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# Enhancement of Super Resolution Image by Support Vector Regression

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Abstract— The higher resolution image can bereconstructed from lower resolution images using Super-Resolution (SR) algorithm based on Support VectorRegression (SVR) by combining the pixel intensity values withlocal gradient information. Support Vector Machine (SVM)can construct a hyperplane in a high or infinite dimensionalspace which can be used for classification. Its regressionversion, Support Vector Regression (SVR) has been used invarious image processing tasks. In this paper, we present theSR algorithm in MATLAB and Mean Square Error (MSE) and Structural Similarity (SSIM) is measured andcompared.

Keywords— Hyperplane, MSE, Super-resolution, Support-Vector-Regression, SSIM.

## I. Introduction

Super-resolution techniques estimate an image at higherresolution from its low-resolution observations. It hasfound useful in many applications like military and civilianapplications, high- resolution (HR) images are desirableand always required. Thus the central aim of Super-Resolution (SR) is to generate a higher resolution imagefrom lower resolution images. HR means that the numberof pixels within a given size of image is large and therebymore details about the original scene. Therefore, an HRimage usually offers important or even critical informationfor various practical applications.

The need for high resolution is common in computer visionapplications for better performance in pattern recognitionand analysis of images. High resolution is of importance inmedical imaging for diagnosis. Many applications requirezooming of a specific area of interest in the image whereinhigh resolution becomes essential, e.g, video surveillanceand automatic target recognition [2], forensic and satelliteimaging applications.However, high resolution images are not always available.This is since the setup for high resolution imaging provesexpensive and also it may not always be feasible due to theinherent limitations of the sensor, optics manufacturingtechnology. These problems can be overcome through theuse of imageprocessing algorithms, which are relativelyinexpensive, giving rise to concept of super-resolution. Itprovides an advantage as itmay cost less and the existing low resolution imaging systems can still be utilized.

Inspired by the pioneer work of Tsai and Huang [3],there has been extensive work in image and video SR.There are different approaches for image SR. The first type of SR algorithms requires multiple LR images from the same scene (i.e., consecutive frames taken from a videostream) as input, then all of those images are registered andfused to generate super-resolved images based on theassumption that each LR image contains relevant yetslightly different information that can contribute to the HRreconstruction.

Another type of SR algorithms is single image basedinterpolation. The well-known techniques such as bicubicinterpolation [4] are easy to implement and fast inprocessing. However, interpolation often gives oversmooth results due to its incapability to reconstruct thehigh-frequency components of the desired HR image. Thiscould be solved by exploiting the natural image priorssuch as local structure gradient profile priors [5]. Thedisadvantage for this kind of approaches is that theheuristics about natural images are made, which would notalways be valid and for images with fine textures thereconstructed HR image may have the water-color likeartifacts. In [6] support vector regression (SVR) is appliedto single image super-resolution in Discrete +Cosine +Transform (DCT) domain. In [7], the SVR is applied tofind the mapping between the LR images and the HRimages in the spatial domain.An image super-resolution algorithm is used based on SVRBy combining the pixel intensity values with local gradientinformation. The learned model by SVR from low-resolution image to high-resolution image is useful androbust to reconstruct edges and fine details in varioustesting images.

In this approach, the SR is also formulated as a regressionproblem which is solved by SVR in the spatial domain.However, there are distinctions between this approach andthe approach in [7]. First, in this approach we do not aim atestimating the high-frequency component of the LR image to be super-resolved. Instead, the prediction of ouralgorithm is the pixel value itself. Second, the featurevectors that we choose not only contain the pixel valuesfrom a neighborhood but also the local gradientinformation. Third, the neighboring pixel values areassigned with different weights because they do notcontribute equally to generate the output pixel in the super-resolved image. Furthermore, in the training process we useimages of small sizes only to form a relatively smalltraining dataset for efficiency consideration. Theexperiments show that even with a small training set ourmethod can still generate visually pleasing results.

