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LOCALLY-ADAPTED CONVOLUTION-BASED SUPER-RESOLUTION OF IRREGULARLY-SAMPLED OCEAN REMOTE SENSING DATA

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ABSTRACT

Super-resolution is a classical problem in image processing, with numerous applications to remote sensing image enhancement. Here, we address the super-resolution of irregularly-sampled remote sensing images. Using an optimal interpolation as the low-resolution reconstruction, we explore locally-adapted multimodal convolutional models and investigate different dictionary-based decompositions, namely based on principal component analysis (PCA), sparse priors and non-negativity constraints. We consider an application to the reconstruction of sea surface height (SSH) fields from two information sources, along-track altimeter data and sea surface temperature (SST) data. The reported experiments demonstrate the relevance of the proposed model, especially locally-adapted parametrizations with non-negativity constraints, to outperform optimally-interpolated reconstructions.

Index Terms— Super-resolution, convolutional model, irregular sampling, dictionary-based decomposition, non-negativity

1. INTRODUCTION

Image super-resolution or upscaling is a classical problem in image processing [1, 2]. Super-resolution techniques also apply to remote sensing image enhancement problems [3]. Contrary to the classical super-resolution setting, numerous satellite remote sensing applications do not only involve low-resolution images but also irregularly-sampled high-resolution information. The latter may be due to specific sampling patterns, such as along-track narrow-swath satellite data, as well as to partial occlusions caused by weather conditions [4, 5]. The availability of such partial high-resolution data supports locally-adapted super-resolution models, rather than models fully trained offline, with a view to accounting for the space-time variabilities of the monitored processes.

In this paper, we address such image super-resolution issues from irregularly-sampled high-resolution information. Following state-of-the-art super-resolution models [6–8], we consider locally-adapted convolution-based models. Our methodological contributions are two-fold: i) the proposed convolution-based models combine both a low-resolution image and a secondary image source, ii) we explore dictionary-based representations of the convolutional operators with different types of constraints, namely orthogonality, non-negativity and sparsity constraints [9, 10]. Such dictionary-based representations and constraints are particularly appealing to

resort to locally-adapted super-resolution models calibrated from a low number of high-resolution training data.

As case study, we apply the proposed framework to multi-source ocean remote sensing data, namely the reconstruction of high-resolution SSH (Sea Surface Height) images from satellite-derived along-track altimeter data, a high-resolution SST (Sea Surface Temperature) image and a low-resolution SSH image. We report numerical experiments, which demonstrate the relevance of the proposed super-resolution models, especially under non-negativity constraints, compared with optimally-interpolated SSH images.

The paper is organized as follows. In Section 2 we introduce the proposed super-resolution model along with the associated calibration schemes. In Section 3, we present the application to the reconstruction of satellite-derived SSH images and described experimental results. Finally, we report concluding remarks and discuss future work in Section 4.

2. MODEL FORMULATION

2.1. Problem statement

We aim at reconstructing a series of high-resolution images $\{Y(t)\}_t$ at different times $\{t_1, \dots, t_T\}$ from the corresponding series of low-resolution images $\{Y_{LR}(t)\}_t$. In the considered application setting, we are also provided with:

- a complementary source of high-resolution images $\{X(t)\}_t$, which may depict some local or global correlation with $\{Y(t)\}_t$;
- an irregularly-sampled dataset of high-resolution point-wise observations $\{\tilde{t}(k), \tilde{s}(k), \tilde{Y}(k)\}_k$, with $\tilde{t}(k)$, $\tilde{s}(k)$ and $\tilde{Y}(k)$ respectively the time, location and value of the k^{th} high-resolution observation.

Figure 1 reports an example of the considered sampling patterns. We let the reader refer to Section 3 for the detailed description of the considered application to ocean remote data.

