Solar Irradiance Forecast System Based on Geostationary Satellite

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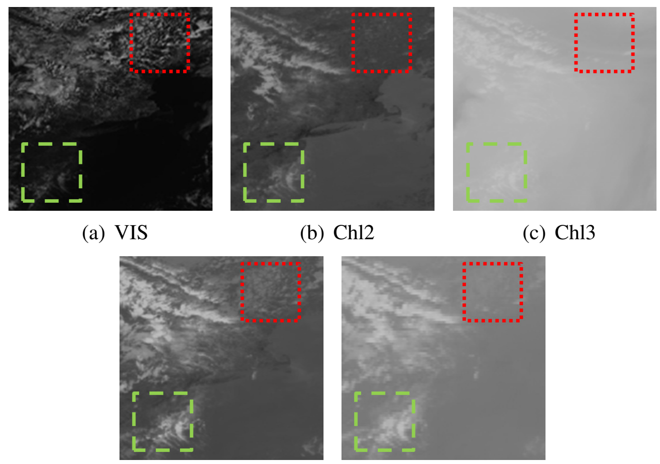
***Abstract*—Solar irradiance variability, left unmitigated, will threat the stability of grid system, and might incur significant economical impacts. This paper focuses on a pipeline to predict solar irradiance from 30 minutes to 5 hours using geostationary satellite. It consists of two parts: 1) cloud motion estimation and 2) solar irradiance prediction using the estimated satellite images. The main challenge is image noise at all levels of processing from motion estimation to irradiance prediction. To overcome this problem, we propose to use optical flow motion estimation, and subsequently combine multiple evidences together using robust support vector regression (SVR). Our systematic evaluation shows significant improvements over the baseline in both motion estimation and irradiance prediction.**

I. Introduction

Solar energy is one of the most promising renewable energy solutions: quieter, fewer installation restrictions, lower maintenance cost, and longer life time than other alternatives. However, as the solar energy penetration keeps increasing, the variability of solar irradiance is the biggest concern in integrating solar energy into the power grid, and affects the grid stability and reservation margin. Highly accurate irradiance prediction could help to reduce the reserve margin, and greatly enhance the solar energy utilization while maintain the power grid system's stability. In particular, hourly predictions (up to five hours) will enable grid operator to make intelligent decisions in bidding solar energy hourly in the energy market. Geosynchronous satellite images can fulfill the prediction requirements in this type of time granularity. Therefore, we propose an irradiance prediction system using geosynchronous satellite, which consists of two parts: 1) cloud motion estimation and 2) irradiance prediction based on cloud motion estimation.

However, it is not an easy task to produce highly accurate solar irradiance predictions. The first difficulty comes from the uncertainties of the cloud. Due to variant cloud shape and unstable motion, cloud tracking and modeling is of highe error rate especially in long time case. Therefore, our irradiance prediction has to be robust enough to noise. Second, it is difficult to identify cloud and/or obtain the thickness of cloud only from the visible channels of satellite due to the large spatial resolution (1km x 1km per pixel) and limited observable cloud types. In other words, cloud could be smaller than the grid size or the visible channel shows only a limited spectrum of clouds, resulting in that not all cloud type can be shown on in the visible channels.



(a) VIS (b) Chl2 (c) Chl3

(d) Chl4 (e) Chl6

Fig. 1. Multi-channel view: Visible channel fails to capture clouds in the left-bottom box but other channels do not show clouds on right-top box

Our approach to these problems are 1) Optical Flow for better motion estimation and 2) Support Vector Regression (SVR) for robust prediction from estimated cloud to irradiance level and 3) diverse evidence (multiple channel, previous timestamp radiation) to cope with limited information of visible satellite channel. More specifically, our contributions are:

1) **Evaluation of motion estimation methods for satellite** Most of previous works used the block-wise cross correlation [1], [2]. But in the case of satellite images, block-wise motion is unable to track small changes of both cloud shape and motion field. Therefore we propose to use the Optical Flow (OF) motion estimation algorithm which is based on the gradient of grey-scale change. Compared with traditional algorithms such as HBM, it is more sensitive to small area change and robust even with shape distortion.
2) **Robust regression analysis for irradiance prediction** Most previous works used a variant of the linear regression model [3]. However, this approach is quite sensitive to noise or outlier. We propose Support Vector Regression

(SVR) which has several advantages over the ordinary linear regression models. First, SVR ignores outlier points, thereby reducing influence of noise from cloud motion tracking. Second, it can easily model linear and non-linear relations by choosing different kernels, and have better modeling capabilities with a limited number of features. We also provide a simple approach to properly normalize solar irradiance level to remove diurnal and seasonal affects, so that the subsequent regression analysis could be simpler.

