In-Vivo Skin Capacitive imaging Analysis by using Grey Level Co-occurrence Matrix (GLCM)

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Abstract

We present our latest work on in-vivo skin capacitive imaging analysis by using grey level co-occurrence matrix (GLCM). The in-vivo skin capacitive images were taken by a capacitance based fingerprint sensor, the skin capacitive images were then analyzed by GLCM. Four different GLCM feature vectors, angular second moment (ASM), entropy (ENT), contrast (CON) and correlation (COR), are selected to describe the skin texture. The results show that angular second moment increases as age increases, and entropy decreases as age increases. The results also suggest that the angular second moment values and the entropy values reflect more about the skin texture, whilst the contrast values and the correlation values reflect more about the topically applied solvents. The overall results shows that the GLCM is an effective way to extract and analyze the skin texture information, which can potentially be a valuable reference for evaluating effects of medical and cosmetic treatments.

Keywords

Capacitive imaging, Grey Level Co-occurrence Matrix, skin texture, feature vectors, solvent penetration, trans-dermal drug delivery.

1. Introduction

Skin capacitive imaging using capacitance based fingerprint sensors has shown potentials in skin hydration imaging, skin texture analysis, skin 3D surface profiles, and skin micro relief measurements (Leveque et al., 2003; Batisse et al., 2006; Xiao et al., 2007; Bevilacqua et al., 2008; Singh et al., 2008). It is based on capacitance measurement principles, and the measurement results depend on the sample's dielectric constants. Our latest studies showed that apart from water, capacitance based fingerprint sensors are also sensitive to many solvents, due to their high dielectric constants. This makes the technique very useful for in-vivo trans-dermal drug delivery studies (Xiao et al., 2012a; Xiao et al., 2012b).

Grey level co-occurrence matrix (GLCM), proposed by Haralick in the 1970s (Haralick, 1973a; Haralick, 1973b; Haralick, 1979), is an image processing technique that has been widely used for measuring of texture in images. It first generates a grey level co-occurrence matrix that is defined as the distribution of co-occurring values at a given offset over a given image, then calculate a set of textual features (usually called Haralick features) from the matrix that can reflect the image texture. There are 14 different textual features, but only 4 are independent (Ulaby et al, 1986), namely angular second moment (ASM), entropy (ENT), contrast (CON) and correlation (COR). In this paper, we have, for the first time, applied the grey level co-occurrence matrix (GLCM) technique for analyzing skin capacitive images. We will first describe the measurement apparatus and the theoretical background from GLCM, then show the GLCM results of skin capacitive images.

2. Materials and Methods

2.1 Capacitance-based Fingerprint Sensor

Capacitance-based fingerprint sensor (Xiao et al., 2012b), shown in Fig. 1, has a matrix of 256 × 300 pixels, with 50 μm spatial resolution per pixel. The total measurement area is $12.8 \times 15mm^2$. Each pixel is essentially a capacitor sensor. 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, higher grayscale values mean higher capacitances, i.e., higher water/solvent concentration, and lower grayscale values mean lower capacitances, i.e., lower water/solvent concentration. The sensor is spring-loaded to provide constant contact pressure during the measurements. The contact time is also limited to 5 seconds for all measurements.

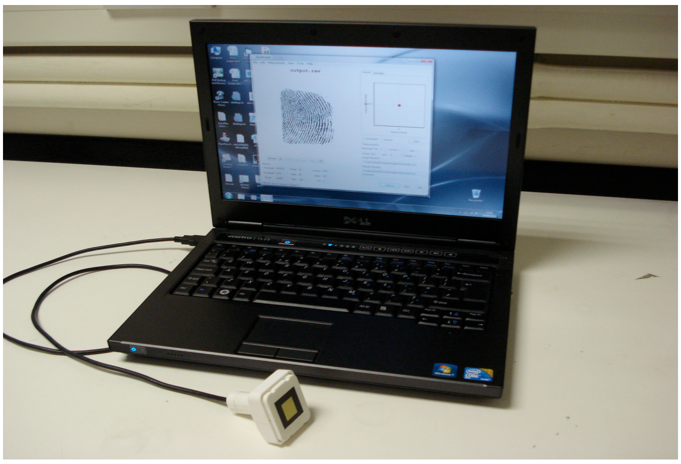


Fig. 1. Capacitance-based fingerprint sensor

2.2 Grey Level Co-occurrence Matrix (GLCM)

Grey Level Co-occurrence Matrix (GLCM) (Haralick, 1979; Siew, 1988; Parekh, 2012, Zhu, 2010) provides a mature and effective statistical method for analyzing texture. It reflects the comprehensive information of the direction, adjacent interval and amplitude variations for image grey-level. For a given image I, the corresponding GLCM can be calculated by:

