Skin Image Retrieval Using Gabor Wavelet Texture Feature

Abstract

OBJECTIVE: Skin imaging plays a key role in many clinical studies. We have used many skin imaging techniques, including the recently developed capacitive contact skin imaging based on fingerprint sensors. The aim of this study is to develop an effective skin image retrieval technique using Gabor wavelet transform, which can be used on different types of skin images, but with a special focus on skin capacitive contact images.

METHODS: Content-based image retrieval (CBIR) is a useful technology to retrieve stored images from database by supplying query images. In a typical CBIR, images are retrieved based on colour, shape, and texture, etc. In this paper, texture feature is used for retrieving skin images, and Gabor wavelet transform is used for texture feature description and extraction.

RESULTS: The results show that the Gabor wavelet texture features can work efficiently on different types of skin images. Although Gabor wavelet transform is slower comparing with other image retrieval techniques, such as Principal Component Analysis (PCA) and Grey level co-occurrence matrix (GLCM), Gabor wavelet transform is the best for retrieving skin capacitive contact images and facial images with different orientations. Gabor wavelet transform can also work well on facial images with different expressions and skin cancer/disease images.

CONCLUSION: We have developed an effective skin image retrieval method based on Gabor wavelet transform, that it is useful for retrieving different types of images, namely digital colour face images, digital colour skin cancer and skin disease images, and grayscale skin capacitive contact images. Gabor wavelet transform can also be potentially useful for face recognition (with different orientation and expressions) and skin cancer/disease diagnosis.

Keywords

Skin imaging, skin capacitive images, content-based image retrieval, Gabor wavelet transform, texture features.

1. Introduction

Skin imaging plays a key role in many research areas, such as dermatology, clinical analysis, pharmacology and cosmetic science. In our previous research, we have used many different imaging technologies, including standard digital camera, DermLite Dermoscopy, Proscope HR and the recently developed capacitive contact skin imaging based on fingerprint sensors [1-4]. As the number of skin images soared, image retrieval became more and more important in our research. The aim of this study is to develop an effective content-based image retrieving technique that can work on different types of skin images, but with a particular focus on grayscale capacitive contact skin images, where images are quite similar to each other, and conventional image retrieving techniques normally do not work well.

Content-based image retrieval (CBIR), which is one of the popular fundamental research in retrieving accurate useful information, is the set of techniques for retrieving relevant images from an image database on the basis of image features automatically extracted from an image database [5]. In the retrieval phase of a CBIR system, the feature vector for each image in the database is calculated and stored in feature database. After selecting a query image by the user, the matching process that calculates the corresponding feature vector and compares it with all the feature vectors related to the images in the database is performed. Images having the minimum distance with the query image will be retrieved in a similarity descending order [6,7]. In a typical CBIR, images are retrieved based on their visual content such as colour, shape, and texture, etc. [8]. In this paper, texture feature is used for retrieving images.

In image processing, texture which generally refers to the structures consisted of large number of texture elements or models similar to each other, it is a key component for human visual perception and plays an important role in image-related applications. Meanwhile, texture features have been researched in the content-based image retrieval, image classification and segmentation. Gray-level co-occurrence matrix (GLCM) [9], Tamura texture feature [10], and Gabor wavelet texture feature [11,12] are the conventional methods used to describe texture feature. Compared with other techniques, Gabor wavelet texture feature is much computationally simpler, and image analysis using Gabor wavelet transform is similar to perception in the human visual system [13]. Gabor wavelet transform has been used in optical character recognition, iris recognition and fingerprint recognition. This paper describes a skin image retrieval technique based on Gabor wavelet texture feature.

2. Materials and Methods

2.1 Instruments

The main focus of this paper is capacitive contact skin images, but other images are also used to test the performance of the algorithm. All the images used in this study were taken by using standard digital camera and capacitance-based fingerprint sensor, except the skin cancer and skin disease images, which were from Skin Cancer page of About.com [21].