3) **Combining multiple evidences** To overcome the limitations of the visible channel, we incorporate other four available channels from satellite imager system to sense the radiant in the different spectrum range (Figure 1). Second, we added the radiation level of the previous timestamp as an additional feature to SVR model have better context information.
4) **Systematic evaluation of whole pipeline** We did systematic cross validations on 6 months data, and evaluated 1) the effects of different cloud motion estimation algorithms, 2) the different irradiation modeling performance from the ground truth cloud image to irradiation level, 3) the effects of the integrated system from the motion estimation to irradiation prediction of up to five hours, and 4) the effects of diverse evidences related to irradiation prediction.

In this paper, previous works and potential approaches are discussed in Section II. In Section III, the preprocessing steps and SVR method are presented in details. Section IV discusses and compares various motion estimation techniques. Section V enumerates seven estimation models for the satellite based prediction: linear and non-linear, regular and SVR and their variations. Section VI presents the performance details of the proposed satellite models. In Section VII, we conclude that the new forecast system has significant improvement for the medium-term radiation forecast.

II. Background

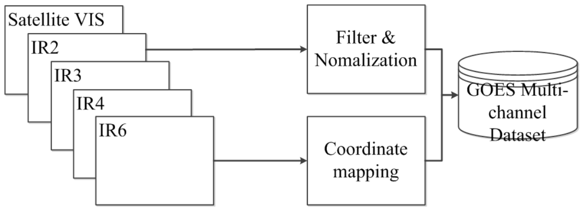
In early years, Satellite models were originally designed to correlate cloud coverage with Global Horizontal Irradiance (GHI) [4], [5]. Later works continued this idea, and studied the linear relationship between Direct Normal Irradiance (DNI) and satellite visible channel [6], [7]. These models use the term "Cloud Index" (CI) to represent the optical density derived from satellite data. Here optical density measures the solar absorption by cloud, and is determined by the observed cloud fraction or coverage. By using multiple empirical clear sky models, the local solar energy distribution is derived from satellite images [8]. Some recent work refined this modell, and added more parameters/factors, such as terrain factor [9]. Some new ideas were proposed based on other fields such as statistical approach [10] and Artificial Neural Network (ANN) method [11]. Some related work, for example, [12] does not even require meteorological data. In fact, the biggest concern with the satellite-based cloud coverage lies in images from the untrusted and unstable visible channel. As shown in Figure 1, visible channel sometimes fails to capture cloud and cannot differentiate cloud types in greyscales. Another concern about visible channel is that snow coverage and variational floating of image with various zenith angles, and confuses with the normal cloud cove, and cauded some difficulties in cloud tracking. As a result, multispectral approach is required for further analysis. The basic idea is to use empirical thresholds on the multi-channel images of satellite, and then perform cloud classification and snow detection. [13], [14].

To use the satellite model for forecasting, we need to implement a cloud tracking scheme required for predicting the cloud distribution in advance. One of the tracking ideas is to estimate the movement of cloud. In previous approaches, cloud motion vectors are generated from blockwise cross-correlation matching [2], [15]. But the most challenging problem comes from the matching technique that oftern assumes the invariant texture and constant movement of cloud. In fact, the existing cloud condition and motion aglorithm is not stable and becomes even more complicated with satellite images. Therefore many recent works tried the no-motion approach, and integrated other sources of information, e.g. ground radar measurement. Here the ground radar based prediction model obtained the continuous radiation fluctuation pattern for performance improvement [16]. But those no-motion methods tend to have low precision outcomes and offter only short forecast time. Since no real cloud tracking is involved, the forecasting is essentailly a statistical approach and its prediction range is between several minutes and up to 2 hours [17].

