Face Image Super-Resolution with Adaptive Patch Size to Scaling Factor

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Abstract—Example-based algorithms are most suitable for face image super-resolution since they typically use specific kinds of images as their dictionary. Recently, a significant method using a set of normalized face images as database was proposed, where a high-resolution face image was estimated by taking into consideration their facial parts. This paper reports parametric analysis of the method, regarding the setting of image-patch size during superresolution process and their relations with image's scaling factor. Our objective is to find the best patch size for the algorithms, which may produces better output highresolution images. We generated training images' patchdatabases with different patch size, i.e. 5x5, 7x7, 9x9, 11x11 and 13x13 in pixels. We ran the method onto several sets of low-resolution face images with different scaling factor of magnification, i.e. 2, 3, 4, 5 and 6 times, to generate highresolution images using different patch size orderly. Then, we observed the average of Peak Signal-to-Noise Ratio (PSNR) values for each set of constructed high-resolution images to analyze which size of patch yielded better results. According to the resulting PSNRs, interestingly we found that the best patch size is adaptable to scaling factor, where if the scaling factor is *n*, the best setting of patch size in the algorithms can be determined by $(2n+1)^2$.

Index Terms—example-based, super-resolution, face image, facial parts, patch size, scaling factor

I. INTRODUCTION

Surveillance cameras are often installed in areas that may need monitoring such as banks, airports, and convenience stores for prevention and detection of crime. These surveillance cameras have been recording digital footage of crime scenes and provide useful information especially criminal's face image that is really helpful as clues in investigation. Unfortunately, most surveillance cameras are long-term recording, so they record lowresolution and highly compressed frames due to storage constraint, causing poor quality of footage. Consequently, most recorded images are frequently too poor to be used in investigation since less information could be obtained.

Therefore, it is very useful to process the LR images by enlarging them into larger and more legible High-Resolution (HR) images. Several methods of image enlargement, such as Bicubic [1] and Lanczos interpolation, are commonly used to infer an HR image. However, these analytic approaches typically suffer from a blurred appearance due to perceived loss of detail in textured regions, causing unsatisfying quality in enlarged images. Hence, Super-Resolution (SR) techniques [2]-[7] have been widely adopted recently to resolve these problems by not only enhancing image resolution, but also estimating the missing texture details to define the enlarged HR image.

Several methods in the SR techniques can be roughly categorized into two major categories: reconstructionbased and learning-based methods. Between those two methods, learning-based methods, or also known as example-based methods are most suitable for specific applications, such as face image super-resolution, since it typically uses specific kinds of images as its database [8], [9]. Example-based methods utilize external information from a set of training LR and HR image pairs. Generally, a patch within an observed LR image is extracted and searched within the training set to estimate suitable HR patch that reconstructs the HR image.

Freeman *et al.* has proposed example-based algorithms [10]-[12], using a bandpass filter to extract image textures and a Markov Random Field (MRF) as a learning model to infer the suitable HR patches. Since then, many algorithms have been developed using different approaches in terms of texture extraction method and type of learning model [13]-[18].

Recently, an SR method specifically for face image enhancement, which takes into consideration the correspondence of facial parts, has been introduced [19]. The method employed a significant concept of using normalized human face images as training database, where the facial parts can be estimated according to patch's original position in image. The method proposed a learning model that enable patch candidates to be selected by not only considering their pattern similarity, but also their compatibility of facial parts, i.e. using eye patches for eyes and nose patches for nose. This approach manage to increase the probability of similarity and produce better HR image compared to the Freeman et al.'s method in terms of face texture quality and Peak Signal-to-Noise Ratio (PSNR) value.

However, there are many variable parameters in this method as well as in Freeman et al.'s method, which may lead to varied possibility of resulting images. Some of the main parameters are image patch size, weighting factor in compatibility functions, number of training images in database and scaling factor of magnification. It is important to find the most suitable parameter's value in

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order to make the application more convenience, stable or less sensitive, besides user-friendly. Therefore, in this paper, we attempt to analyze the algorithms in terms of patch size and scaling factor. Our aim is to find the most suitable patch size for the SR process, which may provides better results.

We conducted an experiment by demonstrating the algorithms onto sets of LR images that have different scaling factor, i.e. 2, 3, 4, 5, and 6 times respectively. We used different size of patch during SR process, i.e. 5x5, 7x7, 9x9, and 11x11, and applied them onto each set of images to find which size provides better results. PSNRs for each set of constructed HR images were observed, and their average values were used for overview analysis. Based on the analysis, interestingly we found a consistent pattern of relationships between best patch size and scaling factor, which can be simplified into a formula. With this formula, we can easily determine what size of patch should be used in the method when we want to enlarge an LR image by a certain scaling factor.

