Automatic Detection of Skin Cancer
Current Status, Path for the Future

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Abstract: How far are we away from a Star-Trek-like device that can analyze a lesion and assess its malignancy? We review the main challenges in this field in light of the Blois paradigm of clinical judgment and computers. The research community has failed to adequately address several challenges ripe for the application of digital technology: 1) early detection of changing lesions, 2) detection of non-melanoma skin cancers, and 3) detection of benign melanoma mimics. We highlight a new device and recent image analysis advances in abnormal color and texture detection. Anthropomorphic paradigms can be applied to machine vision. Data fusion has the potential to move automatic diagnosis of skin lesions closer to clinical practice. The fusion of Blois' high-level clinical information with low-level image data can yield high sensitivity and specificity. Synergy between detection devices and humans can get us closer to this Star-Trek-like device.

1 OVERVIEW

The Machine as a Diagnostic Adjunct: Limiting the Cognitive Span

1.1 Clinical Cognitive Span: The Blois Paradigm

In the *New England Journal of Medicine*, Dr. M. Scott Blois discussed the role of computers in the clinic (Blois, 1980). The Blois paradigm states that computers perform best using 'low level' information derived from physical or chemical measurements, and perform worst using 'high level' information, such as patient statements. When a doctor first sees a patient in the examination room, there is a wide range of possible diagnoses. Complicating the case is the interaction between diagnoses that make the problem more complex. Symptoms may be embellished or diminished. A skilled clinician can adroitly navigate this subjective information, separating benign conditions from harmful conditions—the paramount diagnostic challenge in medicine.

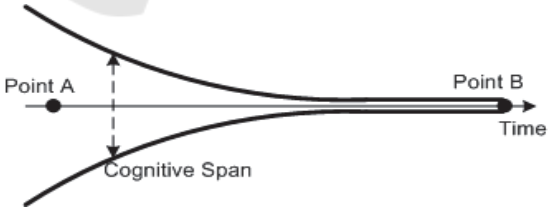

Figure 1: Blois Paradigm: Computers in the Clinic.

The complexity is high during the initial clinic visit, where visual and verbal information is unsorted and the range of possibilities, which Blois termed the 'cognitive span,' is wide (point A, Figure 1). Further into the evaluation, we may have chemical or physical information, e.g. blood samples (point B, Figure 1). Humans function best with the subjective information at point A, and computers function best at point B, once the cognitive span is narrowed. Where do we place image analysis in this scheme, at point A, requiring human assessment, at point B, or somewhere in between? With recent developments, image analysis is still between points A and B, but has moved closer to point B. In this paper, we review several factors that have allowed this advancement in computer image analysis. New image analysis techniques, new data fusion

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techniques that combine clinical and image information, and new uses of classifiers have allowed advancements in the application of computer vision that have increased computer accuracy in diagnosing skin lesions.

1.2 Defining the Problem: Is This Lesion a Skin Cancer, or Do I Have a Skin Cancer Anywhere?

Most skin cancer detection research focuses on the constrained problem: is this lesion a melanoma? In Blois' paradigm, at point A, the patient wants to know: "Is there a skin cancer present anywhere on my skin?" But research has been focused on the narrower problem that is closer to point B: "Given a single lesion, is this lesion a melanoma?" So we ask: "Are there tools that could help us bridge this gap, getting us from point A to point B?".

For decades, total-body photography has been used to assess the skin surface and detect changes (Slue et al., 1988). A new tool called Melanoscan® (Figure 2) eliminates the photographer and partially automates image acquisition (Nguyen et al., 2010).

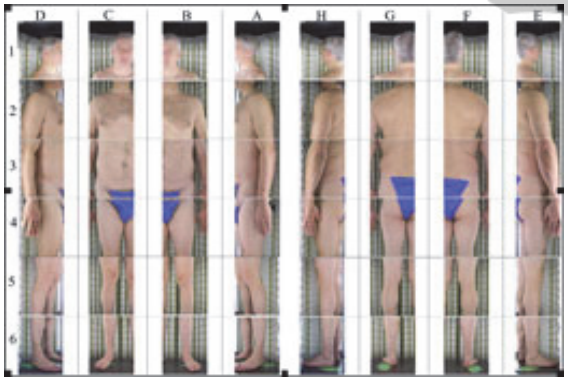

Figure 2: Melanoscan total body images.

Melanoscan still requires the manual comparison of images taken at different times to detect changes. Recent advances in image registration can further automate this process. We now have quantitative information supporting Melanoscan's effectiveness in detecting melanomas at an earlier stage. During the course of a study of melanoma *in situ* (Stricklin et al., 2012), the Melanoscan clinic detected a higher percentage of melanomas at the *in situ* stage (Figure 3). This represents progress toward answering the more general question about having a melanoma anywhere, with the possibility of detecting any changes in skin cancer anywhere.

