



Data regression on sphere for luminance map creation from sky scanner measurements

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Received 30 January 2015; received in revised form 20 April 2015; accepted 24 April 2015

Available online 16 May 2015

Communicated by: Associate Editor Jean-Louis Scartezzini

Abstract

Sky luminance distribution acquired by a whole-sky scanner has well-known constraints in resolution because of the restricted field of view and limited number of measured sky elements. The interpolating methods on measured data can significantly reduce the uncertainties of the scanners to create more accurate sky luminance maps depending on the mathematical approach. The general lack of many regressions is their low adaptability to significant sky luminance changes, e.g. on the cloud edges or near the sun disk. Three regression methods like inverse distance to a power, smoothing splines on the sphere and hybrid adaptive splines were tested on real skies measured with a self-made portable spectral sky scanner. Data regressions are compared and verified by the luxmeter in terms of calculated diffuse horizontal illuminance.

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Keywords: Sky scanner; Interpolation; Adaptive splines; Luminance map

1. Introduction

A sustainable building designing is a worldwide trend, that focuses on saving of energy expended on lighting. The aim is to create a healthy lighting environment for the inhabitants utilizing daylight natural in dynamical changes and spectral composition. Availability of natural daylight in the building interiors is inextricably related with a sky luminance distribution. For its quantitative assessment together with validation of theoretical models it is necessary to know a precise sky luminance distribution depicted as a luminance map. Nowadays, proposed physical sky brightness models (see e.g. Kocifaj, 2012) can be verified by long-term measurements of the sky vault in various atmospheric conditions. Different methods useful for

creation of luminance maps are actual, e.g. all-sky photography (Spasojević and Mahdavi, 2005; Mehlika, 2004), various types of sky scanners (Tregenza, 1987), as well as the equipments utilized on the IDMP stations worldwide (Ng et al., 2007; Rahim et al., 2004).

The whole-sky scanners operating worldwide offer a sky luminance distribution with different resolution depending on the field of view (FOV) and number of measured sky elements. Standardly, 11° restricted area is scanned perpetually in 145 sky patches distributed in accordance with the suggestions of Tregenza (1987). However, data evaluation is weighted by the systematic errors which are generally adjusted by the correction coefficient f_c obtained empirically for different sky conditions (Ferraro et al., 2011). This coefficient is varying from –10% up to +30% in horizontal illuminance calculation due to the incessantly dynamic sky conditions throughout each day. The empirical approach causes inaccurate analysis of the total sky

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brightness and the illuminance on arbitrarily oriented and tilted surfaces, which is important in photovoltaic applications and daylight accessibility studies for sustainable buildings. A straightforward question is, how to calculate missing luminance data between the measured sky elements with high accuracy in an effective way?

The portable sky scanner with a spectroradiometer constructed at the Slovak University of Technology in Bratislava is providing long term scans in a spectral range from 300 nm to 874 nm scanning 145 sky elements in accordance to CIE S 011/E:2003 document. Acquired measurements are usually evaluated in accordance with 15 ISO/CIE sky standards described by the relative gradation and scattering indicatrix functions to categorize the sky types in a different way (Markou et al., 2007; Smola et al., 2012; Kobav et al., 2013; Kómar et al., 2013). Moreover, creation of more-or-less precise sky luminance maps via standardly used interpolation techniques (minimum surface curvature, inverse distance to a power, modified Shepard's method, Kriging method) was studied and presented in Kómar et al. (2014).

However, measured data are obviously weighted by the measurement uncertainties, therefore the method of smoothing splines appears to be a robust solution to get more accurate sky brightness maps from scanner measurements. Smoothing splines are frequently utilized in various fields of science to calculate missing data, e.g. in geosciences (Enting, 1987), neurophysiology (Perrin et al., 1989), economy (Greiner and Kauermann, 2007), etc., so the usage in sky luminance map creation is straightforward.