The rest of the paper is organized as follows. Section 2 describes the algorithms of the example-based methods. Section 3 elaborates the learning model that takes into account correspondence of facial parts. Experimental analysis and proposed algorithms are presented in Section 4, and a conclusion is given at the end of the paper.

II. EXAMPLE-BASED METHOD

Example-based algorithms utilize external information from a set of a large volume of training image pairs of LR images and HR images. Compared to conventional interpolation methods that only use information from input images, example-based methods enable new information to be predicted for the missing texture details.

Example-based algorithms basically consists of two phases, i.e., 1) a database construction phase that extracts patch pairs from both LR and HR training images, and then stores them as training patches into database, and 2) a super-resolution phase that runs a learning model to reconstruct HR images by searching suitable patches in the database that are best matched to the input image patches.

A. Database Construction

A collection of high-resolution images is used to construct a training database. We restrict use of the same kinds of images to obtain better probability of similarity among features. All HR images are downscaled at a certain scaling factor, typically one-quarter the total number of pixels to create LR training images. After that, we initially upscale the LR images back into original size of HR using an analytic interpolation, such as Lanczos. These initial HR images are typically blurry due to the loss of texture during the process.

We preprocess the training images in pair (initially upscaled LR and original HR images) to extract highfrequency information so that only the textures are being observed. We apply a Gaussian filter to the upscaled LR images to extract their textures (middle-frequency component) and store them into database, Po, as outlined in Fig. 1. While textures (high-frequency component) from the original HR images are extracted by subtracting them with the initially upscaled LR images, then we store them as patches in database, Pc. These patches were typically 5x5 or 7x7 pixels.



Figure 1. Database construction process.

B. Image Super-Resolution

Freeman et al. implemented a Markov random field (MRF) network as learning model to estimate plausible texture for an output HR image [10]. The MRF network statistically models the spatial relationship between input image patches and estimated training patches in database, and between neighboring high-resolution patches.

Fig. 2 illustrates the structure of the MRF network where each circle represents a network node and each line indicates the spatial relationship and statistical dependencies between nodes. The nodes Y(i,j) represents the LR patches at the position (i,j) in the observed image. The nodes X(i,j) represents the LR patches in the database whose corresponding HR patches are used to reconstruct HR image.



Figure 2. MRF-network-based learning model.

The dependency between nodes are represented by two compatibility functions, $\phi(.)$ and $\psi(.)$. For a position (i,j) in the MRF network, $\phi[X(i,j),Y(i,j)]$ represents the compatibility between the observed patch Y(i,j) and the training patch X(i,j). For a position (i,j) and its adjacent position (u,v), the function $\psi[X(i,j),X(u,v)]$ represents the compatibility of the common border between the estimated patches X(i,j) and X(u,v). The joint probability over X(.) and Y(.) is defined as

$$P(X | Y) = \prod_{ij} \phi [X(i, j), Y(i, j)] \times \prod_{ij,(u,v) \in NB(i,j)} \psi [X(i, j), X(u,v)]$$
(1)

where NB(i,j) denotes the neighbors of X(i,j) in the MRF network. A number of patch candidates for X(i,j) are previously selected based on the $\phi(.)$. The number of patch candidates is given as a constant parameter m.

To specify the $\phi(.)$ function, we impose a similar quadratic penalty on differences between the observed input image patch, Y(i,j), and the patch candidates found from the training set, X(i,j).

$$\phi[X(i,j),Y(i,j)] = \exp\left\{-\frac{d[X(i,j),Y(i,j)]}{2\sigma_1}\right\}$$
(2)

d(.) is the distance of the two matrices (or vectors) and σ_{1} is a constant parameter.

To specify the $\psi(.)$ function, we sample the input image's patches so that they overlap with each other by

one or more pixels, as shown in Fig. 3. The border compatibility function, $\psi(.)$ is defined as

$$\psi[X(i,j),X(u,v)] = \exp\left[-\frac{d(p,q)}{2\sigma_2}\right]$$
(3)

where p (q) is the vector of pixels of the overlap region in patch X(i,j) (X(u,v), respectively) and σ_2 is a constant parameter.



Figure 3. Overlap region between adjacent patches.

Given an initial set of patch candidates for X(.), the method iterates to change each candidate for X(i,j) in turn to improve P(X|Y) greedily until no improvement is observed. The HR patches corresponding to the finally chosen candidates for X(i,j) forms the estimated texture (high-frequency component). The method combines the initially upscaled LR image and the estimated texture component to obtain a restored HR image.