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## II. Support Vector Regression

The training data is made up of input/output pairs (X1 ;y1), . . . , (Xl ; yl ) , where Xi is input attribute vector froman input image (an interpolated low-resolution image ) andyi are the associated output values in the ground-truthimage (the high-resolution). Traditional linear regressionestimates a linear function WT X + b that minimizes themean square error:

$$min_{w,b} \sum_{i=1}^{l}(y_i - (W^T X_i + b))^2 \qquad (1)$$

To address nonlinearly distributed input data, a mappingfunction φ(x) is introduced in the SVM to map the datainto a higher dimensional space in which the data can belinearly separated. In the high-dimensional space,overfitting occurs. To limit overfitting, a soft margin anda regularization term are incorporated into the objectivefunction. Support vector regression has the followingmodified object function:

$$min_{w,b,\varepsilon,\varepsilon^*} \frac{1}{2} W^T W + C\sum_{i=1}^{l}(\varepsilon_i + \varepsilon_i^*) \qquad (2)$$

Subjected to

$$y_i - (W^T \emptyset(X_i) + b) \le \varepsilon + \varepsilon_i$$

$$(W^T \emptyset(X_i) + b) - y_i \le \varepsilon + \varepsilon_i^*$$

$$\varepsilon_i, \varepsilon_i^* \ge 0, i = 1 \dots . l.$$

ξi is the upper training error (ξ*is the lower trainingerror) subject to the Ɛ−insensitive tube |y − (WT φ(X ) +b)| ≤Ɛ and Ɛ is a threshold. C is the cost of error. Thecost function ignores any training data that is within thethreshold Ɛ to the model prediction. This soft marginmethod increases the robustness of SVR. In the aboveobjective function, (1/2)WT W is a regularization term tosmooth the function WT φ(Xi ) + b in order to limitoverfitting.Effectively, within the Ɛ−insensitive tube, theregularization term constrains the line to be as flat aspossible. This flatness is measured by the norm WT WThe parameters of the regression quality are the cost oferror C, the width of the tube Ɛ, and the mappingfunction φ. Similar to support vector classification, w isa high dimensional vector because φ maps data to ahigher dimensional space; thus, the dual problem issolved instead:

$$min_{\alpha,\alpha^*} \frac{1}{2}(\alpha - \alpha^*)^T Q(\alpha - \alpha^*) + \varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} y_i(\alpha - \alpha^*) \qquad (3)$$

Subjected to

$$\sum_{i=1}^{l}(\alpha - \alpha^*) = 0, 0 \le \alpha, \alpha^* \le C, i = 1 \dots l$$

where Qij = K (Xi , Xj ) ≡ φ(Xi)T φ(Xj ), K (Xi, Xj ) isthe kernel function. Commonly used kernel functionsare linear, polynomial, Gaussian, sigmoid etc. Thederivation of the dual is the same as in support vectorclassification. The primal-dual relation showsthat

$$w = \sum_{i=1}^{l}(-\alpha_i + \alpha_i^*)\emptyset(X_i) \qquad (4)$$

so the approximate function is

$$\sum_{i=1}^{l}(-\alpha_i + \alpha_i^*)K(X_i, X) + b \qquad (5)$$

The i architecture of a regression machineconstructed by the SV algorithm. It is similar to neuralnetwork regression. The difference is that the input layerin SVR are a subset of the training patterns (supportvectors) and the test pattern. Fig. 2 shows thearchitecture of a traditional linear regression where theinput layer is the test pattern alone. The complexity ofSVR is O(nl), where n is the number of pixels in theinput image and l is the number of SVs. The complexityof traditional linear regression is O(nm), where m is thenumber of coefficients (the size of the patch). In theexample shown in Fig. 2, m is 9. SVR has much highercomplexity since l >>m.Another difference is that SVRis adaptive while traditional regression is fixed.

As in Fig.1, (−αi + αi*) can be interpreted as the“weight” for each Xi and K (Xi , X ) can be viewed asthe contribution of each SV. Though the weight is fixed,the contribution of each SV is adaptive to the inputpattern X . When X is closer to a SV, that is, when the SV is a good example for the input pattern, then that SVcontributes more to the final output. On the other hand,if a SV is different from X , then that SV has lessinfluence in determining the output as K(Xi,X) will besmall. Effectively, the kernelfunction K(Xi,X) measuresthe distance between a test pattern and the support vector[8].