Standard digital camera used is SONY DSC--W55 model, which has a 7.2 Mega Pixels with 3X optical zoom. Capacitance-based fingerprint sensor [2-4] is a novel fringing field capacitive contact image technique that was developed in our research group. It has a matrix of 256 × 300 pixels (capacitors) with 50 μm spatial resolution per pixel. The total measurement area is $12.8 \times 15 mm^2$. The fingerprint sensor basically generates a capacitance image of the skin surface. In each image, each pixel is represented by an 8 bit grayscale value, 0~255, the higher grayscale values mean the higher capacitances, and the lower grayscale values mean the lower capacitances. Because in fringing field measurements, capacitance is determined by the dielectric constants of the sample, and water has much higher dielectric constants than dry skin, therefore, the higher capacitance means the higher water content in skin, vice verse. Apart from water, the sensor is also sensitive to many solvents that have relative high dielectric constant, such as dimethyl sulfoxide (DMSO), ethylene glycol, propylene glycol, propanol, glycerol, and alcohol etc. [2]. This makes it a potentially a very useful tool for studying solvent penetrations through membranes or skin, and trans-dermal drug delivery.

2.2 Gabor Wavelet Transform

Gabor wavelet can extract the relevant textural feature at different scales and directions in the frequency domain and also has a good joint resolution in both spatial and frequency domain [14]. Gabor wavelet is widely used to extract texture features from the images for image retrieval and has been shown to be very efficient [15-19].

The typical two dimensional Gabor function can be expressed as the production of Gaussian function and sinusoidal function [19,20]:

$$g(x,y)=\left(\frac{1}{2\pi\sigma_x\sigma_y}e^{-\frac{1}{2}(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2})}\right)\left(e^{2\pi jfx}\right) \qquad (1)$$

Where σ_x and σ_y are the Gaussian variance, which describe the spreads of the Gaussian function, ***j*** is the imaginary unit of complex number, ***f*** is the frequency of the sinusoidal function. Using Eq. 1 as the mother function, we can generate a set of child functions, called Gabor wavelets.

$$g_{mn}(x,y) = a^{-m} g(x', y') \qquad a > 1,\ m, n = \textit{integer}$$

$$\begin{aligned} x' &= x\cos\theta + y\sin\theta \\ y' &= -x\sin\theta + y\cos\theta \end{aligned} \qquad (2)$$

where $\theta = n\pi / K$, n = 0, 1, …, K-1, and K is the total number of the directions which specifies the orientation of a Gabor function; m = 0, 1, …, S-1, and S is the number of scales which specifies the amplitude of a Gabor function. If we use (U_l, U_h) to denote the lower and upper centre frequency of the sinusoidal function, we have

$$\begin{aligned} a &= \left(\frac{U_h}{U_l}\right)^{\frac{1}{S-1}} \\ f &= U_h \end{aligned} \qquad (3)$$

In this paper, the total number of directions (K) and scales (S) and have chosen to be $K = 6$ and $S = 4$, respectively, which is resulting 4x6=24 Gabor wavelet filters to filter the images. U_l and U_h used are 0.05 and 0.4, respectively.

Figure1 (A) shows typical profiles of Gaussian function, sinusoidal function and the corresponding wavelet function; (B) shows the Gabor wavelet profiles at 6 different directions and 4 different scales.

(Figure 1 goes in here)

Gabor wavelet transform can be considered as a wavelet transform whose mother wavelet is Gabor function. For a given image $I(x,y)$ with $M \times N$ pixels, its Gabor wavelet transform is defined as follows:

$$W_{mn}(x,y) = \int I(x_1, y_1) g_{mn} {}^*(x - x_1, y - y_1) d_{x_1} d_{y_1} \quad (4)$$

where * represents the complex conjugate.

2.3 Experimental Procedures

A image database that includes 56 images in JPEG format was setup. Figure 2 shows some sample images from the database, which contains three different types of images: human faces, skin cancer and skin disease images [21], and skin grayscale capacitive contact images.

(Figure 2 goes in here)

A software programme has been developed to search above image database using a query image, based the Gabor wavelet transform. A Graphic User Interface (GUI) was also developed to simplify the operations. Following are the steps of the programme:

1. Convert all the colour images into gray images.
2. Perform the Gabor wavelet transform on all images.
3. Calculate the mean and standard deviation as a texture feature.
4. Compare the texture feature of the query image with that of images in the database, in order to find the best match results.