$$P(i,j,d,\theta) = \sum_{x=0}^{n}\sum_{y=0}^{m}\begin{cases}1, & \mathit{if}\ I(x,y)=i\ \ \mathit{and}\ \ I(x+d\cos\theta, y+d\sin\theta)=j\\ 0, & \mathit{otherwise}\end{cases} \tag{1}$$

where P(i, j, d, θ) in GLCM describes the relative frequencies with which two pixels separated by a particular displacement distance d and a specified angle θ occur on the image, one with grey-level i and the other with grey-level j. Four different GLCM feature vectors, i.e. angular second moment (ASM), entropy (ENT), contrast (CON) and correlation (COR) are selected to describe the skin texture, see Eq.(2) to Eq.(5) for their definitions.

$$\mathrm{ASM} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{\hat{P}(i,j,d,\theta)\}^2 \tag{2}$$

Where $\hat{P}(i,j,d,\theta)$ represents normalized $P(i,j,d,\theta)$, and G is the total number of grey-levels.

$$\mathrm{ENT} = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\hat{P}(i,j,d,\theta)\times\log\left(\hat{P}(i,j,d,\theta)\right) \tag{3}$$

$$\mathrm{CON} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i-j)^2\cdot\hat{P}(i,j,d,\theta) \tag{4}$$

$$\mathrm{COR} = \frac{\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} ij\hat{P}(i,j,d,\theta)-\mu_1\mu_2}{\sigma_1^2\sigma_2^2} \tag{5}$$

Where $\mu_1 = \sum_{i=0}^{G-1} i \sum_{j=0}^{G-1}\hat{P}(i,j,d,\theta)$

$$\mu_2 = \sum_{i=0}^{G-1} j \sum_{j=0}^{G-1}\hat{P}(i,j,d,\theta)$$

$$\sigma_1^2 = \sum_{i=0}^{G-1}(i-\mu_1)^2\sum_{j=0}^{G-1}\hat{P}(i,j,d,\theta)$$

$$\sigma_2^2 = \sum_{i=0}^{G-1}(i-\mu_2)^2\sum_{j=0}^{G-1}\hat{P}(i,j,d,\theta)$$

The angular second moment (ASM) (Rafael et al, 2007; Haralick, 1973a) is the squared sum of all the elements of GLCM, also called energy. ASM measures the texture uniformity, it can also reflect the thickness of skin micro relief lines, i.e. the thicker the micro relief lines, the higher ASM value, and the thinner the micro relief lines, the lower the ASM value (Gao et al, 2010).

The term entropy has originated in thermodynamics. In image processing, the entropy (ENT) (Haralick, 1973a; Haralick, 1973b; Baraldi, 1995) is a statistical measure of the disorder of an image, reflects the randomness of grayscale distribution. Its value achieves the largest when all elements in GLCM are as equal as possible and the smallest when some values are high and others low. The more dense texture is, the more scattered the grayscale distribution, and the more small elements GLCM has. Hence the entropy value is higher.

The contrast (CON) (Kekre et al, 2010; Conners, 1980; Tahir, 2003) is a measure of the amount of the local grey level variations in an image, which is the moment of inertia of the matrix around its main diagonal. Values on the GLCM main diagonal imply no contrast, and contrast value increases away from the main diagonal. The larger amount of the local grey level variations image has, the higher value for the GLCM elements which are further away from the main diagonal, so, create a weight that increases as distance from the diagonal increases. Therefore, the contrast value is higher.

The correlation (COR) (Kekre et al, 2010; Conners, 1980; Tahir, 2003) is a measure of grey level linear-dependencies in an image. This also reflects the degree of the rows (or columns) of the GLCM relative to each other. For example, when the number of the textures in the horizontal direction is more than other directions, the value of the correlation feature is higher along this direction compared to the values for others.

