Automation Characterization for Oral Cancer by Pathological Image Processing with Gray-Level Co-occurrence Matrix

Meng-Jia Lian[1], Chih-Ling Huang[2], and Tzer-Min Lee[1]
[1]School of Dentistry, Kaohsiung Medical University, Kaohsiung 807, Taiwan
[2]Center for Fundamental Science, Kaohsiung Medical University, Kaohsiung 807, Taiwan
Email: sy2es93103@gmail.com, chihling@kmu.edu.tw, tmlee@mail.ncku.edu.tw

***Abstract*—Oral cancer is one of the most prevalent tumors of the head and neck region. As a result, reliable techniques for detecting are urgently required. Accordingly, the present study proposes an optical method using a Scanned Laser Pico-Projection system (SLPP) and Gray-Level Co-occurrence Matrix (GLCM). The validity of the proposed method is demonstrated using five indexes for quantized criteria for oral cancer classifies. The results show that the cancerous pathological sections have the higher Contrast and Entropy, but the lower Correlation, Homogeneity, and Energy. SLPP system with GLCM image processing can differentiate normal & cancerous pathological sections and it works on both full field analysis and specific tissue analysis. The discrimination of normal and cancerous tissues depends on the disorder caused by unusual proliferation and division of the chromosomes and nuclei. Compared to existing methods, the proposed method approach has many advantages, including a lower cost, a larger sample size and a more reliable diagnostic performance. As a result, it provides a highly promising solution for the pathologists/doctors.**

***Index Terms*—Scanned Laser Pico-Projection system (SLPP), Gray-Level Co-occurrence Matrix (GLCM), oral cancer, pathological image processing**

I. Introduction

Oral cancer is originated from the epithelial basal cell lines and invades into the connective tissue and muscle tissues below [1]. In medical practice, we often cut down the tumor and hang it to the pathology department to wait for the analysis. Preparing and diagnosing these pathological sections takes time and is often based on the pathologists' experience. However, pathologists take years training and building up the experience takes a lot of practical operations. We hope to develop a way to give out quantized criteria to help the pathologists/doctors in diagnosing pathological sections.

In recent years, many non-invasive imaging techniques have been proposed for the clinical diagnosis of cancers, including X-rays, Computed Tomography (CT), Positron Emission Tomography (PET), Ultrasonography (US), Magnetic Resonance Imaging (MRI), and tissue polarimetry [2]. However, an urgent requirement exists for more timely and quantitative methods for detecting the presence of oral cells [3]-[5].

Chuang *et al*. [6] presented a method for measuring the two-dimensional (2-D) nanoparticle concentration of solid and liquid solutions via an inspection of the speckle contrast of the images obtained using a Scanned Laser Pico-Projection (SLPP) system. The feasibility of the proposed approach was demonstrated by measuring Type I collagen concentrations ranging from 0.025 ~ 0.125%. SLPP systems have many important practical benefits for optical diagnosis applications, including a good power efficiency, an infinite focus, and an inherently high image contrast [7].

Scanned Laser Pico-Projection (SLPP) is basically a projector with laser emitted light source. Single color laser light has the narrower bandwidth compared to traditional white light and the single-color light originated from filter. It's much more power efficiency, namely cooler when providing the same light intensity [7]. With SLPP as light source, we could obtain a sharper image to characterize the samples. Huang *et al*. [8] found that the speckle contrast measurement provides a reliable means of distinguishing quantitatively between low- and high-metastatic cells of the same origin. Compared to existing metastasis detection methods, the proposed SLPP approach has many advantages, including a higher throughput, a lower cost, a larger sample size and a more reliable diagnostic performance. As a result, it provides a highly promising solution for physical characterization of metastatic cancer cells *in vitro*.

Gray-level Co-occurrence Matrix (GLCM) is a way to recognize pattern in a picture [9]-[11]. First, it counts the frequency of the neighboring-pixel-relation occurred and turn the relationship into a matrix. Second, it extracts five specific parameters, energy, contrast, homogeneity, entropy, and correlation base on the matrix. GLCM has its benefit in showing the picture's pattern with the sampling base on neighboring pixels, compared to normal counting method. Therefore, GLCM is widely used in medical image processing [12]-[15].