3 Results and Discussions

3.1 Image query results

Figure 3 shows the image retrieval results using Gabor texture features. In all the four retrieval results shown, the best three retrieved images are shown for illustration. The retrieved images are ranked in descending order according to the similarity of their Gabor texture features to those of the query image, i.e. the most similar, the second similar, and the third similar images. In this study, for simplicity reasons, the query images are also from the database, and therefore the most similar result should always be the image itself.

(Figure 3 goes in here)

In Figure 3(A), the query image is a grey capacitive image of finger skin, where finger friction ridges are clearly visible. The black spots are the areas that water is actively coming out of skin. As it can be seen, most of the best 3 retrieved images are all similar finger grey capacitive images captured from Fingerprint sensor. Figure 3(B) shows the retrieval results for a human face query image. Human face images in the database are with two different expressions – smile and non-smile. The most similar image is the same of query image. The second most similar image is the same person without smile and the third image is that another person without smile. It shows that this method has certain reference value for human face recognition. It might be even also useful for facial expression recognition. Figure 3(C) and 3(D) are the output of skin cancer/disease retrieval results. The query image in Figure 3(C) is a skin cancer image of melanoma. From the illustration, the three of the most similar images are all skin cancer images. The query image in Figure 3(D) is a skin disease image of leucoderma. From the results, the three of the most similar images are all leucoderma images. The results show that Gabor wavelet transform could also be potentially used for skin disease diagnostics. Users could take a skin image, and search the skin disease database, and find out what possible type of skin disease it might resemble, and seek doctors for early diagnoses.

3.2 The effects of scales (S) and directions (K)

The values of scales (S) and directions (K) in Gabor wavelet transform not only affect the accuracy of retrieval, they will also affect the computational time of program. Figure 4(A) and 4(B) show typical retrieval errors when SxK = 2x2 and Figure 4(C) shows the relationships between computational time and the production of scales and directions (SxK). If any of the best three results is not the right type of images, such as Figure 4(A) or 4(B), we classify it as a retrieval error. Figure 4(C) shows the relationships between retrieval errors and SxK. Generally speaking, the higher the values of SxK, the lower the retrieval errors, but the longer the computational time; the lower the values of SxK, the shorter the computational time, but the higher the retrieval errors. The key is to find the optimum value of SxK that has highest accuracy but lowest possible computational time. From this study, it is found that setting scales and directions to 4 and 6 is a reasonable choice.

(Figure 4 goes in here)

3.3 The effects of U_l and U_h

Although the values of lower and higher centre frequency U_l and U_h do not affect the computational time, they do effect the retrieval accuracy. In general, the values of U_l and U_h are set to 0.05 and 0.4 because the lowest frequency of image is 0 and the highest frequency of image calculated from Nyquist sampling theorem is 0.5. According to the visual characteristics of the human eye, the frequency range from 0.05 to 0.4 can be completely reflect people's perception of texture features [22]. However, the retrieval results using these standard values shown in Figure 5 (A) are unsatisfactory because the query image in Figure 5 (A) is the neck grey capacitive image, but the third most similar image is the face grey capacitive image.

By changing the value of U_l and U_h to 0.2 and 0.3 and the results shown in Figure 5 (B) become much better. From Figure 5, it can be concluded that the values of U_l and U_h might need to be adjusted differently to different type of images in order to have better retrieval accuracy.

(Figure 5 goes in here)

3.4 The performance of Gabor Wavelet Transform against other algorithms

In order to understand the performance of Gabor wavelet transform, we did an image retrieval comparison study, compare Gabor wavelet transform against other two algorithms: Principal Component Analysis (PCA) and Grey level co-occurrence matrix (GLCM).

Table 1 shows the computation time of different algorithms. The results show that GLCM is the fastest for calculating the feature vectors of all the images in the database, whilst Gabor wavelet transform is the slowest. PCA is the fastest for retrieving images, and Gabor wavelet transform is again the slowest.

Table 1 The computation time used of each algorithm.

	PCA	**GLCM**	**Gabor Wavelet Transform**
Time 1	Average	Low	High
Time 2	Low	Average	High

Time 1: the time for calculating the feature vectors of all the images in the database.

Time 2: the time for retrieving the query image.