2.3 Experimental Procedures

In this paper, two sets of experiments are performed. The first experiment involves two healthy male volunteers whose age range are 20-30 years old and 40-50 years old respectively. The capacitive images are taken from their foreheads, eyes and cheeks, and each site is repeated 6 times.

The second experiment is solvent penetration through in-vivo skin combined with tape stripping. In this experiment, two solvents are used: undiluted dimethyl sulfoxide (DMSO) and undiluted ethylene glycol (EG), due to their relatively high dielectric constants compared with dry skin, as shown in Table 1. DMSO and EG are also chosen because they are commonly used in many cosmetic products. In future, we could also study other solvents that has relative high dielectric constant and are also commonly used in cosmetic products, such as propylene glycol, propanol, glycerol, and alcohol etc. In theory, we could also study the solvents that have very low dielectric constant, such as butanol, decanol and heptanol etc, providing we are measuring them from a sample with high dielectric constant, such as wet tissue or wet membrane. The key is the contrast of the dielectric constants of the solvents and sample that they are penetrating through.

Three different skin sites on the volar forearm of a healthy female volunteer (Asian, aged 29 and a mass of 56 kg) are selected, with one skin site is for DMSO, one for EG, and one is used as a control site. Before performing measurements, the volunteer was acclimatized for 20min, and each skin site was wiped clean with EtOH/water (95 %) solution. And then a small amount of solvent (～0.1 mL) is applied for 5min on each test skin site. After the test site is wiped dry, tape stripping is performed. Fingerprint sensor measurements are performed both before and after the solvent applications, and after each stripping. Tape stripping is repeated for 12 times.

Table 1 Dielectric Constants of the solvents and skin

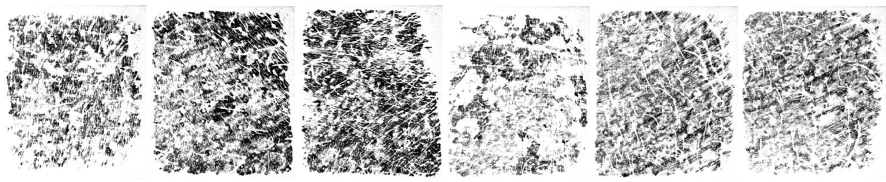
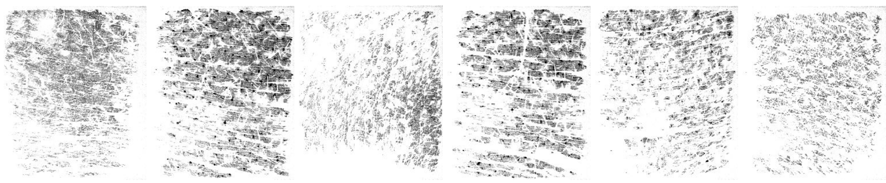
Materials	**Skin**	**Water**	**DMSO**	**Ethylene Glycol**
Dielectric Constant	7	80.4	47.2	37

3 Results and Discussions

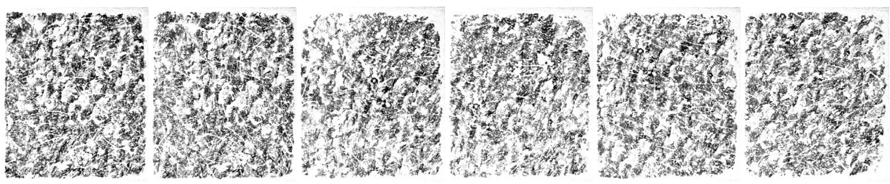
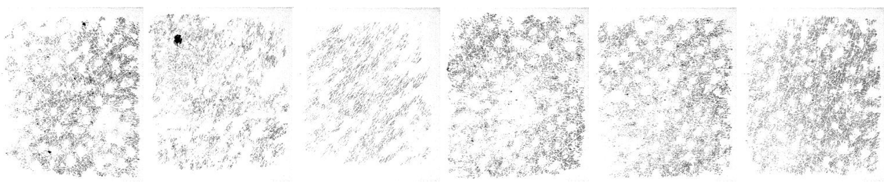
3.1 Experiment 1 – Different Skin Sites

Fig.2 shows the grey capacitive images on the skin sites of forehead, cheek and eye, from two male volunteer with different ages. Fig. 3 shows the corresponding feature vector values, changing with age on the skin sites of forehead, cheek and eye.