The reconstruction of high-resolution image $Y(t)$ given low-resolution image $Y_{LR}(t)$ is stated according to the following convolution-based model:

$$Y(t) = Y_{LR}(t) + H_Y * Y_{LR}(t) + H_X * X(t) + N(t) \quad (1)$$

where N is a space-time noise process. H_Y (resp. H_X) is the two-dimensional impulse response of the Y_{LR} (resp. X) component of the proposed convolutional model. H_Y and H_X are characterized by $(2W_p + 1) \times (2W_p + 1)$ discrete representations onto the considered high-resolution grid. Importantly, H_Y and H_X are space-and-time-varying operators and capture the space-time variabilities

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of (Y, Y_{LR}) and (Y, X) relationships. This model can be regarded as a patch-based super-resolution approach where high-resolution image Y at a given location is computed as a linear combination of $(2 * W_p + 1) \times (2 * W_p + 1)$ patches of images X and Y_{LR} centered at the same location. Parametrization $H_X = 0$ clearly relates to regression-based super-resolution models [6, 7].

2.2. Unconstrained model calibration

The calibration of model (1) amounts to the estimation of the $(2W_p + 1) \times (2W_p + 1)$ matrix representations of operators H_Y and H_X at any space-time location. The availability of the irregularly-sampled dataset $\{\tilde{t}(k), \tilde{s}(k), \tilde{Y}(k)\}_k$ provides the means for this locally-adapted calibration. It may be noted that, in classical image super-resolution issue, such models are trained offline or involve nearest-neighbor techniques using a training dataset of joint low-resolution and high-resolution image patches [6, 7]. Here, we proceed as follows. For a given space-time location (t_0, s_0) , we regard all data such that $\tilde{t}(k) \in [t_0 - D_t, t_0 + D_t]$ and $\|\tilde{s}(k) - s_0\| \leq D_s$ as observations for model (1) at location (t_0, s_0) . Parameters D_t and D_s state respectively the spatio-temporal extent of the considered neighborhood around location (t_0, s_0) . Given the irregular sampling of the high-resolution dataset, no guarantees exist that sampling locations $\tilde{s}(k)$ will lie within the considered X/Y_{LR} grid, and thus $(2W_p + 1) \times (2W_p + 1)$ high-resolution X patches and low-resolution Y_{LR} patches need to be interpolated around spatio-temporal locations $(\tilde{s}(k), \tilde{t}(k))$. Local impulse responses H_X and H_Y are then fitted by minimizing the mean square reconstruction error $\mathcal{E}(H_X, H_Y)$ for the high-resolution detail $dY = Y - Y_{LR}$ at irregularly-sampled dataset positions $(\tilde{s}(k), \tilde{t}(k))$:

$$\mathcal{E}(H_X, H_Y) = \sum_k \left\| d\tilde{Y}(k) - \widehat{d\tilde{Y}}(k) \right\|^2 \quad (2)$$

$$\text{where } \widehat{d\tilde{Y}}(k) = H_Y * Y_{LR}(\tilde{t}(k), \tilde{s}(k)) + H_X * X(\tilde{t}(k), \tilde{s}(k)) \quad (3)$$

Assuming the number of observations is high-enough, minimization (2) resorts to a least-square estimation of operators H_Y and H_X .

2.3. Dictionary-based decompositions

A critical aspect of the above least-square minimization is the number of available training data points and the underlying balance between locally-adapted and robust parametrizations. With a view to improving estimation robustness as well model interpretability, we explore dictionary-based decomposition approaches. They resort to the following decomposition of operators H_X and H_Y :

$$H_{\{X, Y\}} = \sum_{k=1}^K \alpha_k D_k^{\{X, Y\}} \quad (4)$$

where D_k^Y (resp. D_k^X) is the k^{th} component of the dictionary of operators for operator H_Y (resp. H_X) and α_k is the k^{th} scalar coefficient that states the decomposition of operator H_Y (resp. H_X) onto dictionary element D_k^Y (resp. D_k^X). It should be noted that a joint dictionary-based representation is considered in our study, so that decomposition coefficients α_k are shared by the two convolutional operators H_Y and H_X .