Table 2 The retrieval success rates of each algorithm.

	PCA	**GLCM**	**Gabor Wavelet Transform**
Image type 1	Best	Worst	Average
Image type 2	Average	Worst	Best
Image type 3	Worst	Average	Best
Image type 4	Worst	Best	Average

Image type 1: human face images with different expressions.

Image type 2: human face images with different orientations.

Image type 3: grayscale capacitive skin images of different parts of human body.

Image type 4: skin diseases and skin cancer images.

Table 2 shows the successful retrieval rates of three different algorithms on different type of skin images. Gabor wavelet transform is the best for retrieving capacitive skin images and facial images with different orientations, GLCM is the best for retrieving skin cancer / disease images, PCA is the best for retrieving facial images with different expressions. The results also show that Gabor wavelet transform works reasonably well for human faces with different expressions and skin cancer and disease images.

4 Conclusions and Future Works

We have developed an effective skin image retrieval method based on Gabor wavelet transform. Experimental results show that it is useful for retrieving different types of images, namely digital colour face images, digital colour skin cancer and skin disease images, and particularly suitable grayscale skin capacitive images. The results also suggest that using the Gabor wavelets to extract texture features could be useful for recognizing human face with different orientations and different facial expressions, as well as for skin cancers and diseases diagnostics etc. In Gabor wavelet transform, the values of scales, directions, lower and higher centre frequency, might need to be adjusted differently according to different types of images, in order to achieve a better retrieval results. For future work, we will investigate to use another visual content such as colour and shape to retrieve images.

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References

1. Singh, H., Development of a Measurement Instrument Using Capacitance Sensors Techniques to Image and Measure the Skin Surface Hydration, PhD Thesis, London South Bank University, November 2010.
2. Singh, H., Xiao, P., Berg, E.P., and Imhof, R.E., Skin Capacitance Imaging for Surface Profiles and Dynamic Water Concentration Measurements, ISBS Conference, Seoul, Korea, May 7-10, 2008.
3. Ou, X., Pan, W., Xiao, P., In vivo skin capacitive imaging analysis by using grey level co-occurrence matrix (GLCM), International Journal of Pharmaceutics, Available online 2 November 2013, ISSN 0378-5173, http://dx.doi.org/10.1016/j.ijpharm.2013.10.024.
4. Xiao P., Ou X., Ciortea L.I., Berg E.P., Imhof R.E., In Vivo Skin Solvent Penetration Measurements Using Opto-thermal Radiometry and Fingerprint Sensor. Int J Thermophys. 33, 2012, 1787–1794.
5. Wang J.Z., Integrated Region-Based Image Retrieval. Boston:Kluwer Academic 2001, 1-5.
6. Rafiee, G., A review of content-based image retrieval. International Symposium on Communication Systems Networks and Digital Signal Processing (CSNDSP), 2010,7, 775 - 779 .

7. Smeulders, A.W.M., Worring, M., Santini, S., Gupta, A., Jain, R., Content-Based Image Retrieval at the End of the Early Years. IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE. 22, 2000, 1349-1380.

8. Gong, Y., Zhang, H., Chuant, H. and Skauuchi. M., An image database system with contents capturing and fast image indexing abilities. Proceedings of IEEE International Conferences on Multimedia Computing and Systems, Boston,Massachusetts, USA. 1994,5, 121–130.

9. Haralick, R.M., Shanmugam, K., and Dinstein. I., Texture features for image classification. IEEETrans. Syst. Man Cybern. SMC(8), 1973,11, 610–621.

10. Hayes, K.C., Shah, Jr. A.N., and Rosenfeld, A., Texture coarseness: further experiments. IEEETrans SMC-4, 467-472.

11. Yang, J., Liu, L., Jiang T., and Fan, Y., A modified Gabor filter design method for fingerprint image enhancement. Pattern Recognition Letters. 24(12), 2003, 1805-1817.

12. Daugman, J.G., Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by twodimensional visual cortical filters. Journal of The Optical Society of America. 2(7), 1985, 1160-1169.

13. Kruizinga, P., Petkov, N., and Grigorescu, S.E., Comparison of texture features based on Gabor filters. Proceedings of the 10th International Conference on Image Analysis and Processing. September 27-29, 1999, pp.142-147.