Forehead

Volunteer 1	
Volunteer 2	

Cheek

Volunteer 1	
Volunteer 2	

Eye

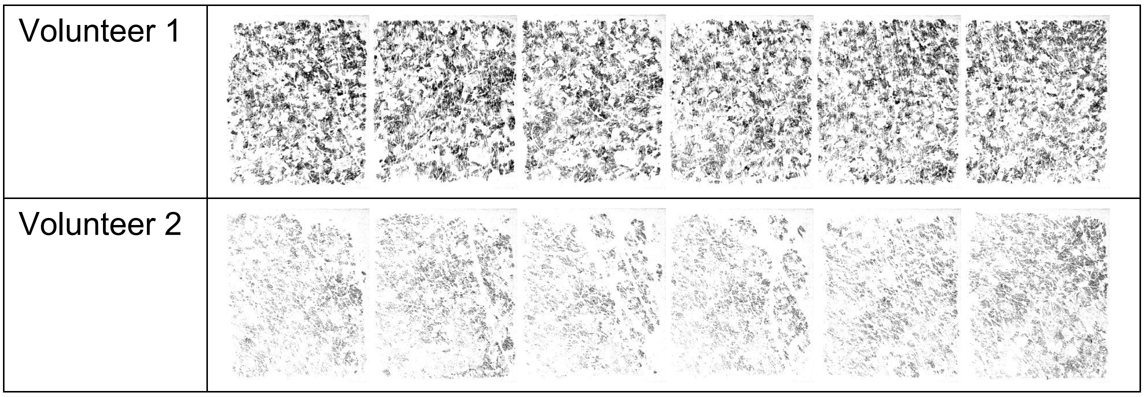


Fig.2. The capacitive images on the forehead, cheek and eye from two male volunteer with different ages, volunteer 1 (age from 20-30) and volunteer 2 (age from 40-50).