II. Materials and Methods

Experimental setup: The optical diagnosis system used in this study comprised a SLPP (SONY; Model: MP-

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CL1A; Resolution: 1920 × 720; Aspect Ratio: 16:9 Widescreen; Contrast Ratio: 80,000:1; Image Size: 40 inch @ 1.15 m) and a microscope (OLYMPUS IX-71). In accordance with the findings of a previous study, the samples were illuminated using a green laser source (wavelength = 532 nm) in order to enhance the sensitivity of the speckle measurements. In obtaining the images of the samples by object mirror (OM), the samples were illuminated using a halogen lamp. The tissue images and speckle images were captured using Olympus DP-80 with CellSens Dimension™ image acquisition software. The speckle images (1360×1024 pixels) were partitioned into sub-images with a size of 150 × 150 pixels. A schematic diagram of our optical diagnosis system is shown in Fig. 1.

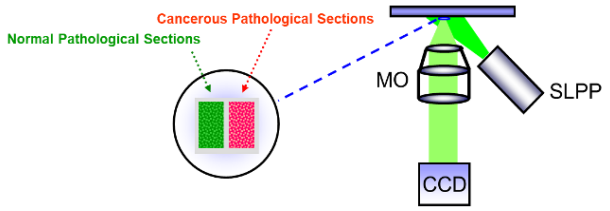

Figure 1. A schematic diagram of our optical diagnosis system.

To evaluate the reliability of the detection method, the statistical differences between the normal and cancerous tissue were evaluated using a One-Way Analysis of Variance (ANOVA) technique. In evaluating the test results, a *P value of <0.05 was statistically significant, a **P value of <0.01 was very statistically significant, and a ***P value of <0.001 was considered to be highly statistically significant.

Sample Preparation: The oral pathological sections are provided by the Division of Oral Pathology & Radiology of Kaohsiung Medical University. The making of these two pathological sections are first cutting part of the oral tissue down from patients' cheek and soaking it into Formalin to prevent corruption. Later, soak it into wax again to fix the shape and slice it. After getting the slide, we use hematoxylin and eosin stain (HE stain) to color the tissue. The basic part and basophilic substances would be dyed blue and the acidic part and acidophilic substances would be dyed red.

We use two pathological sections, no.1408 and no.1414 in KMU DOPR's serial number. No.1408 is normal oral pathological section. No.1414 is squamous-cell carcinoma, SCC, which the cancer cell originated from the epithelial basal cell line and invaded to the connective tissue and muscle tissue. The tumor is well-differentiated, meaning that the cancer cell remains its differentiated characteristics.

III. Results and Discussion

Fig. 2 and Fig. 3 present the pathological images and speckle images of normal and cancerous pathological sections. It seems that for cancerous pathological sections, there are more nuclei and chromosomes dyed due to the unusual proliferation and high rate of cell-division. The linear pattern of the muscle tissue has changed as well, becoming fragmentized when cancer invaded. With the laser light from SLPP system, the dyed matters were enhanced with the green light and the marginals of the tissues were smoothened, which would help lowering the tissue-information and let GLCM better recognizing the nuclei and chromosome patterns.

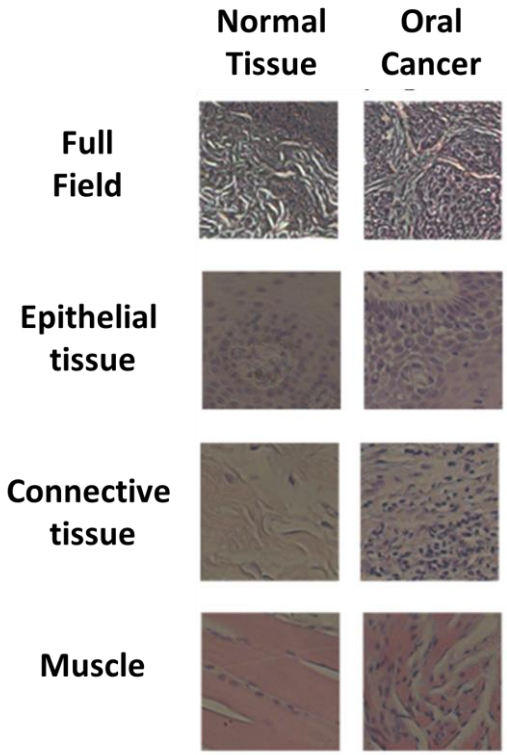

Figure 2. Pathological images for normal tissue and oral cancer.

