Automated Saliency-based Melanoma Detection in Dermoscopic Images

Euijoon Ahn
Youn Hyun Jung, *Dr. Jinman Kim*
Biomedical & Multimedia IT (BMIT) Research Group, School of Information Technologies

INTRODUCTION & BACKGROUND

- Malignant melanoma is one of the most serious skin diseases that cause a considerable number of deaths worldwide.
- **Australia has the highest incidence of melanoma in the world and melanoma is often referred to as Australia's national cancer** [1].
- **Fortunately, malignant melanoma can be cured if diagnosed at early stage using dermoscopy.**
- Dermoscopy is a non-invasive diagnostic technique for the *in vivo* observation of pigmented skin lesions. This technique helps dermatologists to detect early stage of malignant melanomas that are not visible by human naked eyes.

MOTIVATION

Clinical Motivation

- Manual interpretation made by dermatologists is often time consuming and subjective and not reproducible.
- Even experienced dermatologists produce different analyses when it comes to delineating the same skin lesion [5].

Technical Motivation

- Existing state-of-art dermatology segmentation methods are semi-automatic; have difficulties with irregular shapes, sizes, different colors and artifacts such as hair.
- Difficult to determine which particular algorithm outperforms for any lesion due to the different characteristics of each method

METHODOLOGY

Saliency-based Melanoma Detection

- **Visual saliency** based algorithm detects 'salient' objects (skin lesion in our case) by dense and sparse reconstruction using background templates. These templates are created via **Superpixels** using a linear iterative clustering (SLIC) algorithm. For each image region from the template, saliency is firstly measured by the dense and sparse reconstruction errors. These two types of reconstruction errors are propagated based on the image contexts obtained by K-means clustering. The saliency of each pixel is then computed by an integration of **Multi-scale reconstruction errors** and refined by an object-biased Gaussian model. Finally, reconstruction errors from both dense and sparse are integrated by Bayesian inference to create final saliency maps. The overall steps of the algorithm is shown in Figure 1.