Following classical dictionary-based settings [11], we explore their

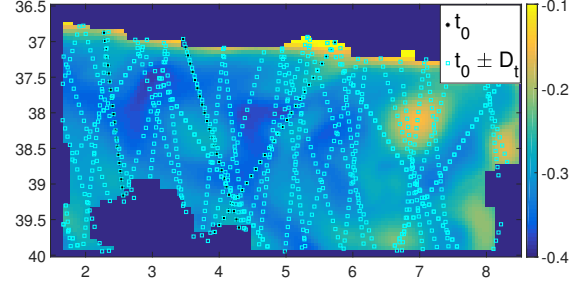


Fig. 1: Illustration of the irregular sampling of high-resolution observations associated with ocean remote sensing data: sea surface height image with the sampled along-track positions by satellite altimeters (cyan squares) in a ± 10 -day time window around April 20th, 2012.

applications to convolution operators. We investigate three different types of constraints for dictionary elements $\{D_k^Y\}$ and decomposition coefficients $\{\alpha_k\}$: namely orthogonality, sparsity and non-negativity constraints. The calibration of these dictionary-based settings first involve the estimation of dictionary elements $\{D_k^Y\}$ using training data. We here assume we are provided with a representative dataset of unconstrained estimates of operators H_Y and H_X from (2), denoted by $\{H_Y^n, H_X^n\}_n$. More precisely, the considered dictionary-based decompositions are as follows:

- **Orthogonality constraint:** under this constraint, dictionary elements $\{D_k^Y\}$ form an orthonormal basis with no other constraints onto coefficients $\{\alpha_k\}$. This decomposition relates to the application of principal component analysis (PCA) [12] to dataset $\{H_Y^n, H_X^n\}_n$. Given the trained dictionary, the estimation of decomposition coefficients $\{\alpha_k\}$ comes to the projection of the unconstrained operator estimates onto dictionary elements $\{D_k^Y\}$.
- **Sparsity constraint:** the sparse dictionary-based decomposition [13] resorts to complementing MSE criterion (2) with the L_1 norm of coefficients $\{\alpha_k\}$. We apply a KSVD scheme to dataset $\{H_Y^n, H_X^n\}_n$ to train dictionary elements $\{D_k^Y\}$. Given the trained dictionary, we proceed similarly to kSVD and use orthogonal matching pursuit [14] for the sparse estimation of decomposition coefficients $\{\alpha_k\}$ for any new unconstrained operator estimate.
- **Non-negativity constraint:** the non-negative dictionary-based decomposition constrains coefficients $\{\alpha_k\}$ to be non-negative. Given dataset $\{H_Y^n, H_X^n\}_n$, the training of dictionary elements $\{D_k^Y\}$ resorts to the minimization of reconstruction error (2) under non-negativity constraints for the decomposition coefficients. We exploit an iterative proximal operator-based algorithm [15]. Given the trained dictionary, the estimation of decomposition coefficients $\{\alpha_k\}$ comes to a least-square estimation under non-negativity constraints.

2.4. Locally-adapted dictionary-based convolutional models

The application of the proposed dictionary-based decompositions to the super-resolution of irregularly-sampled high-resolution images involves the following main steps. For a given dictionary-based decomposition, we first train the associated dictionaries $\{D_k^X, D_k^Y\}$. Considering the entire image time series, we proceed to the unconstrained estimation of operators H_X and H_Y from (2) for a variety