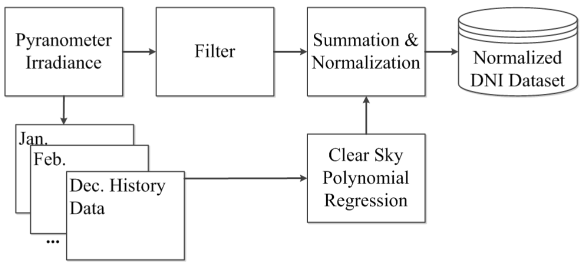
III. Data Preprocessing

Due to the limitation of remote sensing techniques, we have to use all available evidences to reduce abnormalities brought from satellite data. Therefore we expand preprocessing work to multi-channel instead of just visible channel of satellite. From the dataset collected by GOES project [18], we found several frequent error patterns: 1) black rasters of multispectral images due to failure of sensing or raw data processing, 2) luminance variation, especially on visible channel, and 3) missing channel data. We used empirical filters such as mean filter to fill out black raster lines and bad-frame filter to remove low quality or missed frames. We normalized the brightness according to solar zenith angle. The overview of data preprocessing is shown in Figure 2(a).

Another key step in preprocessing pipeline in the Figure 2(b) is handling radiation data measured by pyranometer. There are two concerns: 1) radiation level normalization from bell shape curve to uniform level to avoid daily and seasonal effects and 2) different temporal resolution resolving between satellite (30 minutes) and pyranometer (one second). In previous works, clear sky irradiance is calculated by clear sky models which are based on based on atmospheric parameters such as O2, CO2, Ozone, water vapour and aerosol optical thickness [3]. However, such models are sensitive to the location and ask additional input variables. To address this concern, we propose to use polynomial regression to generate the monthly clear sky radiation curve shown in Figure 3. Then we calculate normalized radiation at t using the average of $[t-N, t+N]$ minutes radiation divided by the average of clear sky values. Normalization using average over $2N$ minutes minimizes the influence of temporal resolution mismatch and smoothes out short-term local irradiance fluctuation.



(a) Satellite Preprocessing



(b) Irradiance Preprocessing

Fig. 2. Data Preprocessing Framework

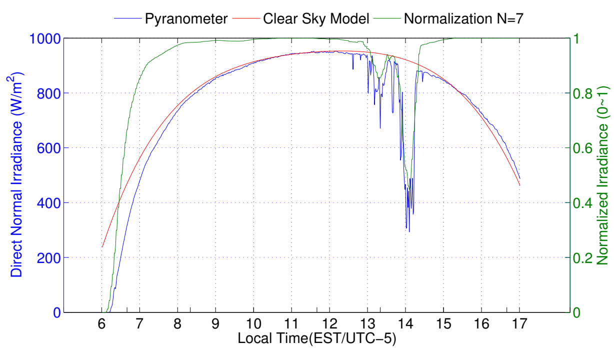


Fig. 3. Irradiance normalization and clear sky profile on March 1st, 2012

IV. Motion Estimation

The sequence of satellite images provide motion information of cloud field and allow us to predict distribution in near future. For this, the motion estimation algorithms play a crucial role for irradiance forecasting. In image processing and multimedia field, a well studied approach is Hierarchical Block Matching(HBM) which is on the basis of similarity check among blocks. It is widely used in video coding and compressing as its properties of fast speed and high compressing ratio. As to accuracy, the performance lies on region size and feature matching which assumes consistence of image segmentation. For satellite image case, cloud variation should be considered in smaller scale instead of blocks. Therefore we propose to use pixel-wise approach.

Optical flow (OF) motion estimation is a branch of methodologies that utilize the gradient of image. Under the assumption of constant illuminance, displacement of pixels will be estimated following gradient change. The implementation of OF idea has a lot of variations as gradient of image is defined differently. In our approach, we choose Lucas-Kanade Optical Flow(LKOF) [19] as the tracking method. For robustness, we implement a pipeline which builds the pyramid of image. The framework of pipeline is presented in Figure 5.

In general, visible channel image is firstly scaled to different resolution levels to build pyramid of image (i.e. 1000x1000 and 500x500). For each level, motion vectors are computed in turn, following gradient starting from pre-knowledge of motion. The start motion vectors are the output of motion from last level in pyramid. When the last level completes motion vector extraction, we utilize this as pre-knowledge of motion on original size. Then the final motion vector is found by seeking for local minima following the gradient recursively. As image prediction based on the pixel-wise motion vector will generate "black hole" due to moving of pixels. we apply mean filter on the OF pipeline output to be our OF_{mean} method so as to reduce information loss.