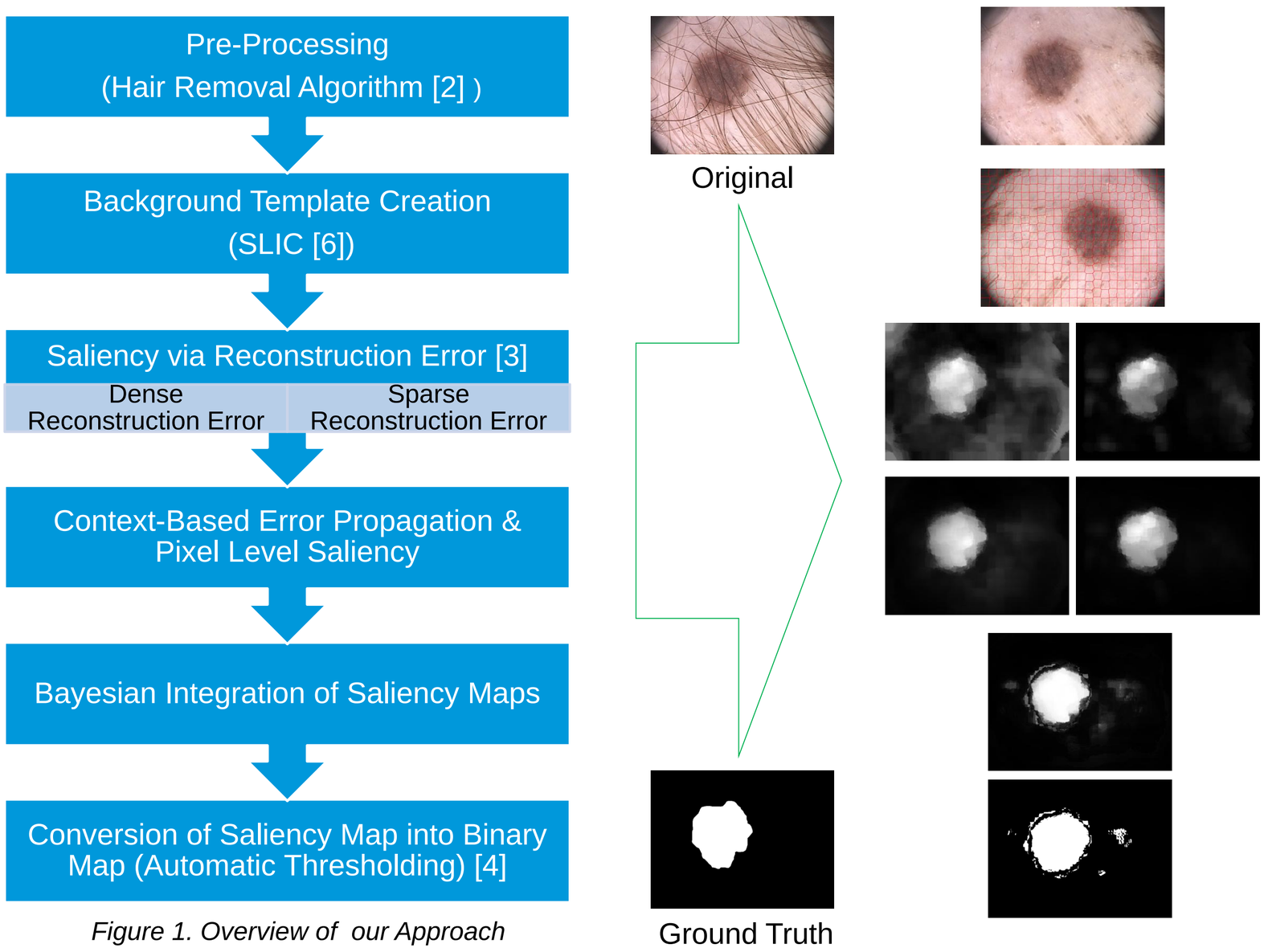

Figure 1. Overview of our Approach

RESULTS

Evaluation

- Segmentation results were evaluated by comparing our results with the ground truth (manual annotations). **Accepted objective evaluation measures** of Dice Similarity Coefficient (DSC), True Detection Rate (TDR), False Positive Rate (FPR), and Hammoude Distance (HM) were used.
- **The database of 200 images** was processed using all the methods under evaluation as shown in Table 1 and Table 2.

DSC Measure	AT	C-LS	Region-Growing	Saliency
Average	0.8009	0.7131	0.6194	**0.8433**
Max	0.9668	0.9747	0.9680	**0.9759**
Min	**0.2521**	0.0016	0.0019	0.1823
Std	**0.1323**	0.2861	0.2813	0.1406

Table1. DSC Measure only calculated for the 200 Images

Methods (Average)	DSC	TDR	FPR	HM
AT	0.8009	0.9130	0.1777	0.3143
C-LS	0.7131	0.8256	0.2892	0.3850
Region-Growing	0.6194	**0.9516**	0.0308	0.4958
Saliency	**0.8433**	0.8327	**0.1630**	**0.2493**

Table2. Results of the Segmentation Methods Calculated for the 200 Images

KEY CONTRIBUTIONS

- **Developed a fully automated visual saliency based algorithm to segment melanoma regions by proposing the use of 'Saliency' that are inherent to dermoscopic images**
- **Extensive comparison to conventional algorithms**
- **Potential use in Computer Aided Diagnosis (CAD) to provide 'second opinion' to the diagnosis; Automation enables 'big data' processing at the population level for statistical analysis and pattern discovery.**
- **Use of public 'PH2' image database to measure the performance of our approach and compare with other methods such as Adaptive Thresholding, Chan-based Level Set, and Region Growing, and various types of Saliency**

CONCLUSION & FUTURE WORK

- Based on the results, we suggest that saliency-based algorithm outperforms other three methods with PH2 dataset.
- Our approach has the highest accuracy on average with minimum errors compared with other methods
- Future work will establish collaborations with clinicians
- Future development of portable cloud-based imaging solution

REFRENCES

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