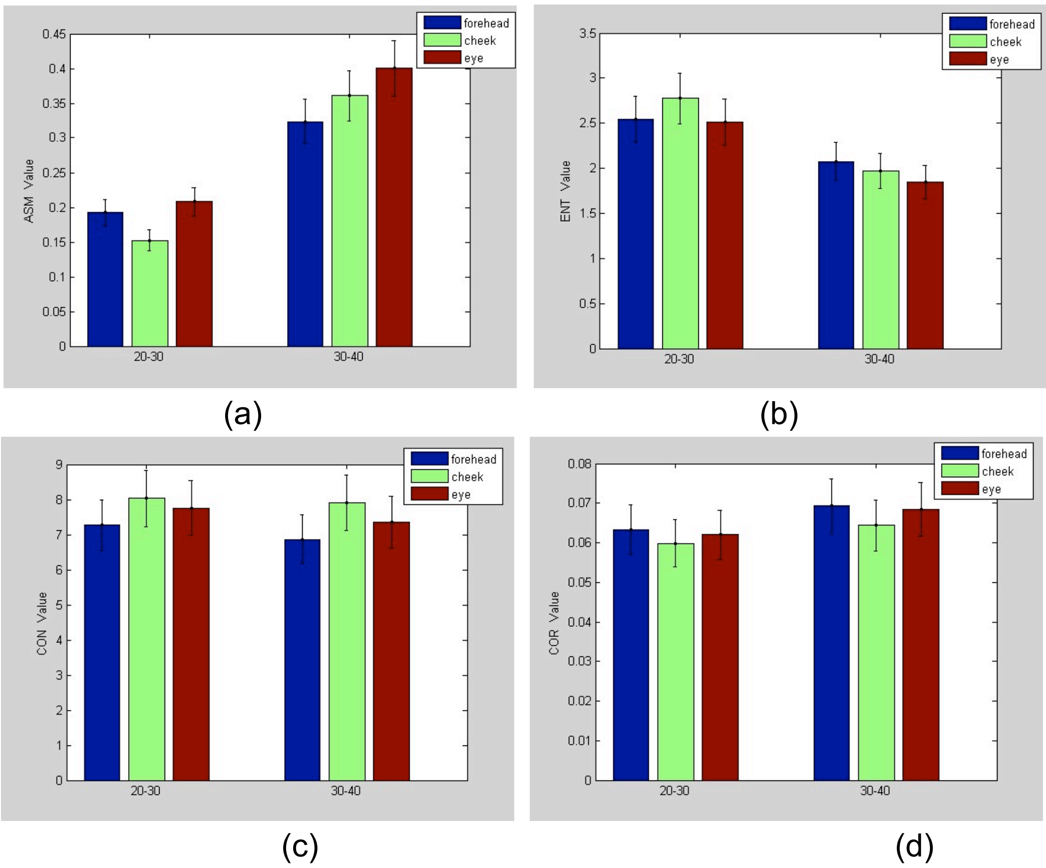


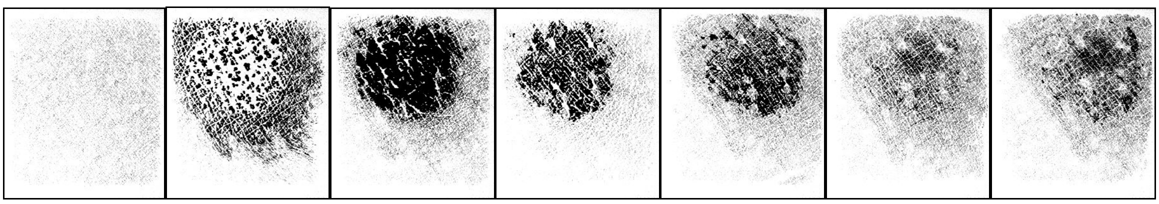
Fig. 3 The corresponding graph of the feature vectors of images of Fig.2, (a) The graph of ASM; (b) The graph of ENT; (c) The graph of CON; (d) The graph of COR. The error bars show the standard deviation of each site, which was repeated 6 times.

The results show that as age increases, the ASM value also increases, indicating the skin textures become more and more coarse, i.e. microrelief lines are getting thicker. The results also show that the entropy values decreases as age increases, which indicates that the skin texture become more and more sparse. The contrast and correlations values show little changes against the age.

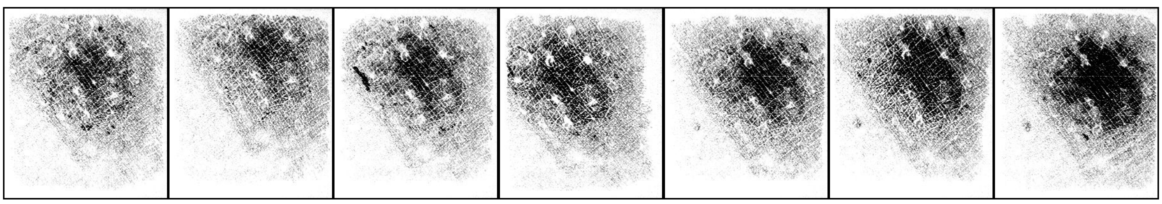
3.2 Experiment 2 – Solvent Penetration with Tape Stripping

Fig. 4 shows the capacitive images of three skin sites of on the volar forearm of a healthy female volunteer during the solvent penetration measurements. The results show that the capacitive images can clearly differentiate the solvents, e.g. DMSO and EG, from the skin. The results also show that DMSO penetrates more and deeper than EG.