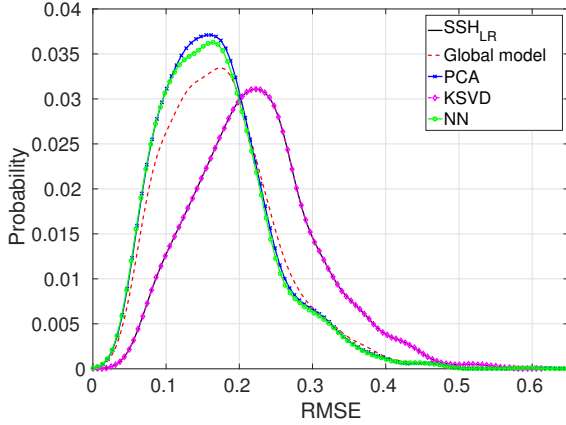


Fig. 2: Probability distribution for the relative root mean square reconstruction error (RMSE) for daily high-resolution SSH images $\{Y(t)\}_t$, for a global convolutional model and for locally-adapted decompositions of a global convolutional model using principal component analysis (PCA) [12], KSVD [13] and non-negative decomposition (NN) and considering $K = 10$ classes. The probability distribution of the RMSE for daily low-resolution SSH images $\{Y_{LR}(t)\}_t$ is given as reference (noted as SSH_{LR}).

of spatio-temporal neighborhoods with given parameters D_s^{Tr} and D_t^{Tr} . Parameters D_s^{Tr} and D_t^{Tr} are set such that the number of high-resolution observations is high enough to solve for least-square criterion (2). We typically sample around 1500 neighborhoods to build a representative dataset of operators H_X and H_Y .

Given the trained dictionaries, we proceed to the super-resolution of an image at a given date t^* as follows. For any given spatial location s^* , we first estimate the associated decomposition coefficients $\{\alpha_k\}$ from the subset of high-resolution observations in a spatio-temporal neighborhood of space-time location (t^*, s^*) with parameters D_s^{SR} and D_t^{SR} . The later parameters typically define smaller spatio-temporal neighborhoods than training neighborhoods with parameters D_s^{Tr} and D_t^{Tr} . As such, estimated coefficients $\{\alpha_k\}$ come to the projection of more local convolutional operators onto the subspace spanned by the estimated dictionaries, thus yielding a more locally-adapted model (1). This calibrated model is then applied to the reconstruction of image Y in a neighborhood of location (t^*, s^*) . To reduce the computational time, we perform this calibration of locally-adapted models for a regular subsampling of the image grid, typically $D_s^{SR}/2$, and use a spatial averaging of overlapping local reconstructions to obtain a single high-resolution reconstruction of image Y .

3. EXPERIMENTS

As case study, we consider an application to ocean remote sensing data, more particularly to the reconstruction of sea-surface height (SSH) image time series from along-track altimeter data. Satellite altimeters are narrow-swath sensors such that high-resolution altimeter data is only acquired along the satellite track path [16], resulting in an particularly scarce and irregular sampling of the ocean surface as illustrated in Fig. 1. Interestingly, numerous studies have pointed out the potential contribution of high-resolution sea surface temperature (SST) images to the reconstruction of SSH images, as they share common geometrical patterns associated with the underlying

Table 1: Relative root mean square reconstruction error (RMSE) for daily high-resolution SSH images $\{Y(t)\}_t$, for a global convolutional model and for locally-adapted decompositions of a global convolutional model using principal component analysis (PCA) [12], KSVD [13] and non-negative decomposition (NN), considering $K = 2$, $K = 5$ and $K = 10$ classes. The RMSE value for daily low-resolution SSH images $\{Y_{LR}(t)\}_t$ is given as reference (noted as SSH_{LR}). Best results for each number of classes K considered are presented in bold. Results that outperform a global convolutional model are underlined.

	$K = 2$	$K = 5$	$K = 10$
PCA	0.1807	0.1734	0.1680
KSVD	0.2228	0.2228	0.2228
NN	0.1807	0.1734	0.1666
Global model			0.1755
SSH_{LR}			0.2228

upper ocean dynamics [17, 18]. In addition, optimally-interpolated products [16] provide a low-resolution reconstruction of the SSH image. Overall, the reconstruction of high-resolution SSH image time series resorts to a super-resolution issue from irregularly-sampled high-resolution information as stated in Section 2. It may be stressed that this case study involves a scaling factor of about 10 between the low-resolution and high-resolution data, which makes it particularly challenging compared with classical image super-resolution issues.