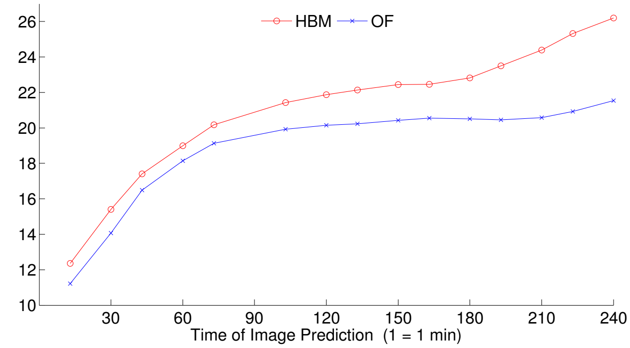


Fig. 4. Motion estimation result comparison against ground truth images (MAE) : OF is much better than HBM with longer prediction time

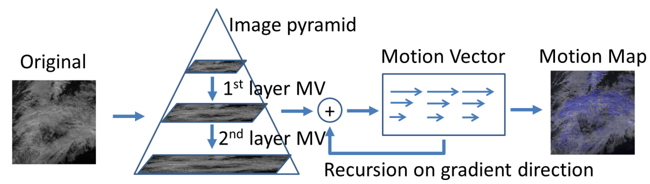
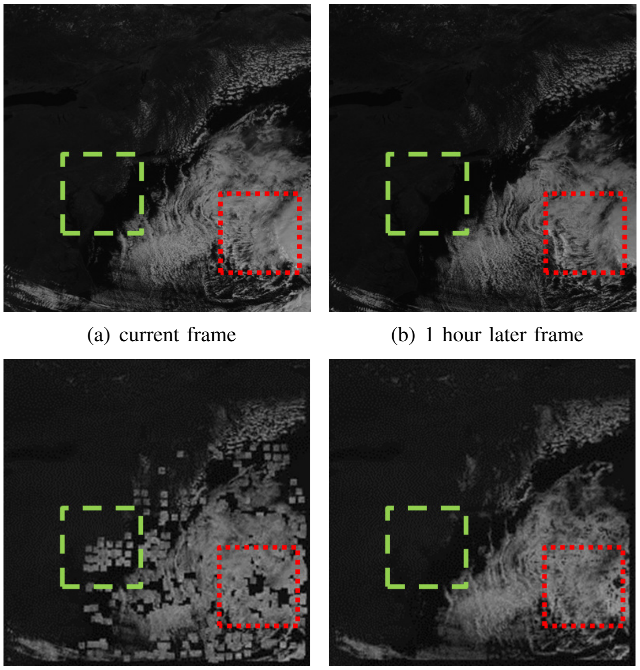


Fig. 5. Optical flow motion estimation pipeline

Intuitively, OF pipeline and HBM outputs can be compared using predicted images. As is shown in Figure 6, in one hour image sequences, OF method is much more robust in terms of tiny texture changes and clouds diminishing. HBM is suffering over-estimated problems as in dash-block case and more information loss such in dot-block case. In terms of whole image deviation from ground truth, the HBM Mean Absolute Error(MAE) in greyscale is much more than Optical Flow approach, especially when prediction time is over 3 hours (Figure 4). In addition to pixel-based or image quality based evaluation, we evaluate irradiance prediction performance using two approaches compared to ground measured solar radiation.

V. Radiation Prediction Models

Given the satellite images, we may model irradiance from the cloud properties at a point of our interest on the ground. Our goal is to find a method that 1) utilizes multiple evidences such as multi-channel features and previous timestamp irradiance and 2) is robust to the noise coming up from preprocessing and motion estimation. In this Section, we will investigate the simplest Cloud Index (CI), Linear Regression (LR, ALR) and Support Vector Regression (SVR).



(a) current frame (b) 1 hour later frame

(c) HBM (d) OF

Fig. 6. Image Esimation of 1 hour later from (a). With reference to ground-truth frame (b), (d) captures more texture changes in red window and is more robust to noise in green window than (c).