A

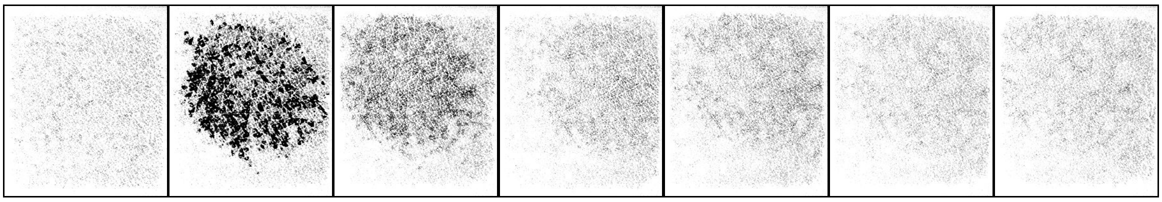


Before After (DMSO) strip 1 strip 2 strip 3 strip 4 strip 5

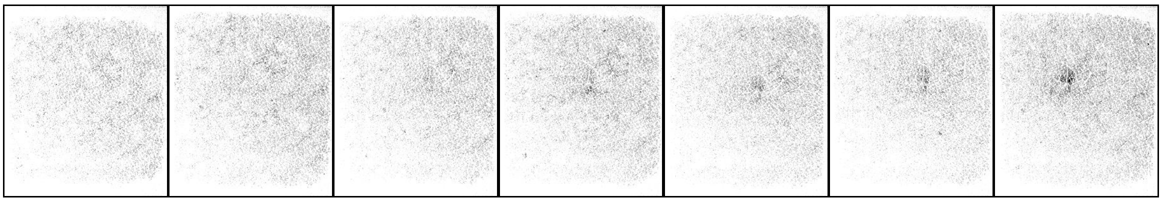


strip 6 strip 7 strip 8 strip 9 strip 10 strip 11 strip 12

B

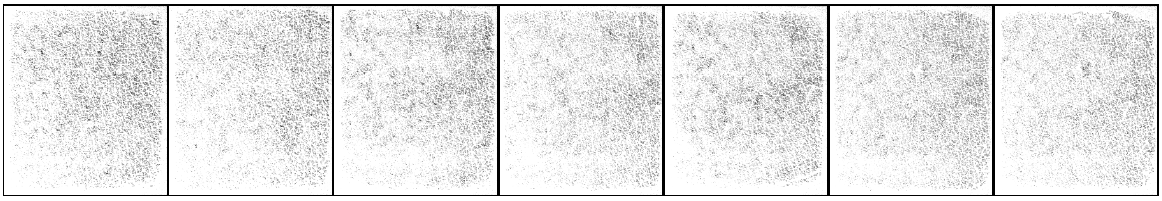


Before **after (EG)** **strip 1** **strip 2** **strip 3** **strip 4** **strip 5**

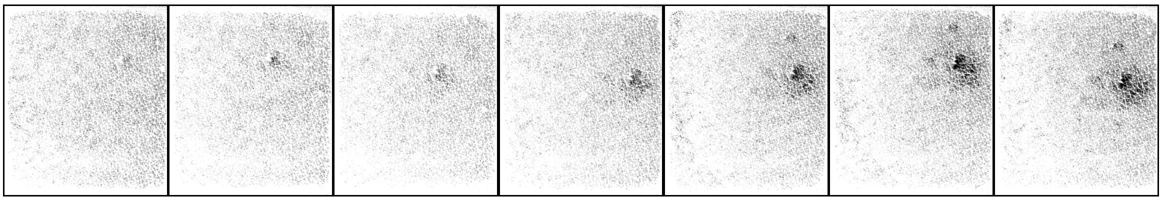


strip 6 **strip 7** **strip 8** **strip 9** **strip 10** **strip 11** **strip 12**

C



Before **After** **strip 1** **strip 2** **strip 3** **strip 4** **strip 5**



strip 6 **strip 7** **strip 8** **strip 9** **strip 10** **strip 11** **strip 12**