In our experiments, we exploit a ground-truthed dataset using an observing system simulation experiment for a case study region in the Western Mediterranean Sea ($36.5^\circ N$ to $40^\circ N$, $1.5^\circ E$ to $8.5^\circ E$). A high-resolution numerical simulation of the WMOP model [19] is used to generate daily high-resolution SSH images from 2009 to 2013 for a $1/20^\circ$ grid. The along-track dataset is simulated by sampling the SSH images at real along-track positions issued from from multiple altimetry missions in 2014 and 2015 (see Figure 1). Given the simulated along-track dataset, optimally-interpolated SSH fields [16], referred to as low-resolution SSH images Y_{LR} , are computed for a $1/8^\circ$ grid resolution. The calibration of the proposed convolutional operators is performed by considering $W_p = 1$, which corresponds to 3×3 convolutional masks. We use the following parameter setting for spatio-temporal neighborhoods: $t_0 \pm D_t$ -day time windows with $D_t = 10$, and $D_s \times D_s$ spatial neighborhoods with $D_s^{Tr} = 7^\circ$ for the training step and $D_s = 2^\circ$ for the locally-adapted calibration steps.

In Table 1, we report the average root mean square reconstruction error (RMSE) for daily high-resolution SSH images $\{Y(t)\}_t$, for a global convolutional model and for locally-adapted convolutional models, using principal component analysis (PCA) [12], KSVD [13] and non-negative dictionary-based decomposition (NN) and considering $K = 2$, $K = 5$ and $K = 10$ elements in the dictionaries. The reconstruction RMSE for daily low-resolution SSH images $\{Y_{LR}(t)\}_t$ (noted as SSH_{LR}) is given as reference.

From Table 1, locally-adapted convolutional models clearly outperform global models for $K \geq 5$ (with the exception of the KSVD-based decomposition), which can be explained by the improved local adaptation to local spatio-temporal variabilities through locally-adapted decomposition coefficients. In this respect, the non-negative decomposition outperforms alternative approaches, with a maximum relative gain (with respect to optimally-interpolated low-resolution SSH images $\{Y_{LR}(t)\}_t$, at $K = 10$) of 25.22% for NN, 24.60% for

