TOWARDS A SHORT TERM SOLAR IRRADIATION FORECAST USING GOES SATELLITE IMAGES AND OPTICAL FLOW TECHNIQUES

Summary

Accurate solar irradiation forecasting is one of the most challenging hindrances for increasing the solar energy contribution into the electricity grids. The main obstacle is the difficulty in predicting the clouds' displacements and deformations. Satellite-based strategies are preferred for the 1 to 6 hours ahead forecast, in which cloud motion field is estimated from the previous images and then used to predict the next ones. In this work we present a technique for cloud motion estimation based on an optical flow algorithm that introduces regularization terms for the displacement vector field on its formulation. Solar irradiation forecast is obtained from the predicted images using a statistical model that we previously proposed, that improves the classic Tarpley model by including brightness dependence. The uncertainty of the forecast for the 1 to 6 hours time horizons is evaluated using high quality ground measurements. Preliminary results show that the proposed methodology is promising for hourly global horizontal irradiation (GHI) forecasting.

Keywords: satellite-based forecasting, hourly solar irradiation, GOES images, optical flow.

1. Introduction

Solar irradiation at ground level is highly variable due to clouds formation and movement. This variability introduces fluctuations in photovoltaic (PV) plants' output which complicate the energy dispatch and increase the grid operation costs. Accurate forecasting of these solar fluctuations is one of the main obstacles to increase the solar PV contribution into electricity grids. Relevant forecast horizons vary from a few minutes to some days ahead depending on the specific application, which include load following strategies, weekly and daily dispatch planning or energy prices establishment, among others. There are four main groups of techniques for solar irradiation forecasting (Diagne et al., 2013; Perez and Hoff, 2013; Antonanzas et al., 2016): time-series analysis, all-sky cameras nowcast, Numerical Weather Predict (NWP) and satellite forecasting. The choice of the technique mostly depends on the spatial and temporal scale under consideration. Satellite-based techniques are usually preferred for the 30 minutes to 6 hours forecast horizons, and account for 1 km spatial resolution and above (Perez and Hoff, 2013; Kühnert et al., 2013).

The key part of a satellite-based forecasting tool is the estimation of the cloud motion field (CMF). Based on the previous and the present time images, a CMF is estimated and then used to predict the next image. The next image can be converted to a solar irradiation forecast using a suitable satellite-to-irradiation model. The well-known technique developed by Lorenz et al. (2004) is being used for CMF estimate in most of the up-to-date solar forecasting applications (Perez and Hoff, 2013; Kühnert et al., 2013). In this technique, the motion is estimated following a local correlation approach based on 110 x 110 km image patches. For each pixel, its surrounding patch is compared to all patches within a search window of the previous image, and the motion assigned to the pixel is chosen to be the displacement to the most similar patch in the mean square error sense. In (Perez et al., 2010) the uncertainty of this forecasting technique when used with the SUNY irradiation model (Perez et al., 2002) is evaluated using high quality irradiance measurements from seven ground stations in the US. In average, it is reported a root mean square deviation from 23.5% to 42.8% for 1 hour ahead to 6 hours ahead point forecast, respectively, with improvements between 8% and 18% in comparison with the persistence forecast's reference level. Kühnert et al. (2013) indicate that the uncertainty of regional forecast based on this methodology and Heliosat method is 7% and 11% for one and three hours ahead respectively, evaluated using data from several ground stations in Germany. These results show that up to now satellite-based strategies are the best known option for hourly solar irradiation forecasting.

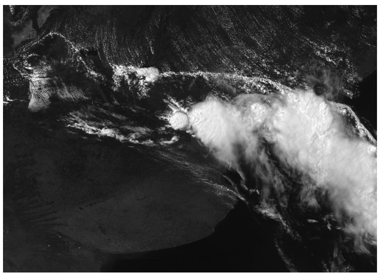
Optical Flow (OF) refers to a dense motion field between a pair of images based on the hypothesis that locally in time objects in the scene preserve their brightness, and its estimation is one of the major problems in computer vision. The brightness invariance assumption leads to the so called optical flow equation (Horn and Schunck, 1981; Lucas and Kanade, 1981). All OF estimation techniques are based on minimizing the residual that arises from fitting this equation with the images intensities, usually using least squares. Since in natural images, and even more in cloudy satellite images, brightness preservation does not hold perfectly true, and because of noise, in general the estimated OF is highly non-smooth, and different regularization techniques and robust estimation methods have been proposed to solve this problem (Black and Anandan, 1996; Zack et al., 2007). Peng et al. (2013) applied the basic Lucas and Kanade's OF estimation to GOES satellite images with good results in comparison with other techniques proposed by the authors.

In this work we apply a regularized OF technique to visible channel GOES satellite images in order to forecast the future cloud position and then, the hourly irradiation, using the BD-JPT statistical model (Alonso-Suárez, 2012) with its coefficients adjusted to local ground measurements.