Cloud Index (CI) Cloud Index (CI) [3] is a widely used estimation model on the basis of linear relation between single channel (visible channel) with radiation. CI for a sample time point i is defined as:

$$CI_i = \frac{x_i - bound_{min}}{bound_{max} - bound_{min}} \tag{1}$$

where $x_i \in [0, 255]$ is a visible channel value and $bound_{min}$ and $bound_{max}$ are minimum and maximum observed x value. In other words, CI_i is a normalized cloud level between zero and one. Given CI_i, the irradiance is calculated:

$$y_i = w \cdot (1 - CI_i) + b \tag{2}$$

where w is the maximum radiation level which is one in our case due to irradiance normalization and b is called the compensation value which is learned by the training data. Cloud Index model is just the observed visual channel output to be rescaled to the radiation level with the compensation value to correct bias. There are couple of problems of this simple method. First of all, CI model will suffer from illuminance changes with solar zenith angle. Due to this problem, we preprocessed the satellite image to be normalized with zenith angle for all of our model input. Second, we can only fit the bias term, so that it can not be fitted well with the data. Third, CI model used only single channel, which means we can not combine the other available evidences.

Linear Regression (LR, ALR) The straight forward extension of CI model is Linear Regression (LR) and Aggregate Linear Regression (ALR) using multiple channels as extra evidence.

$$y_i = \mathbf{w} \cdot \mathbf{x_i} + b \tag{3}$$

where $\mathbf{w} \in R^d$ is a row weight vector and $\mathbf{x_i} \in R^d$ is a column vector for the input, and b is the intercept. The advantages over CI model are that LR models may include multiple evidence as linear relationship and both $\mathbf{w}$ and b are learned from the training data to be better fitted. But LR is suspectible to the noise because of the least square objective function to find optimal $\mathbf{w}$.

$$\min_{\mathbf{w},b} \sum_i (\mathbf{w} \cdot \mathbf{x_i} + b - y_i)^2 \tag{4}$$

If there are outlier points, then $\mathbf{w}$ will be overfitted.

Support Vector Regression (SVR) To avoid such overfitting from noisy data, we propose to use Support Vector Regression (SVR) as our solution.

$$\min_{\mathbf{w},b,\xi,\xi^*} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{5}$$

subject to

$$\begin{aligned}(\mathbf{w} \cdot \mathbf{x_i} + b) - y_i \le \varepsilon + \xi_i, \xi_i \ge 0, \forall i \\ (\mathbf{w} \cdot \mathbf{x_i} + b) - y_i \ge -\varepsilon - \xi_i^*, \xi_i^* \ge 0, \forall i\end{aligned} \tag{6}$$

where ε is the margin for regression, ξ_i and ξ_i^* are slack variables, and C is a regularization parameter. Then, the predicted irradiance will be

$$\begin{aligned} y_i = \mathbf{w} \cdot \mathbf{x_i} + b &\text{ if } 0 \le y_i \le 1 \\ 0 &\text{ if } y_i < 0 \\ 1 &\text{ if } y_i > 1 \end{aligned} \tag{7}$$

The basic idea of SVR is the regression error to be within ε. If it can not be learned within ε bound, the slack variables allow us to fit the model out of ε bound but the slack variable has to be minimized with C regularization term, Equation 5. Since it bounds errors to be within ε, it is much more robust and it is easy to extend non-linear relationship using kernel trick, which projects data into high dimensional space, so that we could model non-linear relationship with linear model[20]. We used RBF (Radial Basis Function) kernel:

$$k(\mathbf{w'}, x) = \phi(\mathbf{w'}) \cdot \phi(\mathbf{x}) = e^{-\frac{\|\mathbf{w'} - \mathbf{x}\|^2}{2\sigma^2}} \tag{8}$$

where σ is a tuning parameter for the smoothness of RBF kernel.

For ALR and SVR, we considered not only visible channel but also the remaining four channels and the previous timestamp irradiance value as the context information. By combining multiple channels, we can overcome the limitations of visible channel and have better cloud distribution information from the other channels. We will evaluate the different evident effects in the next Section.