III. FACE IMAGE SUPER-RESOLUTION METHOD

Recently, the method has been modified for faceimage super-resolution purpose, where a learning model that takes the correspondence of facial parts into account during patch estimation was proposed. The underlying idea is to select patches in the database according to their facial parts, i.e. using eye patches for eyes and nose patches for nose. In order to increase the probability for the patches of the corresponding facial part to be selected, the method uses normalized human face images as training database, where face feature points are approximately in closer position in every image. Therefore, the facial parts can easily be determined by patch's original position in image, and the distance between observed patch and estimated patch is utilized to estimate their facial-parts compatibility.

Let the facial-parts compatibility function is $\lambda(.)$, the function is defined as

$$\lambda [X(i,j)] = \exp\left[-\frac{\ell}{2\sigma_3}\right]$$
(4)

where ℓ is Euclidean distance from original position of the patch X(i,j) in the training face image to the observed position (i,j) in the restored image, and σ_3 is a constant parameter. Hence, the joint probability of X(.) under the condition of Y(.) is an extension of (1) as defined in (5).

$$P(X | Y) = \prod_{ij} \phi [X(i, j), Y(i, j)] \\ \times \prod_{ij,(u,v) \in NB(i,j)} \psi [X(i, j), X(u, v)] \\ \times \prod_{ij} \lambda [X(i, j)]$$
(5)

A. Normalized Face Image Database Construction

We start from a collection of normalized highresolution face images for database. The normalized training images have the same size or ratio of facial features, where facial-feature points (e.g., eye, nose, mouth, chin, and face boundary lines) in each image are at approximately closer positions.

Fig. 4 illustrates a patch-database construction process for normalized face images. Since the learning model already includes $\lambda(.)$, it is unnecessary to categorize the patches into multiple databases based on facial parts. The main characteristic of the database is each patch's original position in the training images, (k,l), as shown in Fig. 4, will be observed during super-resolution process. *m* refers to the number of available training images in database.



Figure 4. Patch-coordinate-based database construction.

Same as the process shown in Fig. 1, we degrade the training images by downsampling them into LR images under certain scaling factor, typically one-quarter the number of original pixels in each dimension (1/16 the total number of pixels). We then resample it back into the original size to create an initial upscaled image. Then, we filter out the lowest frequency component on both original HR and initially upscaled images to retain only their texture component. Both components are then divided into patches in a way where both patches correspond to each other. Patches were divided in a manner of overlapping their neighboring patches by one pixel to later specify $\psi(.)$ in the MRF network.

B. Patch Candidates Selection

A fixed amount of patch candidates for each node is selected in advance so that we do not have to consider thousands of patches available in the database iteratively during the inferring process. The number of patch candidates is set proportional with the number of training images in the database, e.g., if we used 100 training images, 100 patches among the total number of patches would be chosen as candidates.

Patch candidates for each nodes were selected based on $\phi(.)$ and $\lambda(.)$ probability values. Training patch with higher pixel value (pattern) similarity and nearer position (closer facial parts) to an observed input patch has a higher possibility to be selected. To adjust the preference between $\phi(.)$ and $\lambda(.)$, we apply a weighting factor, α as

$$P_{C}(X \mid Y) = \prod_{ij} \phi \left[X(i,j), Y(i,j) \right]^{\alpha} \\ \times \prod_{ij} \lambda \left[X(i,j) \right]^{(1-\alpha)}$$
(6)

The value of α is set between zero and one. Hence, if α is one, the function would not take into account $\lambda(.)$, which means this is the same as that with Freeman et al.'s method. The lower the α value, the higher its dependency on facial parts' compatibility function.

C. Super-Resolution Process

The aim is to find the best set of X(.). By only using the limited number of selected patch candidates, P(X|Y) would typically be at optimum value.

Fig. 5 outlines the super-resolution process, i.e., deriving an output HR image from a single input LR image. We initially upscale the input LR image into a targeted size of HR image, and then extracted its texture. We divided it into patches to find the most similar patches in database Po. Those corresponding patches from database Pc were placed together to build a base image for the MRF learning model. This image would look grainy or blocks since the chosen patches would not yet be compatible with their neighboring patches. Here, we applied an iteration process so that the chosen patches would be compatible with their neighboring patches.



Figure 5. Super-resolution process.