14. Smith, J.R., “Integrated Spatial and Feature Image System: Retrieval, Analysis and Compression”. Ph.D thesis, Columbia University, 1997.

15. Deng, Y., “A Region Representation for Image and Video Retrieval”. Ph.D thesis, University of California, Santa Barbara, 1999.

16. Dimai, A., Rotation Invariant Texture Description using General Moment Invariants and Gabor Filters. Proc. Of the 11th Scandinavian Conf. on Image Analysis. I, 1999, 6, 391-398.

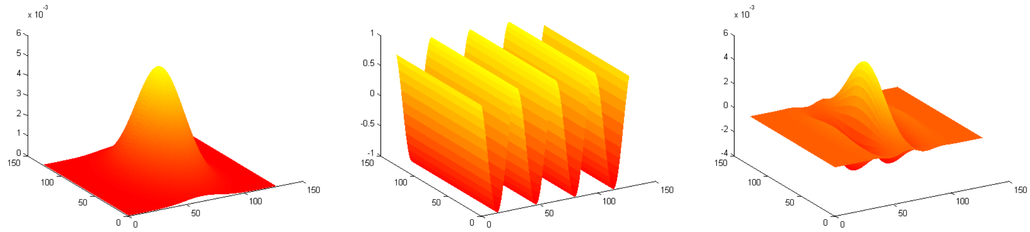
17. Liu, Z, An Improved Face Recognition Method Based on Gabor Wavelet Transform and SVM. Fifth International Symposium on Computational Intelligence and Design (ISCID), 2012,10, 378 – 381.

18. Fischer, S., Minimum entropy transform using Gabor wavelets for image compression. 11th International Conference on Image Analysis and Processing and Proceedings, 2001,9,428 – 433.

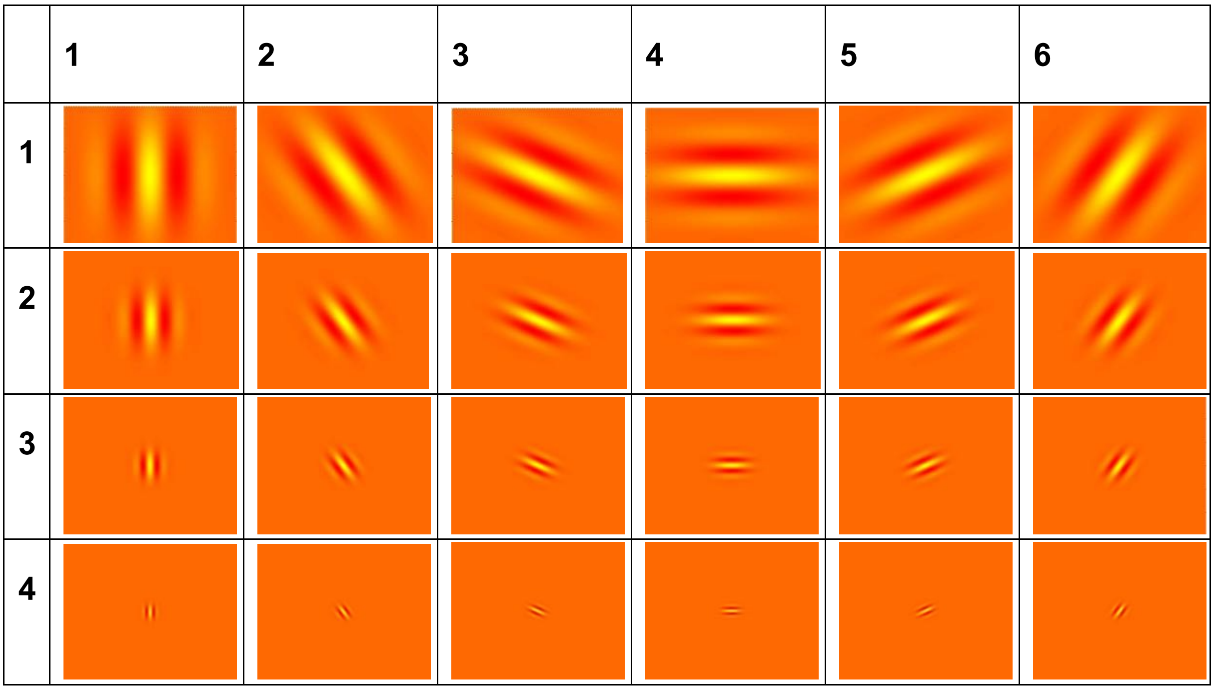
19. Manjunath, B.S., and Ma, W.Y., Texture features for browsing and retrieval of image data. IEEE Trans. Pattern Anal. Machine Intell. 18,1996,8, 837–842.

