Biomedical Signal Processing and Control 8 (2013) 755–763

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Noninvasive diagnosis of melanoma with tensor decomposition-based feature extraction from clinical color image

Ante Jukić[a,*,1], Ivica Kopriva[a], Andrzej Cichocki[b,c]

[a] Division of Laser and Atomic Research and Development, Ruđer Bošković Institute, Bijenička cesta 54, 10000 Zagreb, Croatia
[b] Laboratory for Advanced Brain Signal Processing, Brain Science Institute, RIKEN2-1 Hiroshawa, Wako-shi, Saitama 351-0198, Japan
[c] Warsaw University of Technology and Systems Research Institute, PAN, Poland

ARTICLE INFO

Article history:
Received 28 February 2013
Received in revised form 29 May 2013
Accepted 9 July 2013
Available online 7 August 2013

Keywords:
Multidimensional signal processing
Tensor decomposition
Feature extraction
Noninvasive diagnosis
Melanoma

ABSTRACT

We propose a method for feature extraction from clinical color images, with application in classification of skin lesions. Proposed feature extraction method is based on tensor decomposition of the clinical color image of skin lesion. Since color image is naturally represented as a three-way tensor, it is reasonable to use multi-way techniques to capture the underlying information contained in the image. Extracted features are elements of the core tensor in the corresponding multi-way decomposition, and represent spatial-spectral profile of the lesion. In contrast to common methods that exploit either texture or spectral diversity of the tumor only, the proposed approach simultaneously captures spatial and spectral characteristics. The procedure is tested on a problem of noninvasive diagnosis of melanoma from the clinical color images of skin lesions, with overall sensitivity 82.1% and specificity 86.9%. Our method compares favorably with the state of the art results reported in the literature and provides an interesting alternative to the existing approaches.

1. Introduction

Noninvasive diagnosis of tumor is a procedure of identification and discrimination among various types of tumors by exploiting data that is not collected invasively, e.g., by biopsy. The aim of the noninvasive diagnosis is to detect malignant tumors with high accuracy and to simultaneously reduce the number of biopsies of the innocuous benign tumors. In general, methods for automated noninvasive diagnosis rely on sophisticated processing techniques applied on the collected data. The data can be acquired by various imaging modalities, such as multispectral (MSI) or hyperspectral imaging (HSI) [1,2]. Diagnosis is usually obtained by classifying a set of features extracted from the image of the tumor. Consequently, extraction of tumor-specific features is of central importance for accurate diagnosis. This is in line with the reasoning in the machine learning community that feature extraction matters more than the method used for classification [3,4].

Malignant melanoma is presently among the leading cancers in the white-skinned population, with rapidly increasing incidence and mortality rates over the last decades [5–7]. While advanced form of the cutaneous melanoma is still practically incurable, early diagnosis can significantly increase probability of survival. In fact, very high degree of curability can be achieved if the surgical excision is performed early enough [8]. The increased occurrence, along with the high lethality in case of an advanced melanoma, implies a demand for a simple and accurate screening test as an alternative to biopsy.

In spite of best efforts of researchers, the accuracy of the noninvasive diagnosis of the melanocytic lesions is far from ideal. Even binary problem of distinguishing between malignant melanoma and benign melanocytic lesion without histological examination remains a challenge [9]. One of the most widely used methods for preliminary diagnosis based on visual inspection is the so called ABCDE rule. It is a semi-quantitative diagnosis scheme based on naked eye inspection (i.e., a clinical image) of the skin lesion. The scheme includes examination on the asymmetry (A), border sharpness (B), color variation (C), number of differential structures (D) present in the lesion, and evolution (E) of the lesion in time. Unfortunately, it has shown a limited sensitivity in melanoma diagnosis [7], with overall accuracy depending on the level of expertise of dermatologist. In case of a well-trained dermatologist typical accuracy is around 75% [10]. Since the naked eye inspection achieves such low performance, epiluminescence light microscopy (ELM) or

* Corresponding author. Current address: Signal Processing Group, University of Oldenburg, 26111 Oldenburg, Germany. Tel.: +49 441 798 3377; fax: +49 441 798 3902.
E-mail addresses: ante.jukic@uni-oldenburg.de (A. Jukić), ikopriva@irb.hr (I. Kopriva), cia@brain.riken.jp (A. Cichocki).
[1] This work was done while the author was with the Ruđer Bošković Institute, Zagreb, Croatia.

1746-8094/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.bspc.2013.07.001

dermoscopy was suggested. The idea of ELM is to improve diagnostic performance by evaluating morphological features of lesions [11]. It was reported that the accuracy of the diagnosis obtained by dermoscopy in case of an expert dermatologists is around 75–84% [5,12]. Despite the formal training of dermatologists and availability of comprehensive atlases, interpretation of the features acquired by dermoscopy is often subjective and not reproducible, especially for an inexperienced clinician. Still, standard approach for classification of skin lesions in clinical practice is dermoscopy-based visual inspection, followed by biopsy and tissue analysis if needed [7].

An accurate computer-based automatic diagnostic system is required to reduce the need for highly trained dermatologist and time required for diagnosis. Such system with high levels of sensitivity and specificity (typically above 90%) could provide a second-opinion to dermatologist and also reduce the number of unnecessary biopsies. In [9] a meta-analysis of several studies was performed, and showed that computer-based diagnosis is comparable with performance of a human expert. Also, it was noted that better performance was achieved using dermoscopic images than with clinical images [9,13–16].