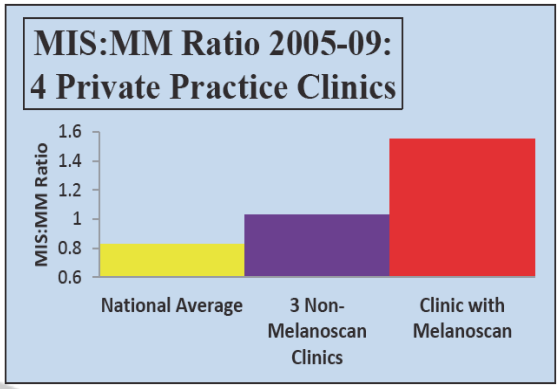

Figure 3: Melanoma *in situ*: invasive melanoma (MIS:MM) ratio 2005-2009: 257 Total Lesions (Data from (Stricklin et al., 2012)).

2 MELANOMA AND SKIN CANCER DETECTION

2.1 Melanoma: Mankind's 'Cinderella Cancer'

The societal burden of invasive melanoma is significant. A measure of impact is the average number of years of life lost (AYLL) caused by the disease. The AYLL to melanoma is 23 years (Burnet et al., 2005). Melanoma ranks 4th among all cancers for AYLL/mortality (Salama et al., 2012), making it one of four 'Cinderella cancers,' (along with brain, uterine, and cervical) for which research, treatment, and diagnostic advancements are significantly lower than expected for the AYLL.

2.2 Importance of Non-Melanoma Skin Cancer

To the societal burden of melanoma, we may add 3.5 million estimated cases of non-melanoma skin cancer (NMSC) in the USA, that are annually responsible for over 2,000 deaths per year (Bickers et al., 2006). Economic costs of these skin cancers exceed $2 billion in the USA, alone. Only scant research has been done on automated NMSC detection, which is now an area that could greatly benefit from the effective application of computer vision techniques (Guvenc et al., 2012); (Kefel et al., 2012).

2.3 New Problem: Detecting a 2mm Melanoma

During the 1990s, a group of researchers in Italy and Austria gathered a large collection of dermoscopy images of melanoma and benign lesions (Argenziano et al., 2000). These advanced lesions had features allowing high diagnostic accuracy in automatic systems, with two reports showing 95-96% diagnostic accuracy (Stanley et al., 2005), (Wadhawan et al., 2011). Recently, the automatic diagnosis problem has become more difficult with earlier and smaller lesions, such as the 2mm melanoma in a 48-year-old (Fig. 4).

2.4 Economic Burden of Benign Lesions

In dermatology clinics, the most common tumor is a benign lesion called a "seborrheic keratosis." These dark, fast-growing lesions alarm patients when they first appear. Dermoscopy changes everything, because it shows benign features with greater clarity. Little research has been done to identify these common lesions, which can be recognizing features such as milia-like cysts (Stricklin et al., 2011).

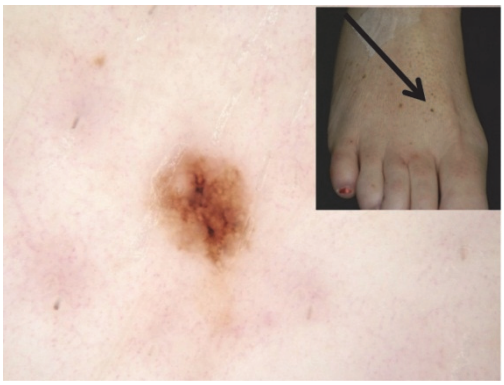

Figure 4: 48y/o, 2mm melanoma on foot.

3 IMAGE BORDERS AND ARTIFACTS

3.1 The Main Unsolved Computer Vision Problems: Borders and Artifacts

Automatic segmentation of skin cancer borders would seem to be an easy task, yet the problem remains unsolved. One leading technique applied to these complex images is minimal energy contours (Caselles et al., 1997). Hair removal, or hair segmentation, is an essential part of image processing, because hair mimics critical melanoma features. Figure 5 shows an example of hair removal from a dermoscopic image. The anisotropic diffusion method of edge detection is employed to accurately identify hair segments (Perona and Malik, 1990). Although this method is capable of segmenting a majority of hairs, it is prone to producing noise in the form of non-hair areas. Morphological noise removal techniques are then used to remove these non-hair segments.Figure 5: (a) Original image, (b) Perona-Malik anisotropic diffusion, (c) Hair mask after application of multiple morphological noise removal techniques, (d) Hair mask (cerulean) overlaid on original image.