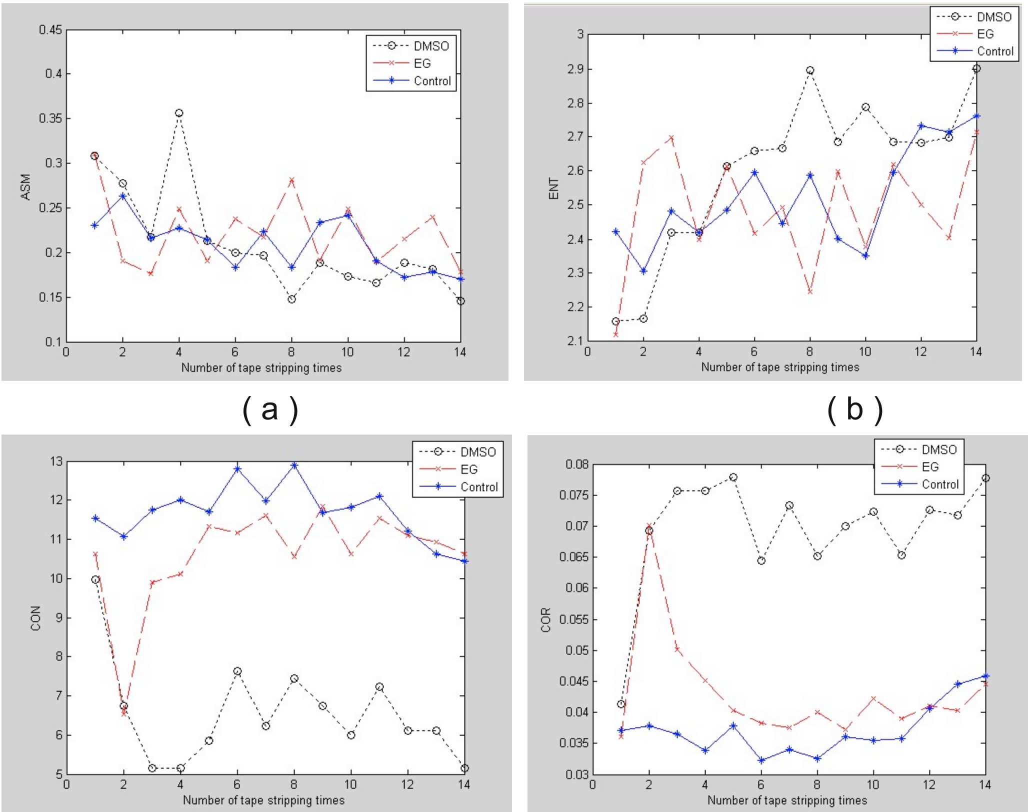
Fig.4 The capacitive images of (A) the DMSO skin site, (B) the ethylene glycol site, and (C) the control site, before and after solvent application and subsequently during tape stripping

Fig. 5 shows the corresponding GLCM feature vector results of the Fig. 4 images.

The angular second moment values appear a downward trend on three different skin sites, this is likely because the texture on three different skin sites shown in Fig. 4 became thinner and thinner with the increasing number of tape stripping.

The entropy values present upward trend on three different skin sites, this is likely because the texture on three different skin sites shown in Fig. 4 become more and more dense with the increasing number of tape stripping. It is interesting to point out that neither the angular second moment values nor the entropy values are affected by the solvents applied, as three skin sites follow exactly the same trend.

It is quite different for the contrast results. The control site increased first then gradually decreased. The EG site dropped significantly immediate after the EG application, then gradually increased to the similar level as the control site. This suggests that with the increasing number of the tape stripping, the amount of EG in skin is decreasing, until it is almost exactly the same as the control site. For DMSO site, it also decreased sharply after the DMSO application, indicates the presence of DMSO in skin, but it did not recover back to the control site level, this indicates that DMSO has penetrated much deeper and probably cost more damage than EG. A similar reversely trend can also be observed in the correlation results.



(a) (b)

(c) (d)

Fig. 5 The trend graph of feature vectors on three different skin sites (a) The trend graph of ASM on three different skin sites (b) The trend graph of ENT on three different skin sites (c) The trend graph of CON on three different skin sites (d) The trend graph of COR on three different skin sites

The results suggest that the angular second moment values and the entropy values reflect more about the skin texture, rather than topically applied solvents, whilst the contrast values and the correlation values reflect more about the topically applied solvents. The fluctuation of the results is likely due to the non-uniformity of each tape stripping. These results show that GLCM could be potentially a powerful tool for skin aging studies and skin solvent penetration studies, we could use GLCM to quantify the skin texture and skin aging. Through proper calibrations, it is also possible to use GLCM to quantify the solvent absorption within skin, and the solvent penetration through skin.

4 Conclusions

We have developed a new approach to analyze the capacitive skin images by using Grey Level Co-occurrence Matrix (GLCM) technique. Four different GLCM feature vectors, which are angular second moment, entropy, contrast and correlation, are used in the study. The results show that GLCM could be an effective way for researching skin texture image. GLCM could also be a valuable reference for skin aging study and supply strong technical support to assess efficacy of skin solvent penetration.

Acknowledgement

We thank London South Bank University for the financial support.

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