Standard lack of various interpolating methods (including smoothing splines) is a low adaptability to rapid changes in measured data for less dense calculation grid due to the possible abrupt luminance changes on the cloud edges or near the sun disk. In that case, adaptive methods have to be used, such as smoothing splines with locally variable smoothing parameters, adaptive placing of knots in a calculation grid (adaptive selection of spline basis function), or some hybrid method combining features of both techniques presented e.g. in Lou and Wahba (1997).

Three different mathematical approaches are tested (inverse distance to a power, smoothing splines on the sphere and hybrid adaptive splines) to find the effective and accurate interpolation technique for creating detailed sky luminance maps. Horizontal diffuse illuminances under real sky conditions were calculated using depicted luminance maps to compare various regression techniques. Approaches are verified by the luxmeter measurements. The paper is mainly focused on application of the hybrid adaptive splines on sky luminance map creation. After description of smoothing splines on the sphere in Section 2 and hybrid adaptive splines in Section 3, we were focused on the sky scanner data evaluation in Section 4. Detailed sky luminance maps and calculated horizontal diffuse illuminances are compared and validated in Section 5.

2. Smoothing splines

When observational data are weighted by measurement errors, it is not desirable for a function approximating some unknown true function to coincide exactly with given data points, as various interpolation methods require. For estimation of an unknown function based on such noisy data, the method of smoothing splines appears to be convenient. A smoothing spline forms a trade-off between fidelity to the data and a requirement of adequate smoothness of a regression function.

In general, suppose a function f of a multivariate variable $\vec{x} = (x_1, \dots, x_d)$. Let us consider the data model

$$w_k = f(\vec{x}_k) + \varepsilon_k; \quad k = 1, \dots, N, \quad (1)$$

where w_k are observed values of some quantity corresponding to \vec{x}_k and ε_k are zero-mean independent random errors with a common variance σ^2 . We are looking for a such regression function f which minimizes the spline functional

$$F_{m,\lambda}(f) = \frac{1}{N} \sum_{k=1}^N (w_k - f(\vec{x}_k))^2 + \lambda J_m(f), \quad (2)$$

where J_m is in general some functional which secures smoothness of f up to an "order" m (m is an integer ≥ 2). The smoothing parameter λ controls the trade-off between smoothness of the regression function and fidelity to the data. For $\lambda = 0$, the spline interpolates the data and therefore estimates the true function with possibly large variance. For $\lambda \rightarrow \infty$, the spline approaches to the best fitting plane. The optimal values of λ and m have to be determined from the data.

2.1. Smoothing splines on sphere

In our case, we try to estimate a distribution of luminance over the sky, thus we will use the method of smoothing spline on the sphere as can be found in Wahba (1981). We have a set of measured values w_k ($k = 1, \dots, N$) in points (ϑ_k, φ_k) , where $\vartheta \in \langle 0, \pi \rangle$ is a spherical latitude and $\varphi \in \langle 0, 2\pi \rangle$ is a spherical longitude. The functional J_m now has the form

$$J_m(f) = \int_0^{2\pi} \int_0^\pi [\Delta^{m/2} f(\vartheta, \varphi)]^2 \sin \vartheta \, d\vartheta \, d\varphi, \\ m \text{ even} = \int_0^{2\pi} \int_0^\pi \left\{ \frac{1}{\sin^2 \vartheta} \left[\frac{\partial}{\partial \varphi} \left(\Delta^{\frac{m-1}{2}} f(\vartheta, \varphi) \right) \right]^2 \right. \\ \left. + \left[\frac{\partial}{\partial \vartheta} \left(\Delta^{\frac{m-1}{2}} f(\vartheta, \varphi) \right) \right]^2 \right\} \sin \vartheta \, d\vartheta \, d\varphi, \quad m \text{ odd}, \quad (3)$$

where Δ represents the Laplace operator, which on the sphere has the form

$$\Delta \equiv \frac{1}{\sin^2 \vartheta} \frac{\partial^2}{\partial \varphi^2} + \frac{1}{\sin \vartheta} \frac{\partial}{\partial \vartheta} \left(\sin \vartheta \frac{\partial}{\partial \vartheta} \right). \quad (4)$$

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