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Least squares support vector machine regression combined with Monte Carlo simulation based on the spatial frequency domain imaging for the detection of optical properties of pear

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ABSTRACT

A spatial frequency domain imaging system to nondestructively measure wide-field optical properties of biological tissue has been developed. Optical parameters of absorption (μ_a) and reduced scattering coefficients (μ'_s) of 'Crown' pears were estimated based on spatial frequency dependent diffuse reflectance (*Rd*). Because of the limitation of diffusion approximation (DA), least squares support vector machine (LSSVM) regression was introduced to model the relationship between the μ_a, μ'_s and *Rd* that were generated by Monte Carlo (MC) simulation. To accelerate the detection speed, two spatial frequencies of $f_x = 0\ \mathrm{m}^{-1}$ and nonzero f_x were chosen according to the correlation coefficients between the measured and simulated results of *Rd* of 60 liquid phantoms. The results showed that the f_x of 250 m^{-1} presents the highest correlation. The forward LSSVR models at the two f_x were trained based on a series of MC simulations with a wide range of μ_a, μ'_s and albedo, and then validated by the phantoms by comparing predicted *Rd* and MC simulated *Rd*. The validation results showed that two models were capable of describing the forward relationship with little deviation, and that both the determination coefficients were close to 1 at two f_x. The μ_a and μ'_s of phantoms were predicted after an optimal searching of models. The inverse validation results showed that the mean relative errors for μ_a and μ'_s were 5.27% and 2.65% respectively. Compared with the calculation results by DA, the proposed method was capable of measuring the optical properties of tissue simulation phantoms accurately, especially when the albedo is less than 50. A case study on the inspection of pear bruises was carried out to verify the application prospect of the proposed method. Results indicated that the fresh bruise which is not obviously distinguishable by naked eyes, can be identified in μ'_s maps.

1. Introduction

Light propagation in turbid media has been a focus of intense research because of its application in the biomedical (Abookasis et al., 2008, Rehman et al., 2015, Hung et al., 2015) and phototherapy fields (Nilsson et al., 1995, Honda et al., 2011, Sandell and Zhu, 2011, Genina et al., 2015), as well as for nondestructive quality assessment of agro-products (Qin et al., 2009, Kao et al., 2016, He et al., 2016). The interaction between light and turbid media is a complicated phenomenon mainly takes place in the form of absorption and scattering, which can be characterized by the absorption coefficient (μ_a) and reduced scattering coefficient (μ'_s). The μ_a and μ'_s of biological tissue can provide useful information about its composition, physiological function, and structure (Alexandrakis et al., 2001). For example, the μ_a can be used to deduce the concentration of biologically important endogenous (e.g., hemoglobin, myoglobin, water, melanin, fat and yellow pigments (Jacques, 2013) or exogenous chromophores (e.g., near-infrared absorbing drugs) (Glazner et al., 2010). Also, μ'_s offers insight into the composition, density, and organization of tissue structures, such as cells, subcellular organelles, and connective tissue/extracellular matrix (Tuchin and Tuchin, 2007). Therefore, the research on the development of a rapid, effective and noninvasive method for estimation of the μ_a and $\mu'_s$is important for quality inspection of agro-products.

Currently, there are several techniques available to non-destructively decouple these two parameters, including the spatially resolved method (Naglič et al., 2016, Chen et al., 2016a,b,c, Watté et al., 2016), time resolved method (Eccher Zerbini et al., 2008, Torricelli et al., 2008, Konagaya et al., 2016, Milej et al., 2016, Suzuki et al., 2016) and

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frequency domain method (Chen et al., 2016a,b,c). Each differs experimentally in that the source intensity is either continuous, pulsed in time, or sinusoidally modulated. Both the time resolved and the frequency domain technique requires expensive, sophisticated equipment, and good contact between the detecting probe and the sample, which limits their applications. The spatially resolved method has the advantages of lower cost in instrumentation and easier implementation in measurement with the reflectance mode, it can be implemented in different sensing configurations, including a fiber-optics probe, monochromatic imaging, hyperspectral imaging and spatial frequency domain imaging (SFDI) (Lu, 2016).

SFDI is the spatial analog to frequency domain method except that light source is modulated in space rather than time. Spatially modulated illumination patterns are projected onto the tissue at different spatial frequencies and phases, and the resulting reflectance is captured by a camera. Compared with other techniques, it provides noncontact wide-field imaging of tissue optical properties. In addition, it is able to acquire depth-resolved information about tissue by varying the modulation frequency due to the frequency-dependent light attenuation within the tissue.