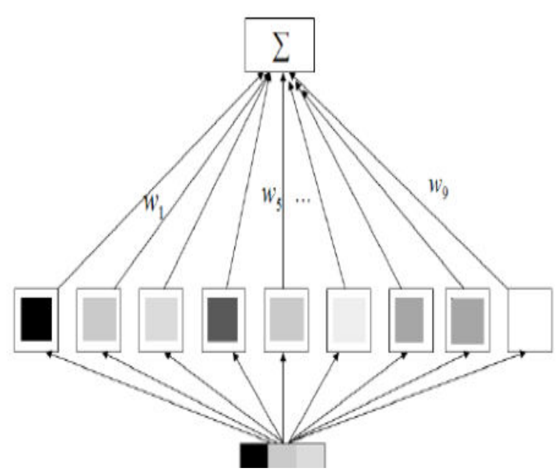
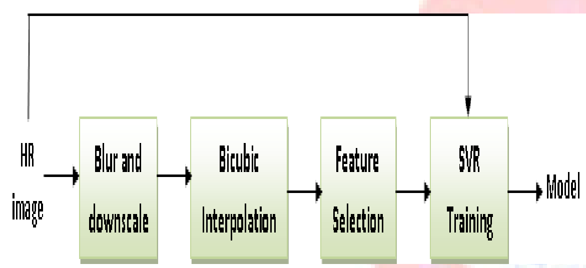


Fig. 1: Linear regression diagram. The intercept b is added to the sum.

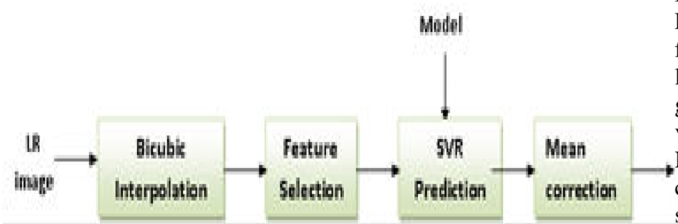
In this approach xp comes from the initial estimation of theLR image and yp is from the corresponding HR image.Where xp is the vector and yp is the correspondingobservation. Then a model is learned by SVR. In theprediction process, the learned model will be applied to the input LR image to generate a super-resolved HR image.

## III. SUPER-RESOLUTION

The algorithm consists of two processes: training andprediction, as shown in Fig. 3




(a)




(b)

Fig 3. (a) Training process (b) Prediction Process

In the training process, we first blur the HR images andthen downscale them by a factor of 2 to create the LRimages. An initial estimation of the HR image is carried outusing bicubic interpolation with an upscaling factor of 2 onthe generated LR image. For each pixel at location (i , j) inthe upscaled image, we take a local image patch of size m *m centered at (i , j) . This image patch is then weighted by amatrix of the same size. This matrix is constructed from a2-D Discrete Cosine Transform that assigns largest weight to thepixel at (i , j) and smaller weight to the other pixels that are further away from the center pixel in the local patch. Theweighted image patch is then converted to a row vector:

$$X_{i,j} = vec\left(W_c\left(R_{i,j}I_{BI}\right)\right) \qquad (6)$$

Where $I_{BI}$ is the bicubic interpolated image and $W_c(R_{i,j},I_{BI})$is the weighted local image patch taken at (i , j) by thepatch extraction operator $R_{i,j}$ . Function vec reshapes thematrix into a row vector $x_{i,j}$ of length $m^2$.

The gradient of the bicubic interpolated image is calculatedin both horizontal and vertical direction at each pixel

$$g_h(i,j) = \frac{1}{2}\left(\left(I_{i,j+1} - I_{i,j}\right)\right) + \left(I_{i+1,j+1} - I_{i+1,j}\right)$$
$$g_v(i,j) = \frac{1}{2}\left(\left(I_{i+1,j} - I_{i,j}\right)\right) + \left(I_{i+1,j+1} - I_{i,j+1}\right)) \qquad (7)$$

$I_{i,j}$ is the pixel value at (i, j) . The horizontal gradientmagnitude $g_h(i,j)$ and the vertical gradient magnitude $g_v(i,j)$are concatenated to the row vector $x_{i,j}$.For each pixel in the initially interpolated image at (i, j) ,$x_{i,j}$ is now a $m^2$+ 2 dimensional feature vector. Thecorresponding observation $y_{i,j}$ is the pixel value at position(i, j) in the HR image. SVR is supplied with all the featurevectors constructed from the training dataset and theircorresponding observations. The generated model is thensaved for the future use.