According to (7), we replace X^{C} with the chosen candidates alternately to find the best X(.). $P_{C}(X|Y)$ is the known probability value from (6), which is different for each patch candidates.

$$P(X | Y) = \prod_{(u,v) \in NB(i,j)} \psi \left[X^{C}(i,j), X(u,v) \right]$$

$$\times P_{C}(X | Y)$$
(7)

We replace the initial chosen patches with the best patches that are compatible with the neighboring patches (patches with the best $\psi(.)$ values) among the patch candidates on each node. The first iteration is done when all nodes have been processed. This resulting image is smoother than that from the initial image model. We carry out the same procedure iteratively until the P(X|Y) value shows no significant improvement. Finally, selected HR patches on each node were stitched together to form an estimated texture (high-frequency component) image, and then we combined them with the previously upscaled image to obtain the final output HR image.

IV. PROPOSED METHOD

We want to analyze the SR methods in terms of parameter setting. Till now, the size of patch used in those methods is typically 5x5 or 7x7 in pixels, and the scaling factor is set typically as 2 or 4 times enlargement (4 or 16 times the total number of pixels of LR image, respectively). However, there is no experimental analysis yet regarding those two parameters, i.e. patch size and scaling factor. Is it really the best patch size for the SR process? How about other cases of magnification, where their scaling factor is different? What is the most suitable setting of patch size when we want to enlarge an LR image by different scaling factor, e.g. 3 times or 5 times?

It is important to find the most suitable setting of parameters in order to make the application more convenience, stable or less sensitive, besides userfriendly. Therefore, we attempt to analyze the algorithms in terms of patch size and scaling factor. Our aim is to find the most suitable patch size, which may provides better results, for different cases of magnification.

A. Experimental Analysis

We conducted an experiment by demonstrating the SR algorithms onto several sets of input LR images that have different scaling factor, i.e. 2, 3, 4, 5, and 6 times respectively. We used different size of patch during SR process, i.e. 5x5, 7x7, 9x9, and 11x11, and applied them onto each set of images to reconstruct HR images. The overlap region between patches is one pixel. Since the image size must be fit or compatible to the scaling factor and patch size to avoid any unnecessary remain part of image during SR process, we beforehand processed all the original HR face images by adjusting them to a desired size. The adjusted sizes of HR images are respectively shown in Table I.

 TABLE I.
 Adjusted Size of HR Images [(Width) x (Height)]

 That Is Fit with Scaling Factor and Patch Size Setting

Patch Size	Scaling factor					
	2	3	4	5	6	
5x5	240x288	240x288	240x288	240x280	240x288	
7x7	240x288	240x288	240x288	240x300	240x288	
9x9	240x288	240x288	240x288	240x280	240x288	
11x11	240x280	240x300	240x280	240x280	240x300	
13x13	240x288	240x288	240x288	240x300	240x288	

According to Table I, if an image's original size is 240x288 and scaling factor is 2, the size of downscaled image (LR image) is 120x144. We generated training face images (HR and LR) and input images according to Table I, producing 25 sets of training database and input images, respectively. Each set of training database consists of 110 face images, while the set of input LR images (excluded from database) consists of 30 face samples. We ran the SR method onto those input LR images to reconstruct HR images. Weighting factor for MRF functions, α , was set variably between zero and one, then we found the best amongst output HR images according to Peak Signal-to-Noise Ratios (PSNR) evaluation. The higher PSNR values indicate better quality results. 30 best output HR images for each set were collected for assessment.

For overview analysis, we observed the average values of PSNRs for each set of 30 output HR images. The resulting average PSNRs are shown in Table II. The bolded values note the best patch size for each case of magnification. We can observe in Table II a consistent pattern between the best patch size and scaling factor, which also means that the best patch size is adaptable to the scaling factor. Let the scaling factor is n, we can conclude that the best setting of patch size for each scaling factor can be expressed as $(2n+1)^2$. With this formula, we can now easily determine the size of patch to be used in the method when we want to enlarge an LR image under a certain scaling factor.

 TABLE II.
 Average PSNR [dB] for Sets of 30 Output HR IMAGES

Patch	Scaling factor						
Size	2	3	4	5	6		
5x5	35.973	31.112	28.913	25.572	24.103		
7x7	35.852	32.027	28.487	26.123	25.624		
9x9	35.600	31.498	29.262	26.523	24.904		
11x11	35.280	30.924	28.506	27.070	25.163		
13x13	35.221	31.442	28.898	26.578	25.718		

B. Proposed Algorithms

We employed the formula into the SR method. The proposed algorithms are simply illustrated in Fig. 6. The bolded lines indicate the preferred flow of SR. For example, if we want to magnify an LR image by 3 times, the algorithms will select the most suitable database, i.e. 7x7 patch database, to be used in SR process, yielding the best possible output HR image.



Figure 6. Proposed algorithms for the using of best patch size in SR process.