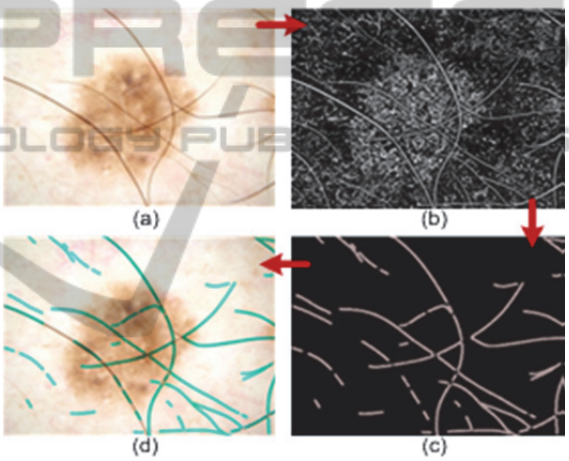

Figure 5: (a) Original image, (b) Perona-Malik anisotropic diffusion, (c) Hair mask after application of multiple morphological noise removal techniques, (d) Hair mask (cerulean) overlaid on original image.

4 ANTHROPOMORPHISM IN IMAGE ANALYSIS

Innovation in computer vision can start with an insight from human experience. Using the computer vision technique "anthropomorphism," we train the computer to see objects that humans can see. To detect amelanotic melanoma, the difficult variant lacking pigment, we mimicked the observation of Menzies, who noted that amelanotic melanoma has more than one shade of pink (Menzies et al., 2008). Yet the computers need a way to separate melanoma pink from benign pink. We therefore analyzed a different set of lesions—melanomas and benign mimics having pink areas. We studied pink shade

and location variants, finding that location outweighs shade. Using the anthropomorphic finding that locations and shades of pink are germane, we found varied shades of pink and used the distance transform to overlay concentric quintiles on these shades (Figure 6).

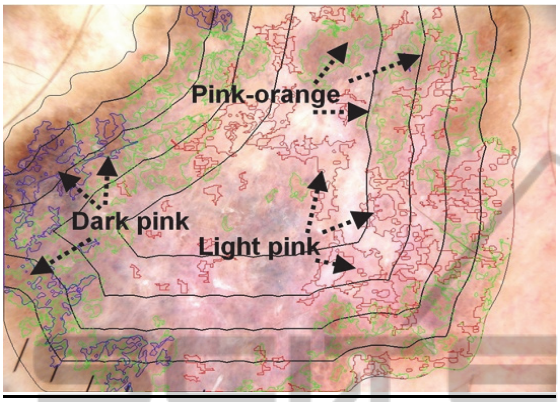

Figure 6: Automatically detected pink areas using 3-shade analysis, lesion quintile map overlaid.

Calculating color, texture and blob features in detected pink areas has yielded a high diagnostic accuracy in preliminary research. Thus, the anthropomorphic technique can provide useful feature measurement for detecting skin cancer.

5 EARLIEST DETECTABLE CHANGES IN MELANOMA: ATYPICAL PIGMENT NETWORK

An atypical pigment network (APN) is a critical feature for successfully classifying melanoma. Clinical APN presence yields an odds ratio of 9.0 for melanoma (Argenziano et al., 2003). Figure 7 shows the steps for automatic APN detection, which is used as classifier inputs to predict malignancy. This technique was successful in finding APN in the 2mm melanoma in Fig. 4.

6 DATA FUSION AND THE BLOIS PARADIGM

The tiny melanoma presented earlier was diagnosed when we added clinical information, specifically, the patient's concern and observation of lesion change. A logistic regression analysis on 885 pigmented lesions shows that the two features with the highest Chi-square significance are clinical features: the patient's age and concern about the lesion, allowing diagnosis of these images by clinical information alone.

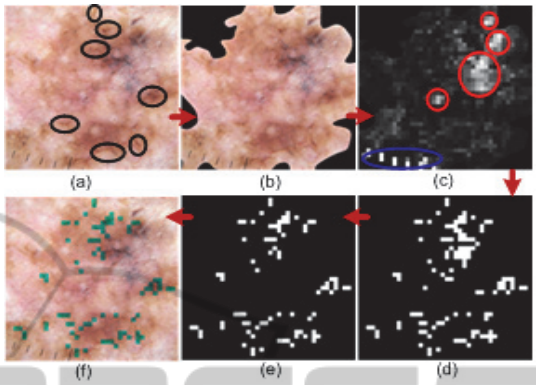

Figure 7: Melanoma *in situ*. (a) Original image, (APN circled) (b) lesion mask, (c) relative red plane variance, highest for granularity: red circles and blue oval (ruler markings), (d) red variance mask after threshold, (e) mask after threshold for green-to-blue ratio applied, (f) final overlaid APN mask (green).

Data fusion using clinical and skin lesion image information has been shown to improve lesion discrimination by 19.9% over clinical and image information only, while image features yield higher lesion discrimination than clinical features by as much as 9.7% (Cheng et al., 2012).

