convolution of  $Y_1$  and  $Y_2$ ),  $V_2$ (convolution of  $Y_2$  and  $Y_3$ ) and  $V_3$ (convolution of  $Y_3$  and  $Y_1$ ).



**Figure 4.** Three fingerprints of the same person.



**Figure 5.** Convolution vectors  $V_i$  and  $V_j$  of fingerprints of the same person using Canny filter.

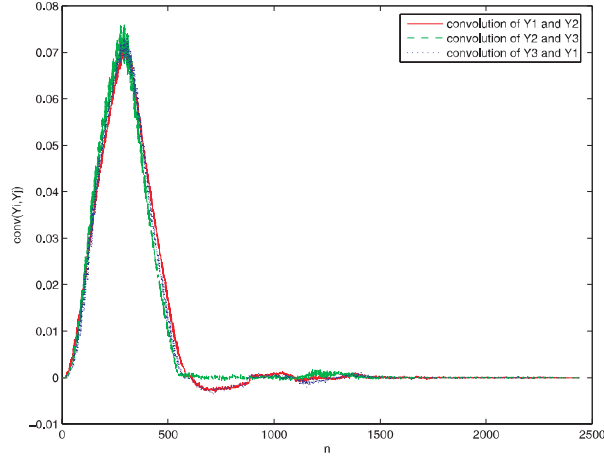


**Figure 6.** Convolution vectors  $V_i$  and  $V_j$  of fingerprints of the same person using DGW-Canny filter.

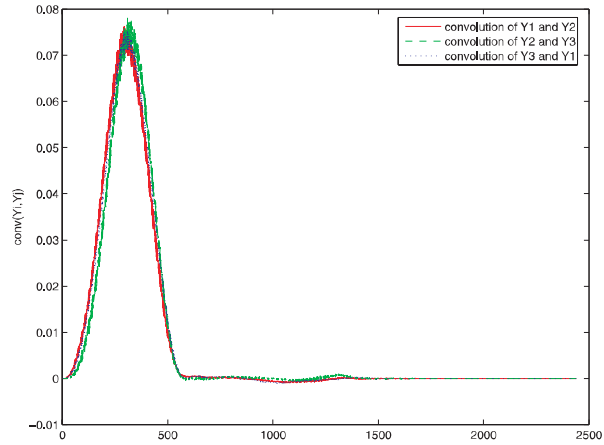
Figure 5 displays  $V_1$ ,  $V_2$  and  $V_3$  after normalization. The process is repeated using DGW-Canny as the edge detector. Figure 6 depicts their convolution curves after normalization. It can be inferred