V. CONCLUSIONS

This paper reports the parametric analysis of face image super-resolution method. We conducted an experiment using different setting of patch size and scaling factor, to find the most suitable patch size and analyze their relationship with scaling factor. According to resulting PSNRs assessment, the best patch size is adaptable to the scaling factor of magnification. The best setting of patch size for SR method can be determined by $(2n+1)^2$, where *n* refers to scaling factor. This formula contributes to make the application of the method more stable and convenience, since the method has many variable parameters, which may lead to varied possibility of results. By using the algorithms to determine a patch size for SR process, we are able to narrow down the ways of finding the best possible resulting HR image for the method.

REFERENCES

- R. Keys, "Cubic convolution interpolation for digital image processing," *IEEE Trans. Acoustics, Speech, Signal Processing*, vol. 29, no. 6, pp. 1153-1160, 1981.
- [2] S. C. Park, M. K. Park, and M. G. Kang, "Super-Resolution image reconstruction: A technical overview," *IEEE Signal Processing Magazine*, vol. 20, pp. 21–36, 2003.
- [3] D. Capel and A. Zisserman, "Computer vision applied to super resolution," *IEEE Signal Processing Magazine*, vol. 20, pp. 75–86, 2003.
- [4] H. Ozdemir and B. Sankur, "Subjective evaluation of single-frame super-resolution algorithms," in *Proc. EUSIPCO*, 2009, pp. 1102– 1106.
- [5] H. He and W. C. Siu, "Single image super-resolution using Gaussian process regression," in *Proc. IEEE Int. Conf. Comp. Vision and Pattern Recog.*, 2011, pp. 449–456.
- [6] J. Sun, J. Sun, Z. Xu, and H. Y. Shum, "Gradient profile prior and its applications in image super-resolution and enhancement," *IEEE Trans. on Image Processing*, vol. 20, no. 6, pp. 1529–1542, 2011.
- [7] S. Baker and T. Kanade, "Limits on super-resolution and how to break them," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 24, no. 9, pp. 1167–1183, 2002.
- [8] W. C. Siu and K. W. Hung, "Review of image interpolation and super-resolution," in *Proc. Signal & Information Process. Assoc. Annual Summit and Conf.*, 2012, pp. 1–10.

- [9] Z. Lin and H. Y. Shum, "Fundamental limits of reconstructionbased super-resolution algorithms under local translation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no. 1, 2004.
- [10] W. T. Freeman, T. R. Jones, and E. C. Pasztor, "Example-based super-resolution," *IEEE Comp. Graphics Appl.*, vol. 22, no. 2, pp. 56–65, 2002.
- [11] W. T. Freeman, E. C. Pasztor, and O. T. Carmichael, "Learning low-level vision," *International Journal of Computer Vision*, vol. 40, no. 1, pp. 25–47, 2000.
- [12] W. T. Freeman and E. C. Pasztor, "Markov networks for superresolution," in *Proc. 34th Ann. Conf. Info. Sciences and Systems*, 2000.
- [13] S. F. Lui, J. Y. Wu, and H. S. Mao, "Learning-based superresolution system using single facial image and multi-resolution wavelet synthesis," *Lect. Notes Comp. Sci.*, vol. 4844, pp. 96–105, 2007.
- [14] J. Yang, J. Wright, T. S. Huang, and Y. Ma., "Image superresolution via sparse representation," *IEEE Trans. on Image Process.*, vol. 19, no. 11, pp. 2861–2873, 2010.
- [15] J. Yang, Z. Wang, Z. Lin, and S. Cohen, "Coupled dictionary training for image super-resolution," *IEEE Trans. on Image Process.*, vol. 21, no. 8, pp. 3467–3478, 2012.
- [16] C. V. Jiji and S. Chaudhuri, "Single frame super-resolution using learned wavelet coefficients," *Int. Journal of Imaging Systems and Tech.*, vol. 14, no. 3, pp. 105-112, 2004.
- [17] C. V. Jiji and S. Chaudhuri, "Single-frame images superresolution through contourlet learning," *EURASIP Journal on Advances in Signal Processing*, pp. 1–11, 2006.
- [18] W. Wu, Z. Liu, W. Gueaieb, and X. He, "Single-image superresolution based on Markov Random Field and contourlet transform," *SPIE Journal of Electronic Imaging*, vol. 20, no. 2, 023005, 2011.
- [19] S. Hamdan, Y. Fukumizu, T. Izumi, and H. Yamauchi, "Examplebased face image super-resolution taking into consideration correspondence of facial parts," *IEEJ Trans. on Electronics, Information and Systems*, vol. 12, no. 6, 2017.



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