20. Skin cancer and skin diseases images, http://skincancer.about.com/od/symptoms/ss/mole_all.htm

21. Anne H., Solberg S., Jain A.K. Texture fusion and feature selection applied to SAR imagety [J]. IEEE transaction on Geoscience and Remote sensing. 35(2), 1997, 475-478.



(A) Gaussian function Sinusoidal function Gabor function



(B) Top view of Gabor wavelet profiles at 6 different directions (columns) and 4 scales (rows).

Figure 1. Gabor wavelet profiles with at different directions and scales.

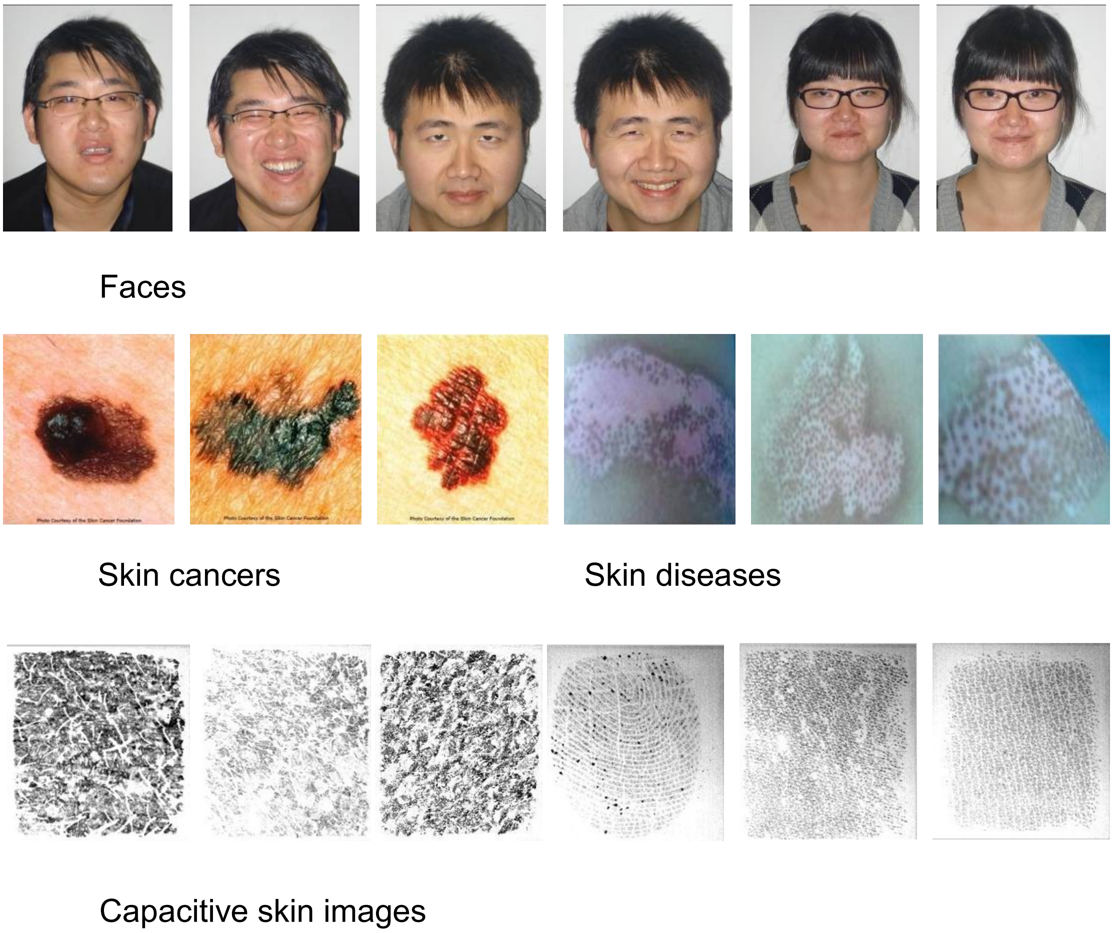
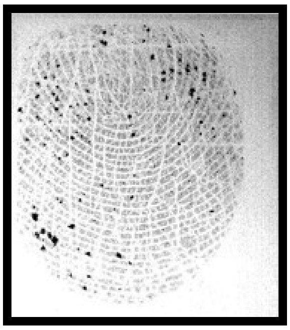
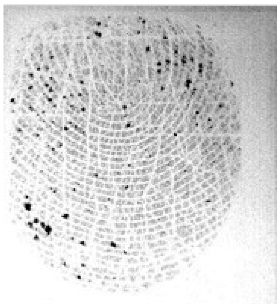
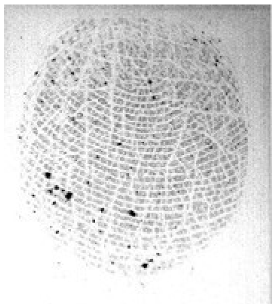