**Figure 7.** Three fingerprints of different persons.

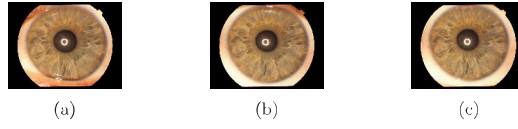


**Figure 8.** Convolution vectors  $V_i$  and  $V_j$  of fingerprints of different persons using Canny filter.

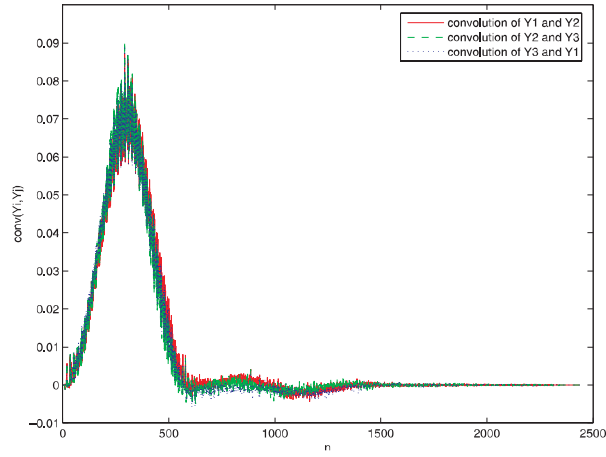


**Figure 9.** Convolution vectors  $V_i$  and  $V_j$  of fingerprints of different persons using DGW-Canny filter.

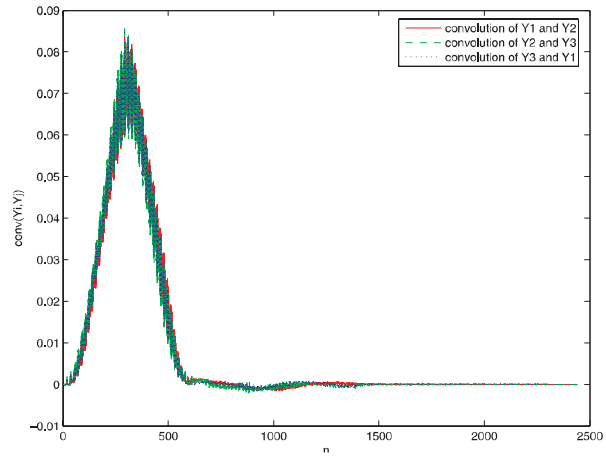
from Figures 5 and 6 that DGW-Canny is performing better than Canny in recognizing the fact that these images belong to the same person as it is giving better overlapping graph around the peaks.



**Figure 10.** Three iris scans of the same person.

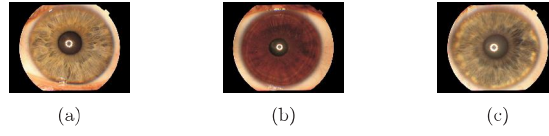


**Figure 11.** Convolution vectors  $V_i$  and  $V_j$  of iris of the same person using Canny filter.

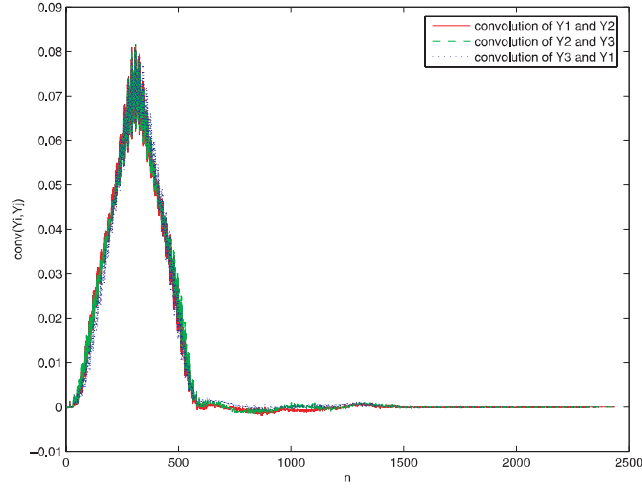


**Figure 12.** Convolution vectors  $V_i$  and  $V_j$  of iris of the same person using DGW-Canny filter.

Figure 7 shows three fingerprints of different persons. The same process as discussed above is carried out on them. Figure 8 displays the corresponding  $V_1$ ,  $V_2$  and  $V_3$  after normalization using Canny whereas Figure 9 does the same for DGW-Canny. Non-overlapping behavior of the curve



**Figure 13.** Three iris scans of different persons.



**Figure 14.** Convolution vectors  $V_i$  and  $V_j$  of iris of different persons using Canny filter.

around the peaks signifies that they belong to different individuals. Here also one can see that DGW-Canny is marginally overpowering Canny.

### 3.2 Iris simulation

For iris simulation, [7–9] are used for data-set. The above mentioned process is iterated with iris scans of same and different individuals. Figure 10 depicts the set of iris scan of the same individual. Figures 11 and 12 correspond to the findings on the same entity using Canny and DGW-Canny respectively.

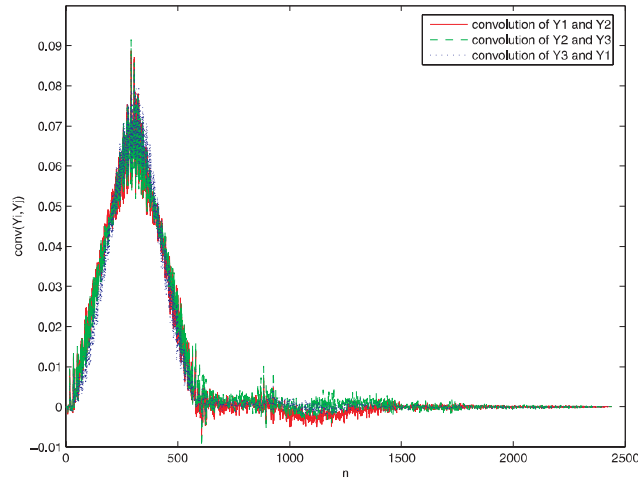
Figure 13 depicts the set of iris scan of different individuals. Figures 14 and 15 correspond to the findings on the different entities using Canny and DGW-Canny respectively.