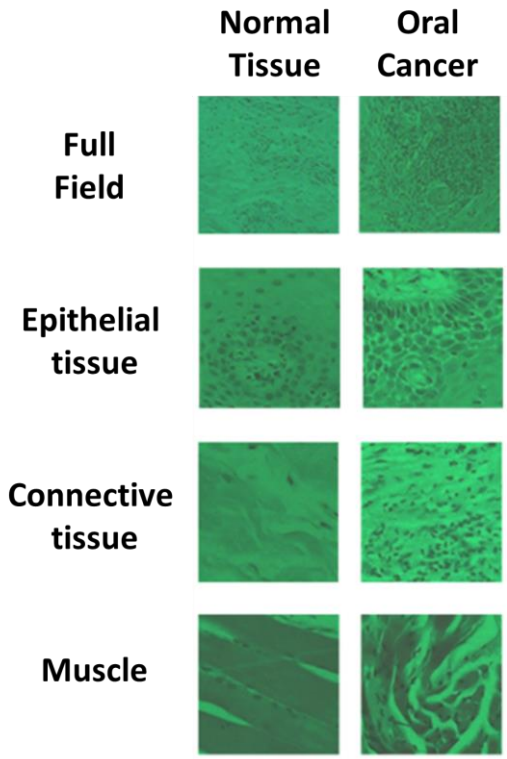

Figure 3. Speckle images for normal tissue and oral cancer.

TABLE I. TEXTURE ANALYSIS OF GLCM FOR PATHOLOGICAL IMAGES OF NORMAL AND ORAL CANCER TISSUE

		Energy (10^-3)	*Contrast (10^1)*	*Correlation (10^-3)*	*Homogeneity (10^-2)*	*Entropy (10^0)*
Full Field	normal	0.23 ±0.1	57 ±6.8	0.71 ±0.1	8.7 ±1.1	8.9 ±0.2
	cancer	0.16 ±0.0	99 ±10	0.45 ±0.0	5.7 ±0.5	9.2 ±0.1
		P = 0.83	*P* = 0.19	*P* = 0.77	*P* = 0.10	*P* = 0.94
Epithelial Tissue	normal	6.8 ±1.7	4.2 ±0.6	11 ±1.0	39 ±3.0	5.9 ±0.2
	cancer	2.0 ±0.0	8.3 ±1.4	5.3 ±0.5	24 ±2.0	7.0 ±0.2
		*	**	*	**	**
Connective Tissue	normal	4.5 ±2.4	5.1 ±1.2	9.3 ±2.2	31 ±5.8	6.2 ±0.4
	cancer	4.5 ±3.3	7.2 ±4.1	7.8 ±4.6	30 ±9.4	6.5 ±0.8
		P = 0.90	*P* = 0.24	*P* = 0.35	*P* = 0.60	*P* = 0.44
Muscle Tissue	normal	8.0 ±3.0	13 ±3.6	2.6 ±2.2	33 ±5.5	5.8 ±0.4
	cancer	4.3 ±5.2	27 ±8.0	6.0 ±1.4	14 ±7.2	6.3 ±1.3
	normal	*P* = 0.18	**	**	**	*P* = 0.32

Note: Interpixel distance d1 = 1, and d2 = 5. *P<0.05, **P<0.01 and ***P<0.001.

TABLE II. TEXTURE ANALYSIS OF GLCM FOR SPECKLE IMAGES OF NORMAL AND ORAL CANCER TISSUE

		Energy (10^-3)	*Contrast (10^1)*	*Correlation (10^-3)*	*Homogeneity (10^-2)*	*Entropy (10^0)*
Full Field	normal	6.5 ±3.5	3.6 ±1.1	11 ±3.4	41 ±6.7	5.9 ±0.4
	cancer	3.5 ±1.7	6.9 ±3.9	8.5 ±3.7	28 ±6.6	6.5 ±0.5
		P = 0.05	*	*P* = 0.18	**	*
Epithelial Tissue	normal	20 ±18	2.0 ±1.0	35 ±41	50 ±4.5	4.9 ±1.1
	cancer	2 ±0	7.1 ±0.4	5.8 ±0.5	27 ±0.9	6.9 ±0.1
		*	***	*P* = 0.12	***	**
Connective Tissue	normal	14 ±2.6	2.1 ±0.3	23 ±1.9	54 ±3.3	4.9 ±0.1
	cancer	6.3 ±3.3	4.6 ±2.4	11 ±5.3	40 ±8.3	6.0 ±0.7
		**	*	***	**	**
Muscle Tissue	normal	12 ±8.3	9.7 ±5.9	6.0 ±2.0	39 ±8.0	5.6 ±0.6
	cancer	0.8 ±0.2	33 ±3.8	1.5 ±0.6	14 ±1.6	7.6 ±0.2
	normal	*	***	***	***	***