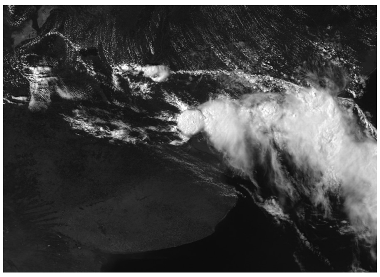
2. Proposed technique and methodology

In this implementation we use GOES-East visible channel images which are regularly available with 30 minutes time resolution for South America. The images, originally obtained in geo-referenced raw counts, are calibrated and converted to planetary albedo following the NOAA's (National Oceanic and Atmospheric Administration) recommendations. Let $\mathbf{z} = (x,y)$ be the position in an image $I(\mathbf{z})$ and $\mathbf{w} = (u(\mathbf{z}), v(\mathbf{z}))$ the CMF to be estimated from two consecutive images. The OF cost function $E(\mathbf{w})$ that we consider here is based on Zach et al. (2007) and it is composed of a data fit term which is robust to outliers, and of a regularization term which promotes a piecewise constant model for the displacement field solution. The data fit term imposes that the displacement field $\mathbf{w}$ complies with the OF equation, and robustness to outliers is promoted by the use of a robust norm (here the $L1$-norm). The regularization term is the Total Variation semi-norm of $\mathbf{w}$, whose minimization is known to lead to piecewise constant solutions, therefore allowing for discontinuities (Rudin et al., 1992). The functional $E(\mathbf{w})$ being non-linear and non-differentiable, its minimization is only made possible by very recent and sophisticated optimization techniques (Sánchez-Pérez et al., 2013).

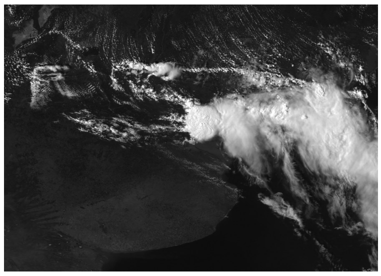
A result of the application of this methodology to CMF estimation is shown in Fig. 1, where two consecutive images (a) and (b) are used to predict the next image (d) based on the estimated CMF (e). The real third image is shown in (c) and the residual of the prediction in (f). As it is seen in Fig. 1(d) the CMF captures the main cloud motion structures in the scene, which is essentially a translation from west to east of the higher clouds. The image background, where there is no moving cloudiness, is not altered by the algorithm. The estimation of the CMF for this particular scene is complex since there are different types of clouds moving in different directions and some of them are growing, like the cumulus in the center of the image. We have tested this algorithm with several images from the year 2016 and found a good agreement between the predicted image and the real image, including translation and rotation movements of the clouds.



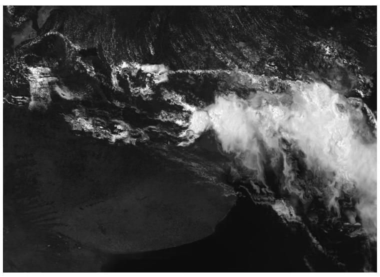
(a) First image. Time: t-1.



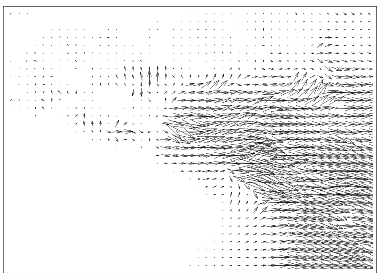
(b) Second image. Time: t.



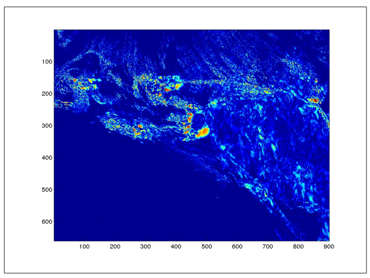
(c) Real third image. Time: t+1.



(d) Predicted third image. Time: t+1.



(e) CMF estimate.



(f) Residual of the prediction.

Fig. 1: example of the CMF estimation using the proposed methodology.

The predicted images are converted to an hourly GHI forecast using the BD-JPT model (Alonso-Suárez, 2012, 2014). The forecast for 1 to 6 hours ahead is compared with high quality ground measurements recorded at the Solar Energy Laboratory (UdelaR, Uruguay). The instrument for the GHI measurement is a Kipp & Zonen CMP10 Secondary Standard which is mounted in a Kipp & Zonen Solys 2 station that receives daily maintenance, as recommended by the World Meteorological Organization. The mean bias deviation (MBD) and the root mean square deviation (RMSD) are computed for every time horizon, and are compared with the satellite reference level for hourly resource characterization estimates.

3. Conclusion

In this work we proposed a technique for CMF estimation which is novel in the context of satellite cloud tracking and solar resource forecast. This technique follows very recent advances in Optical Flow estimation, a classic problem in the image processing field. Results show that the approach is promising for hourly solar forecasting. Further evaluation using controlled quality solar irradiance measurements are being performed in order to completely assess its performance.

4. References

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