VI. Experiment Results

A. Dataset

We collected satellite dataset from April 1st 2012 to November 1st 2012, covering partial spring, full summer, and most autumn. The radiation data is from pyranometer on-site measurement from Brookhaven National Laboratory. For both satellite images and pyranometer measurements, the raw input data has been preprocessed by removing data points which

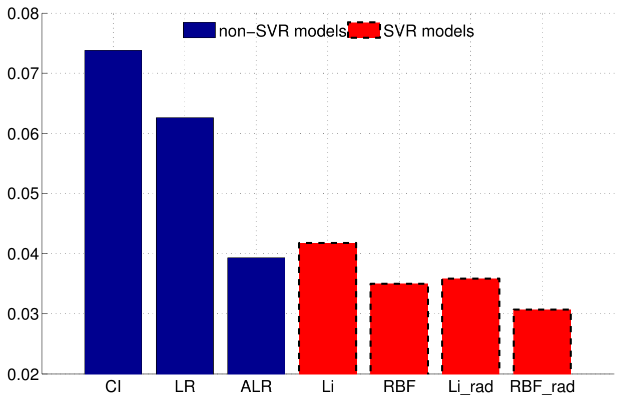


Fig. 7. MSE Plot of 5-fold cross validation. SVR models show less amounts of errors than non-SVR models in general.

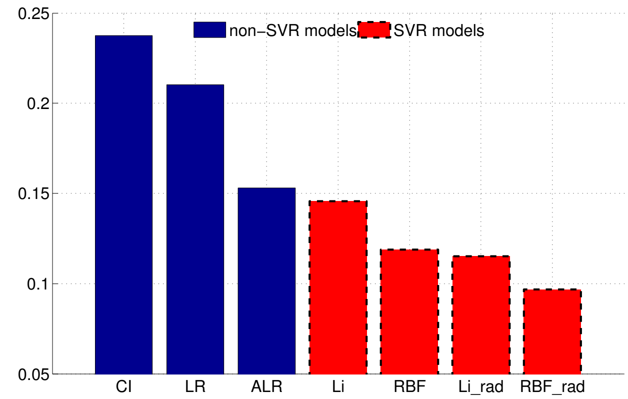


Fig. 8. MAE Plot of 5-fold cross validation. SVR models show less amounts of errors especially combined with previous radiation feature.

have 1) any bad-frame of multi-channels 2) failure of ground radiation sensor 3) multi-channel timestamp mismatch and 4) low solar angles. In total, we extract daytime dataset which has 8477 frames for each channel and radiation timestamp continuously. Each radiation data point is a result of normalization and average value in range of 15 minutes. The detailed information of dataset is summarized in Table I.

TABLE I. SATELLITE DATASET

Dimension	size	temporal resolution	spatial resolution
Channel 1	8477	15min,30min	1km x 1km
Channel 2,3,4,6	8477	15min,30min	4km x 4km
radiation	8477	15min	NA

B. Parameter Tuning and Evaluation Metrics

For whole dataset, we used five-fold cross validation to split training and testing and used five-fold cross validation again to tune model parameters within training data. In our experiment, Mean Square Error (MSE) and Mean Absolute Error (MAE) are used to evaluate the predicted model accuracy. They are defined as:

$$MAE = \frac{1}{N}\sum_i |\hat{y}_i - y_i| \tag{9}$$

$$MSE = \frac{1}{N}\sum_i (\hat{y}_i - y_i)^2 \tag{10}$$

where $\hat{y}_i$ is the predicted radiation level, and $y_i \in [0, 1]$ is the ground truth radiation level. Note that the radiation level is normalized by clear sky irradiance value.

C. Model Comparison

We evaluate the irradiance modeling power using ground truth images. As we described, we compare CI, LR with single channel, ALR which is LR with multi-channel, SVR_{Li} - SVR with multi-channel and linear kernel, SVR_{RBF} - SVR with multi-channel and RBF kernel, SVR_{Li_rad} - SVR_{Li} with the previous timestamp radiation level, SVR_{RBF_rad} - SVR_{RBF} with the previous timestamp radiation level.

First of all, Figure 7 and 8 shows that CI is worse than LR, which confirms that the weight coefficient learning help to learn better model. Second, multi-channel data significantly decrease error rates (LR vs ALR) and the previous timestamp radiation level is helpful to decrease error rates as well. SVR models are better than non-SVR models and non-linear kernel SVR models are even better. Since SVR_{RBF_rad} showed the best performance, we will use it for motion estimation analysis.