## 4. Results

This paper considers coefficient of correlation as a paradigm to test the effectiveness of the framework.

The correlation coefficient ( $r$ ) is a direct measure of how well two sample populations vary jointly. A value of  $r$  close to  $+1$  or  $-1$  indicates a high degree of correlation and a good fit to a linear model. A value of  $r$  close to  $0$  indicates a poor fit to a linear model as mentioned in [11].





**Figure 15.** Convolution vectors  $V_i$  and  $V_j$  of iris of different persons using DGW-Canny filter.

**Table 1.** Values of coefficient of correlation.

Biometric Feature	Canny Filter		DGW-Canny Filter	
	Same Persons	Different Persons	Same Persons	Different Persons
Fingerprint	0.9836	0.9832	0.9906	0.9697
Iris	0.9933	0.9409	0.9971	0.9334

We have calculated the coefficient of correlation of  $V_1$ ,  $V_2$  and  $V_3$  (as described in the previous Section) for the data-set used in the Experiment Section.

A comparison is made between the two methods (one using Canny as a filter and other using DGW-Canny) on this parameter as shown in Table 1. It is seen that the deviation in correlation values of same and different persons for Canny is less as compared to DGW-Canny for both the biometrics studied. It can also be inferred that DGW-Canny performs better than Canny in recognizing both the correct and the fluke cases in both the biometrics studied and this performance is further enhanced as we move from low granularity to higher one i.e. from fingerprint to iris.

## References

- [1] Gupta, A., Dalal, R. K., Gupta, R. and Wadhwa, P.: DGW-Canny: An Improvised Version of Canny Edge Detector. In *International Symposium on Intelligent Signal Processing and Communications Systems*, 1–6 (2011).
- [2] Manza, R., Gornale, S. S., Humbe, V. and Kale, K. V.: Noisy and Noiseless Fingerprint Image Compression Using Wavelet Packet. In *Proceedings of International Conference on Cognition and Recognition*, 885–890 (2005).
- [3] Manza, R., Gornale, S. S., Humbe, V. and Kale, K. V.: Performance Analysis of Biorthogonal Wavelet Filters for Lossy Fingerprint Image Compression. In *International Journal of Imaging Science and Engineering*, 1(1) (2007).

- [4] Sonka, M. and Boyle, R.: Image Processing Analysis and Machine Vision. International Thomson Computer Press (1996).
- [5] Begum, N., Alam, M. and Islam, I.: Application of Canny Filter and DWT in Fingerprint Detection a New Approach. In *13th International Conference on Computer and Information Technology*, 256–260 (2010).
- [6] Grigic, S., Grigic, M. and Cihlar, B. Z.: Optimal Decomposition for Wavelet Image Compression. In *First International Workshop on Image and Signal Processing and Analysis* (2000).
- [7] Dobe, M., Martinek, J., Skoupil, D., Dobeov, Z. and Pospil, J.: Human Eye Localization Using the Modified Hough Transform. In *Optik*, Elsevier, 117(10), 468–473 (2006).
- [8] Dobe, M., Machala, L., Tichavsk, P. and Pospil, J.: Human Eye Iris Recognition Using the Mutual Information. In *Optik*, Elsevier 115(9), 399–405, (2004).
- [9] Iris Database, Available at <http://www.inf.upol.cz/iris/>
- [10] Fingerprint Database, Available at <http://www.advancedsourcecode.com/PNGfingerprint.rar>
- [11] Coefficient of Correlation, Information available at [http://www.physics.nyu.edu/grierlab/idl\\_html\\_help/mathematics6.html](http://www.physics.nyu.edu/grierlab/idl_html_help/mathematics6.html)