Figure 2. Sample images from the database.

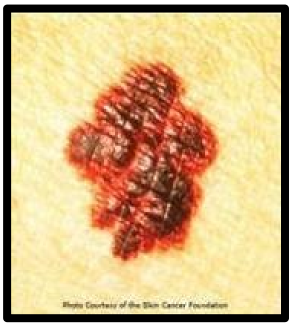
(A)

Query Image	Search Results		
	Best	2nd	3rd
			

(B)

Query Image	Search Results		
	Best	2nd	3rd
			

(C)

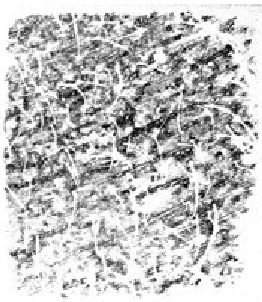
Query Image	Search Results		
	Best	2nd	3rd
			

(D)

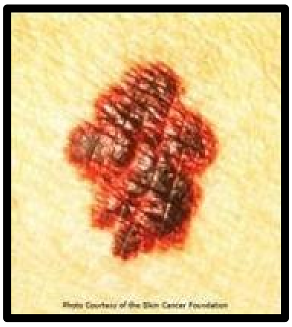
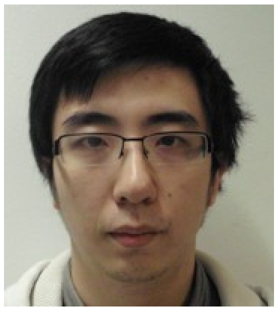
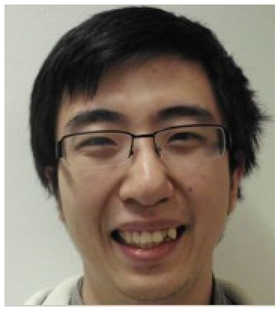
Query Image	Search Results		
	Best	2nd	3rd
			

Figure 3. Image retrieval results using Gabor texture features.

(A)

Query Image	Search Results		
	Best	2nd	3rd
			

(B)

Query Image	Search Results		
	Best	2nd	3rd
			

(C)