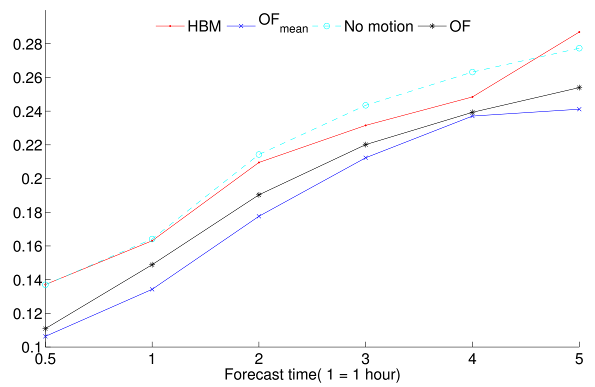


Fig. 9. Motion estimation analysis using SVR_{RBF_rad} model (MAE). Both OF_{mean} and OF show less amounts of errors than HBM in 5 hours prediction

D. Motion Estimation Evaluation

To evaluate motion estimation in the context of radiation forecast applications, the motion estimation output of HBM and OF_{mean} are compared as the input to SVR models. We evaluated them from 0.5 to 5 hours of SVR_{RBF_rad} forecast results. As a reference, we also add no motion estimation as our baseline (0 hour image as motion estimated image) and the original OF which has no mean filter. The MAE score is shown in Figure 9. No motion estimation shows obviously the worst prediction quality but HBM shows slightly improvements over the baseline. Both OF and OF_{mean} shows significantly better prediction quality and the mean filter is helpful across different forecast time. It confirms that OF with mean filter is the best choice for satellite motion estimation and we will use OF_{mean} as our motion estimation method for next analysis.

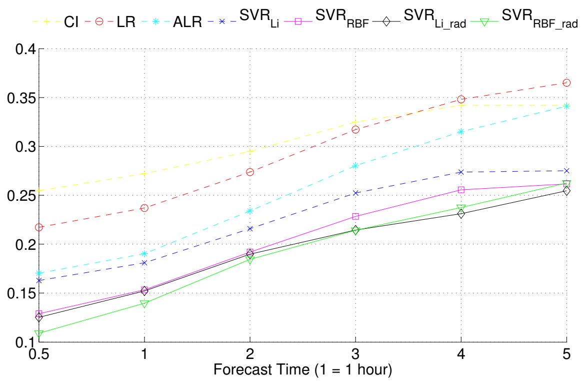


Fig. 10. MAE score of 7 forecasting models using OF_{mean}.

E. Irradiance Prediction Evaluation

We analyze whether our model estimation results (without any forecast) are still hold or not. In other words, we investigate the noise effects of the motion estimation on the irradiance prediction problem.

Since there are more errors due to motion estimation, LR or ALR shows even worse results than CI (Figure 10) after four or five hours, which is different from the model estimation results and expected as we discussed in Section V. However, the multi-channel of ALR is still helpful to get much less error rates than LR. In case of SVR, SVR_{Li} is the worst among SVR models but with the additional radiation feature, it shows the best performance on or after three hours, which is also different from the model estimation results. RBF kernel with the radiation feature is still the best results under two hours but as we have more and more errors from the motion estimation, it is not as robust as SVR_{Li_rad}. If we have an easy day for motion estimation, SVR_{RBF_rad} can be a good choice even after three hours but if it is difficult to do good motion estimation and/or longer time forecasting, then SVR_{Li_rad} will be our choice.

VII. Conclusion

In this paper, a new mid-term forecast system is developed with innovations on both modeling and predicting aspect. To choose and compare the best satellite models, we evaluated CI, LR, and SVR covering both linear and non-linear approaches. In cloud motion estimation, Optical Flow with mean filter shows the best performance in both image-level analysis and forecasting evaluation. In hours' forecasting, we find that SVR related models significantly improve the prediction accuracy than non-SVR approaches. Although noise from cloud prediction increase exponentially with time, the SVR with non-linear kernel and the previous radiation level still show the best results upto two hours but the SVR with linear kernel and the previous radiation level could be a good candidate after three or more hour prediction ranges. The accuracy improvement is more than 50% in 30 minutes prediction and 10% in 5 hours prediction than the baseline satellite model.

VIII. Acknowledgment

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