There are two commonly-used approaches to deduce the μ_a and μ'_s from the obtained diffuse reflectance. One is diffuse approximation (DA), which can be used to approximate radiative transfer equation (RTE) (Cuccia et al., 2009). The RTE describes the photon propagation based on the conservation of energy, but it cannot be calculated unless it is approximated by DA. However, DA is valid only when the μ'_s is much greater ($\geq 10\times$) than the μ_a, and the analyzed source-detector separation at least three to four times the transport length. In the spatial frequency domain, the latter constraint dictates that DA is valid only at some specific spatial frequencies. In general, when approaching these constraints, the diffusion model overestimates reflectance at low spatial frequencies and underestimates reflectance at high frequencies (O' Sullivan et al., 2012). The other way for simulation the light propagation is probabilistic method through Monte Carlo (MC) simulation, which can be used to build forward relationship from optical properties and spatial frequency to diffuse reflectance. This method is able to provide results with desired accuracy, if the required computational load is affordable. It is thus often regarded as a gold standard method for the modeling of light propagation in tissues, and the results are usually used as the reference to verify the effectiveness of other methods. However, MC simulation is time-consuming due to its statistical nature, and therefore it is not suitable to solve inverse problems for fast determination of optical properties. Cuccia et al. (2009) put forward a rapid two-frequency (zero and non-zero) look up table approach which based on the DA equations by inputting different values of (μ_a, μ'_s) to calculate the corresponding *Rd*. Erickson et al. (2010) presented an empirical method that employed a phantom-based look-up table (LUT) approach to analyze SFDI signals in highly absorbing tissues with albedos (μ'_s/μ_a) < 8, and the LUT was further linearly interpolated both the absolute diffuse reflectance and the frequency-dependent modulation by using 126 phantoms. In this study, we proposed a simulation-based method which uses MC simulations to obtain a series of (μ_a, μ'_s, *Rd*). By using least squares support vector machine regression and optimal searching method, the forward and inverse problems were investigated.

Pears are susceptible to bruise before harvest, at harvest, and during post-harvest operations such as transport, storage, and retail distribution. Bruising downgrade of fruit quality can result in significant economic losses for producers and retailers. Thus, identifying fresh bruise of fruit helps with making informed decisions about storage regimes to avoid quality degradation. Numerous researches have been carried out on the detection of surface bruise of fruit using visible and near infrared spectroscopy (VIS/NIR) (Xing et al., 2003, 2005a, b; Xing and Baerdemaeker, 2007), broadband imaging, multi- (Kleynen et al., 2005) and hyper-spectral imaging (Lu, 2003; Xing and Baerdemaeker, 2005; Xing et al., 2005a, 2007) modalities. However, it is still challenging to detect sub-surface defects that are invisible from the surface or defects that are very similar in appearance to the surrounding healthy tissue. The aforementioned research was done on the detection of old bruises in fruit. Fresh bruises that have occurred within a short time period (i.e., a few minutes) are usually absent of visible external symptoms, and are much more difficult to detect (Martinsen et al., 2014). Magnetic resonance imaging (MRI) (Thybo et al., 2004), X-ray imaging (Diels et al., 2017) and optical coherence tomography (OCT) (Zhou et al., 2018) have showed great potential for detecting sub-surface or internal defects, but they are expensive and need long scanning time. Lu et al. (2010) demonstrated that bruising has a greater impact on scattering than on absorption. In this study, the proposed method was used to test fresh bruise of pears which is not distinguishable by naked eyes.

The specific objectives of this study were to:

(1) select optimal spatial frequencies (f_x) according to correlation coefficients between the experimentally obtained and the MC simulation results of diffuse reflectance of 60 phantoms;
(2) build forward LSSVR models between *Rd* and optical properties of the two f_x (one is 0 m^{-1}, the other is the optimal f_x) based on a series of MC simulations with a wide range of μ_a, μ'_s and albedo;
(3) predict the optical properties of 60 phantoms by the optimal searching on models;
(4) compare the performance of the proposed method with the diffusion approximation;
(5) apply the method to test pear bruise to verify the application prospect of the method in the field of quality inspection of agricultural products.

2. Materials and methods

2.1. Instrumentation

A typical SFDI system consists of three fundamental components: a light source, a spatial light modulator, and a camera. As shown in Fig. 1, the light source and spatial light modulator used in this study is a commercial projector (NEC V260W+, NEC Corporation, Tokyo, Japan) which based on a digital micromirror-based digital light processing (DLP) light engine (TI, Inc., Texas, USA) and an ultra-high performance mercury lamp. Sinusoidal grayscale patterns via various spatial frequencies were generated in LabVIEW (LabVIEW 2014, National Instrument) and directly projected onto the surface of sample. A neutral density filter (NE2R10 A, Thorlabs, Inc., New Jersey, USA) was used to reduce light intensity uniformly. Diffuse reflected light was captured by a monochrome 12-bit CCD camera (DMK 23G618, The Imaging Source Asia Co., Ltd., Taiwan). A bandpass filter (Mega-9 Co., Ltd, Shanghai, China) with wavelength of 527 nm and bandwidth of 10 nm was mounted on a filter wheel, for detection of a narrow wavelength band. A pair of cross polarizers were implemented at the projection and imaging sections to eliminate specular reflection and capture diffusely reflected light. All components were fixed into a light-tight enclosure. The projector and the camera were connected to the computer.

2.2. Least squares support vector machine regression

Least squares support vector machines (LSSVM) is a powerful nonlinear black-box regression method, which builds a linear model in the so-called feature space where the inputs have been transformed by means of a (possibly infinite dimensional) nonlinear mapping. When LSSVM can be used for spectral regression purpose, it is called least squares support vector regression (LSSVR).

LSSVR is an interesting formulation of support vector machine (SVM) regression proposed by Suykens et al. (2002). It uses a linear set of equations instead of a quadratic programming problem to obtain the support vectors. Therefore, LSSVR not only possesses the advantage of good generalization performance as SVM but also has a simpler