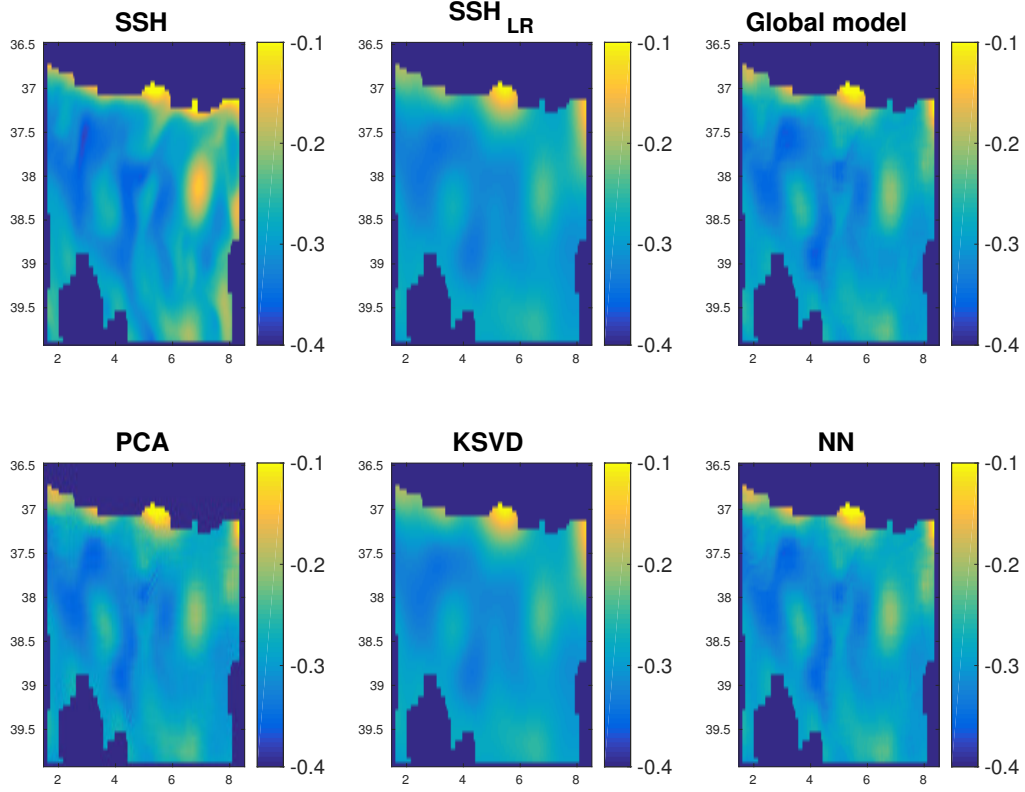


Fig. 3: High-resolution SSH image Y reconstruction, April 20th, 2012: first row, from left to right, real high-resolution SSH image Y , low-resolution SSH image Y_{LR} (noted as SSH_{LR}), reconstruction of high-resolution SSH image Y using global convolutional model (1); second row, reconstruction of high-resolution SSH image Y using a 10-class locally-adapted decomposition (4) of global convolutional model (1) using, from left to right, principal component analysis (PCA) [12], KSVD [13] and non-negative decomposition (NN).

PCA and 21.23% for a global convolutional model.

These results are further illustrated by the reconstruction of high-resolution SSH image Y for sample date April 20th, 2012 presented in Figure 3 and by the probability distributions of daily reconstruction root mean square error for high-resolution SSH images $\{Y(t)\}_t$, computed for the global convolutional model and for each one of the considered locally-adapted models with $K = 10$, presented in Figure 2. Visually, the proposed super-resolution models clearly improve the reconstruction of finer-scale details compared to the low-resolution image. The model using non-negativity constraints seems to involve slightly sharper gradients compared with the unconstrained model. The PCA-based model appears visually less relevant, while the KSVD-based model seems unable to exploit the high-resolution information sources to enhance the low-resolution altimetry field.

4. CONCLUSION

In this paper, we addressed the multimodal super-resolution of irregularly-sampled high-resolution images. This issue arises in a number of remote sensing applications, where several sensors associated with different regular and irregular sampling patterns may contribute to the reconstruction of a given high-resolution image.

As a case study, we considered an application to the reconstruction of high-resolution sea surface height (SSH) images. From a methodological point of view, we complement previous convolution-based super-resolution models [7, 8] with the evaluation of different dictionary-based decompositions and the use of a complementary high-resolution image source. Dictionary-based decompositions are regarded as a means to better account for spatio-temporal variabilities through more locally-adapted model calibrations. Our numerical experiments support the selection of non-negativity constraints to achieve a better local adaptation. They demonstrate the relevance of the proposed approach to achieve a better reconstruction of higher-resolution details, compared with the optimally-interpolated fields. Future work includes non-local extensions of the proposed model to combine spatio-temporal and similarity-based neighborhoods as considered in regression-based super-resolution models [7, 8]. Non-linear dictionary-based decomposition seems particularly appealing to combine non-linear mapping, for instance CNN-based models [20], and locally-adapted models. As far as ocean remote sensing applications are considered, applying the proposed models to different sampling patterns, for instance along-track narrow-swath satellite data vs. wide-swath satellite data, appears to be of interest, the later possibly enabling the modeling of higher-order geometrical details.