7 DIAGNOSTIC ASSISTANT IN THE CLINIC

We have presented advances that further the goal of automatic detection of skin cancer. The US Food and Drug Administration noted the need to include critical patient information in devices to maximize diagnostic accuracy. Thus, even the early lesions showing up more commonly in the clinic can now be diagnosed. The path to success from research to clinic should focus on the patient-centered problem, "Do I have a skin cancer?" For the best patient acceptance of automatic devices, assessment of lesion change and non-melanoma skin cancers, as well as benign melanoma mimics, should be included in the research agenda of the computer vision community.

REFERENCES

Argenziano, G., Soyer, H. P., De Giorgi, V., Piccolo, D., Carli, P., Delfino, M., Wolf, I. H., (2000). *Interactive atlas of dermoscopy CD*: EDRA Medical Publishing and New Media, Milan.

Argenziano, G., Soyer, H. P., Chimenti, S., Talamini, R., Corona, R., Sera, F., Kopf, A. W., (2003). Dermoscopy of pigmented skin lesions: results of a consensus meeting via the Internet. *Journal of the American Academy of Dermatology*, 48(5), 679-83.

Bickers, D. R., Lim, H. W., Margolis, D., Weinstock, M. A., Goodman, C., Faulkner, E., Dall T., (2006). The burden of skin disease: 2004, a joint project of the American Academy of Dermatology Association and the Society for Investigative Dermatology. *Journal of the Academy of Dermatology*, 55(3), 490-500.

Blois, M. S., (1980). Clinical judgment and computers. *New England Journal of Medicine*, 303(4), 192-7.

Burnet, N. G., Jefferies, S. J., Benson, R. J., Hunt, D. P. and Treasure, F. P., (2005). Years of life lost (YLL) from cancer is an important measure of population burden—and should be considered when allocating research funds. *British Journal of Dermatology*, 92(2), 241-5.

Caselles, V., Kimmel, R., Sapiro, G. (1997). Geodesic active contours, *International Journal of Computer Vision*, 22(1): 61-79.

Cheng, B., Stanley, R. J., Stoecker, W. V., Stricklin, S. M., Hinton, K. A. Nguyen, T. K., Moss, R. H. (2012). Analysis of clinical and dermoscopic features for basal cell carcinoma neural network classification. In press, *Skin Research and Technology*.

Drugge, R. J., Nguyen, C., Gliga, L. and Drugge, E. D. (2010). Clinical pathway for melanoma detection using comprehensive cutaneous analysis with Melanoscan. *Dermatology Online Journal*, 16(8), 1.

Guvenc, P., LeAnder, R. W., Kefel, S., Stoecker, W. V., Rader, R. K., Hinton, K. A., Moss, R. H. (2012) Sector expansion and elliptical modeling of blue-gray ovoids for basal cell carcinoma discrimination in dermoscopy images. In press, *Skin Research and Technology*.

Kefel, S., Guvenc, P., LeAnder, R., Stricklin, S. M., Stoecker, W. V. (2012). Discrimination of basal cell carcinoma from benign lesions based on extraction of ulcer features in polarized-light dermoscopy images. *Skin Research and Technology*, 18(4), 471-5.

Menzies, S. W., Kreusch, J., Byth, K., Pizzichetta, M. A., Marghoob, A., Braun, R, Johr, R. (2008). Dermoscopic evaluation of amelanotic and hypomelanotic melanoma. *Archives of Dermatology*, 144(9), 1120-7.

Perona, P. and Malik, J. (1990). Scale-space and edge detection using anisotropic diffusion. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(7), 629-39.

Salama, A. K., Rosa, N. D., Scheri, R. P., Herndon, J. E., Tyler, D. S., Marcello, J., Abernethy, A. P. (2012). The effect of metastatic site and decade of diagnosis on the individual burden of metastatic melanoma: contemporary estimates of average years of life lost. *Cancer Investigation*, 30(9), 637-41.

Slue, W., Kopf, A.W. and Rivers, J. K., (1988). Total-body photographs of dysplastic nevi. *Archives of Dermatology*, 124(8), 1239-43.

Stanley, R. J., Stoecker, W. V., Moss, R. H., Gupta, K., Jella, P. (2005). Color and structural features for automatic skin lesion discrimination in dermoscopy images. *6th World Congress on Melanoma,* Vancouver, BC, September 7, 2005.

Stricklin, S. M., Stoecker, W. V., Malters, J. M., Drugge, R., Oliviero, M. & Rabinovitz, H. S., (2012). Melanoma *in situ* in a private practice setting 2005 through 2009: Location, lesion size, lack of concern. *Journal of the American Academy of Dermatology*, 67(3), e105-9.