Opposed to inspection of morphological features, another line of research was focused on the MSI and HSI systems, with discrimination among tumors based on their spectral profiles. In [1], a MSI system with 10 channels in range 430–950 nm was designed and used for automatic discrimination between benign nevus and malignant melanoma by using auto-fluorescence of the tumor. A HSI system with 21 channels between 440 and 660 nm was used in [2] for automatic discrimination among benign and malignant skin tumors on laboratory mice based on fluorescence induced by fluorophore.

While automatic systems based on dermoscopic and high spectral resolution MSI/HSI systems show great potential, it was demonstrated in [9], as well as recently in [17], that automatic diagnosis of melanoma is possible using auto-fluorescent macroscopic (clinical) color images. These methods use clinical red-green-blue (RGB) color images, and achieve sensitivity in range 80–94% and specificity in range 46–95%. While dermoscopic images captures subsurface structure of the lesion, clinical capture what a clinician sees in naked eye inspection [18]. Results of the twelve studies that used clinical images [9] as well as results from [17] are summarized in Table 1. Practical importance of these results is in demonstration that accurate automatic diagnosis of melanoma is possible from clinical images using affordable RGB auto-fluorescence imaging. A more detailed methodological review of computerized analysis of pigmented skin lesions can be found in [18], and references therein.

Aim of this paper is to present a novel method for feature extraction, suitable for analysis of MSI data, and to demonstrate it on automated noninvasive diagnosis of cutaneous melanoma from clinical color images. The paper proposes a method for feature extraction from multi-way data using tensor decomposition [19,20], used for analysis of RGB color images. For this purpose experimental multispectral medical image is represented by its Tucker3 decomposition. Dimensionality analysis yields that the extracted features simultaneously contain spatial and spectral information about the image. To account for possible nonlinear nature of the acquired data, images are nonlinearly transformed prior to decomposition. The proposed scheme is demonstrated on noninvasive diagnosis of melanoma from clinical auto-fluorescent color images, and sensitivity and specificity are estimated through a two-fold cross-validation procedure.

The rest of the paper is organized as follows. In Section 2 we provide preliminaries on tensor algebra, and define a nonlinear transformation based on kernel methods. In Section 3 we propose a method for feature extraction. The experimental results are presented in Section 4, with concluding remarks contained in Section 5.

2. Preliminaries

This section contains basics of multi-way analysis, as well as definition of nonlinear transformation related to kernels. Also, interpretation of multispectral image as tensor is presented, with focus on RGB color image. In the following, scalars will be denoted by lowercase italic letters (e.g., x), vectors by bold lowercase letters (e.g., $\mathbf{x}$), matrices by bold capital letters (e.g., $\mathbf{X}$), and tensors by underlined bold letters (e.g., $\underline{\mathbf{X}}$).

2.1. Tensor algebra and Tucker3 decomposition

Tensors are generalization of matrices and vectors. A tensor can be represented by a multi-way array with arbitrary number of indices, for example, an N-mode tensor has N indices. For clarity, and motivated by application in RGB image analysis, we will focus on tensors with three indices. In this paper an image RGB color image is represented by tensor $\underline{\mathbf{X}} \in \mathbb{R}_{0+}^{I_1 \times I_2 \times I_3}$, that consists of elements $x_{i_1 i_2 i_3} \in \mathbb{R}_{0+}$, with $\mathbb{R}_{0+}$ denoting the set of nonnegative real numbers. Each index in tensor is called way or mode, and number of levels on a mode represents dimension of that mode, e.g., dimension of mode-1 is I_1. This is in line with the standard notation used in multi-way analysis [21]. RGB image $\underline{\mathbf{X}}$ is a set of $I_3 = 3$ spectral images, corresponding to red, green and blue color channels

Table 1
Comparative performance analysis of fifteen studies related to image analysis based automated diagnoses of melanoma from clinical images.[a]

Source	Sample size	Melan. [%]	Method of analysis	Sens. [%]	Spec. [%]
Green et al., 1991	70	7	Single set	80	91
Cascinelli et al., 1992	88	49	Single set	83	60
Claridge et al., 1992	88	49	Single set	91	69
Schindewolf et al., 1993	353	61	Ten-fold CV	94	88
Green et al., 1994	164	11	Single set	89	89
Ercal et al., 1994	214	56	Single set	80	86
Schindewolf et al., 1994	404	59	Ten-fold CV	90	88
Bono et al., 1996	43	42	Single set	83	72
Cristofolini et al., 1997	176	20	Single set	78	46
Seidenari et al., 1998	90	34	Single set	93	95
Smith et al., 2000	60	47	Single set	86	94
Farina et al., 2000	237	28	Single set	80	46
Tabatabaie et al., 2008, [17]	160	50	Single set	82.5	92.5
Tabatabaie et al., evaluated herein	180	50	Two-fold CV	79.9	79.1
Proposed method	180	50	Two-fold CV	82.1	86.9

[a] Full references to first twelve studies are given in [9]. (Method of analysis refers to a procedure used to validate the method. Single set means that the cross-validation procedure was not used, and that the reported performance was based on a result of prediction on a single test set.)