5. REFERENCES

- [1] W. C. Siu and K. W. Hung, "Review of image interpolation and super-resolution," in *Proceedings of The 2012 Asia Pacific Signal and Information Processing Association Annual Summit and Conference*, Dec 2012, pp. 1–10.
- [2] D. Glasner, S. Bagon, and M. Irani, "Super-resolution from a single image," in *2009 IEEE 12th International Conference on Computer Vision*, Sept 2009, pp. 349–356.
- [3] D. Yang, Z. Li, Y. Xia, and Z. Chen, "Remote sensing image super-resolution: Challenges and approaches," in *2015 IEEE International Conference on Digital Signal Processing (DSP)*, July 2015, pp. 196–200.
- [4] R. Fablet and F. Rousseau, "Joint interpolation of multisensor sea surface temperature fields using nonlocal and statistical priors," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 9, no. 6, pp. 2665–2675, June 2016.
- [5] M. E. Gheche, J. F. Aujol, Y. Berthoumieu, C. A. Deledalle, and R. Fablet, "Texture synthesis guided by a low-resolution image," in *2016 IEEE 12th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP)*, July 2016, pp. 1–5.
- [6] R. Timofte, V. De Smet, and L. Van Gool, "Anchored neighborhood regression for fast example-based super-resolution," in *The IEEE International Conference on Computer Vision (ICCV)*, December 2013.
- [7] R. Timofte, V. De Smet, and L. Van Gool, "A+: Adjusted anchored neighborhood regression for fast super-resolution," in *Asian Conference on Computer Vision*. Springer, 2014, pp. 111–126.
- [8] E. Agustsson, Timofte R., and L. Van Gool, "Regressor Basis Learning for Anchored Super-Resolution," in *IEEE International Conference on Pattern Recognition (ICPR)*, Cancun, Mexico, Dec. 2016.
- [9] M. Bevilacqua, A. Roumy, C. Guillemot, and M. L. Alberi Morel, "Low-complexity single-image super-resolution based on nonnegative neighbor embedding,".
- [10] J. Yang, J. Wright, T.S. Huang, and Y. Ma, "Image super-resolution via sparse representation," *IEEE Transactions on Image Processing*, vol. 19, no. 11, pp. 2861–2873, Nov 2010.
- [11] B. A. Olshausen and D. J. Field, "Sparse coding with an overcomplete basis set: A strategy employed by v1?," *Vision Research*, vol. 37, no. 23, pp. 3311 – 3325, 1997.
- [12] K. Pearson, "On lines and planes of closest fit to systems of points in space," *Philosophical Magazine Series 6*, vol. 2, no. 11, pp. 559–572, 1901.
- [13] M. Aharon, M. Elad, and A. Bruckstein, "K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation," *IEEE Transactions on Signal Processing*, vol. 54, no. 11, pp. 4311–4322, Nov 2006.
- [14] Y. C. Pati, R. Rezaiifar, and P. S. Krishnaprasad, "Orthogonal matching pursuit: recursive function approximation with applications to wavelet decomposition," in *Proceedings of 27th Asilomar Conference on Signals, Systems and Computers*, Nov 1993, pp. 40–44 vol.1.
- [15] P. L. Combettes and J.C. Pesquet, "Proximal Splitting Methods in Signal Processing," in *Fixed-Point Algorithms for Inverse Problems in Science and Engineering*, R.S.; Combettes P.L.; Elser V.; Luke D.R.; Wolkowicz H. (Eds.) Bauschke, H.H.; Burchchik, Ed., pp. 185–212. Springer, 2011.
- [16] M. I. Pujol and G. Larnicol, "Mediterranean sea eddy kinetic energy variability from 11 years of altimetric data," *Journal of Marine Systems*, vol. 58, no. 3–4, pp. 121–142, Dec. 2005.
- [17] G. Lapeyre and P. Klein, "Dynamics of the upper oceanic layers in terms of surface quasigeostrophy theory," 2006.
- [18] P. Klein, B.L. Hua, G. Lapeyre, et al., "Upper ocean turbulence from high-resolution 3d simulations," 2008.
- [19] M. Juza, B. Mourre, L. Renault, S. Gómara, K. Sebastián, S. Lora, J. P. Beltran, B. Frontera, B. Garau, C. Troupin, M. Torner, E. Heslop, B. Casas, R. Escudier, G. Vizoso, and J. Tintoré, "SOCIB operational ocean forecasting system and multi-platform validation in the Western Mediterranean Sea," *Journal of Operational Oceanography*, vol. 9, no. sup1, pp. s155–s166, Feb. 2016.
- [20] C. Dong, C. C. Loy, K. He, and X. Tang, "Image super-resolution using deep convolutional networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 38, no. 2, pp. 295–307, Feb 2016.