Note: Interpixel distance d1 = 1, and d2 = 5. *P<0.05, **P<0.01 and ***P<0.001.

Table I presents the texture analysis of GLCM for pathological images of normal and cancerous pathological sections. It shows that the cancerous tissue has higher Contrast, Entropy, and lower Energy, Correlation, Homogeneity. It also shows that some texture characteristic value of cell images has significant difference in the pair of normal and cancerous tissues. Table II presents the texture analysis of GLCM for speckle images of normal and cancerous pathollogical sections. It shows that the cancerous tissue has the higher Contrast, Entropy, and lower Energy, Correlation, Homogeneity. It also shows that most of the texture characteristic value of cell images have significant difference in the pair of normal and cancerous tissues. Also, much of the P-value from ANOVA is lower in speckle image than in cell image, which means much more difference could be captured using the SLPP technics.

IV. CONCLUSIONS

The cancerous pathological sections have the higher Contrast and Entropy, but the lower Correlation, Homogeneity, and Energy. SLPP system with GLCM image processing can differentiate normal & cancerous pathological sections and it works on both full field analysis and specific tissue analysis. The discrimination of normal and cancerous tissues depends on the disorder caused by unusual proliferation and division of the chromosomes and nuclei. The method provides quantized criteria to classify pathological sections with normal and cancerous tissues. In the future, analysis of Squamous Cell Carcinoma of the Oral Cavity (SCCOC) and different morphology of medicine-resistant cancer cells will keep going. A rapid and non-invasion with quantized criteria cancer diagnosis system will be developed and it is promising for quick and diagnosis reference.

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Meng-Jia Lian is a collage student of School of Dentistry, Kaohsiung Medical University. Since 2017, he join the research group of Kaohsiung Medical University and his research interest is image processing. He got the Excellent Oral Presentation of 2018 International Conference on Smart Materials Applications (ICSMA 2018), Singapore, Jan. 2018.

Chih-Ling Huang received her BS, MS, and PhD degrees from the Department of Material Science and Engineering, National Cheng Kung University, Taiwan, China, in 2003, 2005, and 2010, respectively. After graduation, she has been a postdoctoral researcher in Department of Mechanical Engineering, National Cheng Kung University. Since 2016, she has been a member of the Center for Fundamental Science, Kaohsiung Medical University, where she is now an assistant professor. She got the 2015 Young Scholar Award of Taiwan Comprehensive University System and 2016 Outstanding Research Award of Kaohsiung Medical University.

Dr. Tzer-Min Lee received the B.S. degree from the B.S., M.S., Ph.D. degrees from National Cheng Kung University (NCKU) in 1991, 1993, and 1998, respectively, all in materials science and engineering. In 2003 he joined the Institute of Oral Medicine at the National Cheng Kung University (NCKU) as an Assistant Professor (non-clinical). In 2006 he was promoted to the position of Associate Professor and was named a full Professor in 2010. He is also Professor of Biomedical Engineering, NCKU. He has served as Vice Dean of College of Medicine, NCKU. He has appointed as Deputy Director of Medical Device Innovation Center (MOE University Advancement). Dr. Lee was named Dean of College of Dental Medicine, Kaohsiung Medical University in 2015. He gained 2005 Young Investigator Research Award, College of Medicine, National Cheng Kung University; 2008 Ta-You Wu Memorial Award, National Science Foundation, Taiwan; 2006/ 2009/ 2010/ 2012/ 2013/ 2014/ 2015 Best Paper Award, Cheng Kung Medicine Foundation for Education. His research activities involve bioactive ceramic coatings, model surfaces for cell culture and animal testing, and implant surface modifications and testing. He has published 65 journal papers, 120 conference papers, and 2 book chapters.