In the prediction process, we first upscale the testing LRimage also using bicubic interpolation by the same factor of2. For each pixel in the interpolated image, the local imagepatch of the same size is taken and the image gradient intwo directions is calculated to get the features vectors in thesame manner as we do in the training process. Now theoutput image z is constructed. The last step is to correct themean of z since the mean of the upscaled image should bepreserved to be the same as that of the input LR image dueto the unchanged image structures and contents in theupscaling process. The pixel value of the final output at (i ,j) is:

$$\bar{Z}_{i,j} = \frac{m_{LR}}{m_z} z_{i,j} \qquad (8)$$

where mLR is the mean pixel value of the LR image and mz is the mean pixel value of z .

## IV. EXPERIMENTAL RESULT

For the implementation of SVR LibSVM [9] is used. Wechoose DCT function as the kernel function. The downscaling factor for the HR imagesand the corresponding upscaling factor for the LR imagesare both 2. For both training and testing we only considerthe luminance component of the images.All the images used in the training and testing processes areoriginally taken from the USC-SIPI Image Database [10].Both Mean Square Error (MSE) and structuralsimilarity (SSIM) are used to measure the quality of the super-resolved images compared to original HR images.MSE between two images of size M ×N is calculated by

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad (9)$$

where 255 is the maximum possible gray pixel intensityvalue, I(i, j) and K(i, j) are the pixel values at the samelocation (i, j) from image Iand K.SSIM is designed to better match the human perceptioncompared to PSNR, which sometimes is inconsistent withthe visual observation . SSIM [11] defined as

$$SSIM = \frac{\left(2\mu_x\mu_y + c_1\right)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (10)$$

where x and y are the two images to be compared, μ and σare respectively the average and variance of the pixelvalues of the images I or K . $\sigma_{xy}$ is the covariance of I an K. The value of SSIM is a scalar less than or equal to 1 and1 means the two images in comparison are exactly thesame.

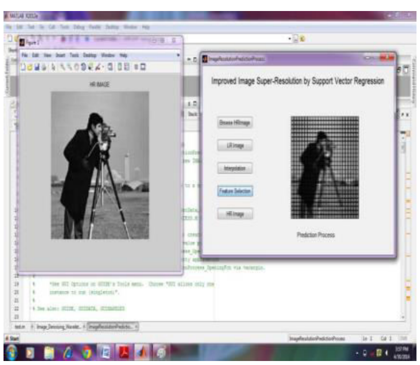


Fig. 4: MATLAB output showing HR image

In this method feature selection is based on the pixelintensity values and gradient magnitude is comparing theresult of the proposed method to the output of SVR withfeature vectors that only contain the pixel values assimilarly proposed method. It can be seen that by addingimage gradient information to the feature vectors, themodel learnt by SVR is capable of reconstructing edges andfine details from LR images. Final output HR image isshown in Fig.4.The proposed super-resolution algorithm is compared withstate-of-the-art methods including sparse coding SC[12]and kernel regression KR[13]. Also results by bicubicinterpolation BI [4] are provided as reference .

## V. Conclusion

In this paper, an algorithm for single image super resolutionbased on support vector regression is implemented inMATLAB and compares the result with other state of artmethods. In this paper we combining the pixel intensityvalues with local gradient information, the learned modelby SVR from low-resolution image to high-resolutionimage is useful and robust for image super-resolution.The experiment is conducted on different types of images.Furthermore, the size of the training set is limited which makes the training relatively fast while still achieving goodresults. By comparing our method to the previous works,we find out that our method is able to produce better super-resolved images than state-of-the-art approaches. Webelieve that by selecting more informative features besidespixel intensity and gradient, the result can be furtherimproved. By adopting a larger and more comprehensiveimage dataset for training, the generated model would yield better results for image super resolution .

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