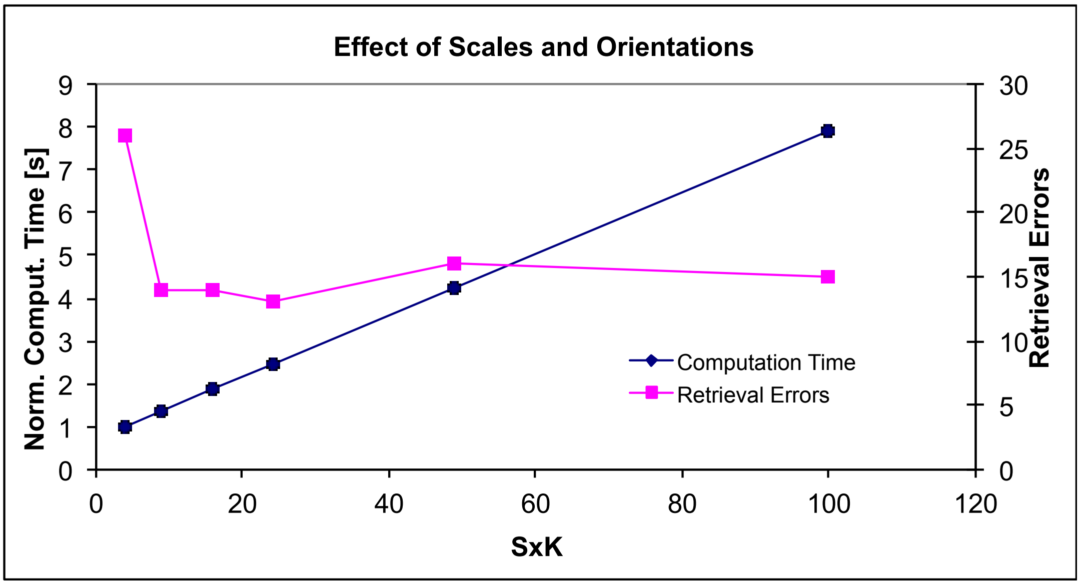
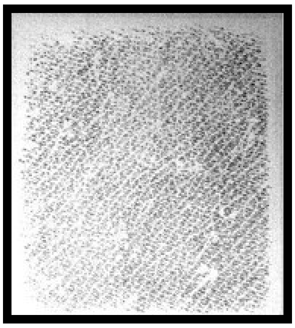
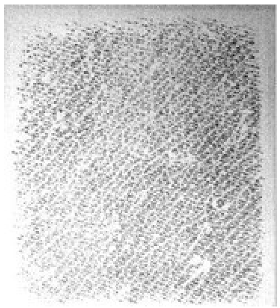
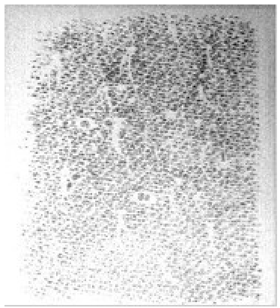
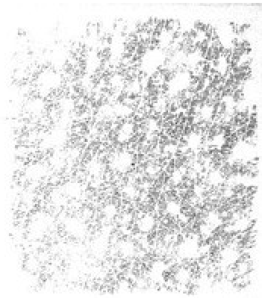


Figure 4. (A) and (B) are typical image retrieval errors when SxK = 2x2, (C) is computational times and retrieval errors against the production of scales and directions SxK.

(A)

Query Image	Search Results		
	Best	2nd	3rd
			

(B)

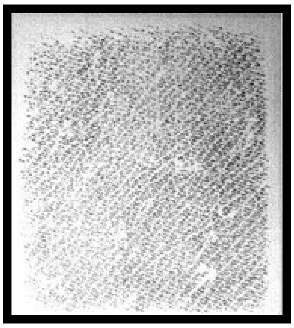
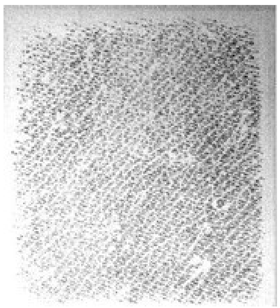
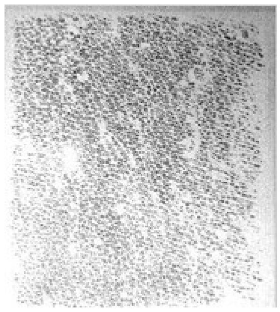
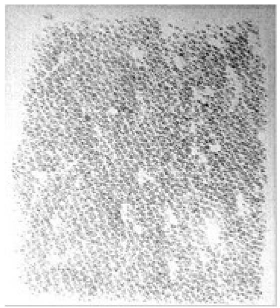
Query Image	Search Results		
	Best	2nd	3rd
			

Figure 5. Image retrieval results using Gabor texture features when (A) U_l = 0.05 and U_h = 0.4 and (B) U_l = 0.2 and U_h = 0.3.