DE-BLURRING METHODOLOGY OF LICENSE PLATE USING SPARSE REPRESENTATION

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Abstract: **A super-resolution reconstruction from single image algorithm designed for license plate recognition is proposed in this paper. Low resolution images database is generated by down sampling and adding white Gaussian noise to the super resolution license plate database. The low-resolution image can be viewed as a down sampled version of a high-resolution image, where its patches are assumed to have a sparse representation with respect to an over-complete dictionary of prototype signal atoms. The principle of compressed sensing ensures that under mild conditions, the sparse representation can be correctly recovered from the down sampled signal. Therefore, two dictionary of low and high resolution from same images patches are trained. . Finally, super resolution images from single low resolution image are recovered, by solving an optimization problem by genetic algorithm.**

Keywords: Super resolution, sparse representation, genetic algorithm.

I. Introduction

Super-resolution (SR) image reconstruction is currently a noticeable area of research that aims to produce a higher-resolution image based on one or a set of images taken from the same scene. One of the reasons of low resolution images can be identified as motion blurring caused by camera shaking or relative speed of camera and the scene. Since high resolution (HR) digital cameras are expensive, finding a way to increase the current resolution level is needed. One of the promising approaches is using signal processing techniques to convert the low resolution images to high resolution ones. One application of this method is the License Plate Recognition (LPR), where the movement pattern of object is comparatively simple for estimation.

Some of the most significant applications of LPR algorithm or commercial LPR system is in unattended parking lots, security control of restricted areas, toll gates, traffic law enforcement and congestion pricing in which it is easy to capture a clear and sharp photo of vehicle license plate when they are motionless or move at a very low speed.

The first article that clearly introduced the idea of combing SR and LPR to identify moving vehicles was written by Suresh and Kumar [1]. They proposed a robust super-resolution algorithm, in which the HR image is modeled as MRF with a discontinuity adaptive regularization (denoted as "DAMRF").

Other authors applied a method for estimating the regularization parameter automatically to the generalized DAMRF super-resolution reconstruction method [2]. Since the raw data were non-convex, they used a graduated non-convex (GNC) pattern which is a determining annealing algorithm for performing optimization. However, the complexity of functions in their Maximum a posterior (MAP) based method prevent it from real-time applications. A fast MAP-based SR algorithm was proposed by Yuan and et al, [3].

SR based on non-uniform interpolation of registered LR images was proposed by Gambotto and et al.(2009)[4]. The advantage of this work was the computational speed, while the disadvantage was more sensitivity to motion estimates. Weili and Xiaobo are proposed an alternative generalized model of DAMRF based on the bilateral filtering which connects the bilateral filtering with the Bayesian MAP[5].

In this work, by using Wiener filtering, the computation complexity is decreased. But because of removing the a-priori and registration errors, this method becomes unstable.

In the following, several other methods, such as Bayesian probability, bilateral filtering, and Wiener filtering and non-uniform interpolation method are used for solving the blurring problem. In continue, we consider SR images modeling techniques in section II and sparse representation problem in sections III and genetic algorithm in section IV that used to create two dictionaries Dl and Dh, and finally in section V, we explain our method for de-blurring low resolution images.

II. SR Images Modeling

The SR image techniques can be divided into four types: (i) frequency domain-based approach, (ii) interpolation-based approach, (iii) regularization-based approach, and (iv) learning-based approach. The difference between the first three and the last one is that, in (i), (ii) and (iii) classifying methods, higher-resolution images are provided from a set of lower-resolution input images, while in the fourth one

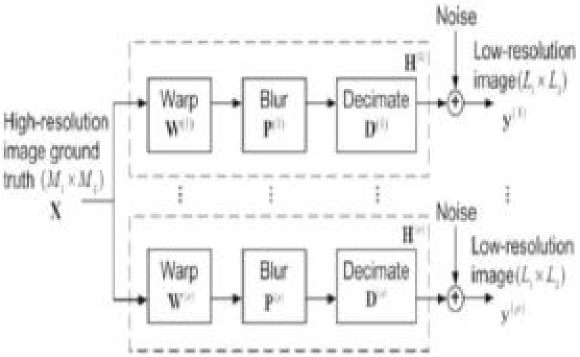

Figure 1. General Model for super-resolution image

gets the same objective by exploiting the information provided by an image database.

Chu Duc and et al in [6] modeled high resolution images as Markov random field. A learning-based framework has been proposed by Rajaram and et al for zooming the digits in a license plate, which have been blured using an unknown kernel it is our aim to produce uniform conference proceedings [7]. The disadvantages of these methods are the requirement of some similar vehicle images to have equivalent pixels of them. Since the images of the vehicles, unlike the fixed objects, are not in a same size due to motion, the efficiency of these methods are decreased.

Formulating a comprehensive model to join the original HR image to the observed LR images is the first stage in our method. To present a basic concept of SR reconstruction techniques, the observation model for super-resolution image is explained.

Figure 1 shows four operations of image processing. The first one is a geometric transformation which includes translation, rotation, and scaling, the second one is blurring, the third one is down-sampling by a factor of q1 × q2, and the last one is adding white Gaussian noise. The given image (with a size of M1 × M2) is taken at high-resolution ground accuracy, that is compared with the high-resolution image reconstructed from a set of low-resolution images using the following equation (with the size of $L_1 \times L_2$ each; that is, $L_1 = M_1/q_1$ and $L_2 = M_2/q_2$).

$$Y_{(k)} = D_{(k)}P_{(k)}W_{(k)}X + V_{(k)} = H_{(k)}X + V_{(k)} \qquad (1)$$

Where, Y(k) and X denote the kth $L_1 \times L_2$ low-resolution image and the original M1×M2 high-resolution image, respectively, and k = 1, 2, . . . , L_1L_2. D(k) is the decimation matrix with a size of $L_1L_2 \times M_1M_2$, P(k) is the blurring matrix of size $M_1M_2 \times M_1M_2$, and W(k) is the warping matrix of size $M_1M_2 \times M_1M_2$.

Consequently, three operations can be combined into one transform matrix H(k) = D(k)P(k)W(k) with a size of $L_1L_2 \times M_1M_2$. Lastly, V(k) is a $L_1L_2 \times 1$ vector, representing the white Gaussian noise encountered during the image acquisition process. Computing one high-resolution image X based on $Y(_1)$, $Y(_2)$, . . . , $Y(L_1L_2)$ is the aim of the SR image reconstruction [8].

Super-resolution remains extremely ill-posed, since for a given low-resolution input Y , infinitely many high-resolution images X satisfy the above reconstruction constraint.

In this approach, instead of direct computing of sparse representation for high resolution patches , two coupled dictionaries, D_h for high-resolution patches, and D_l for low-resolution ones are considered.

The sparse representation of a low-resolution patch in terms of D_l will be directly used to recover the corresponding high resolution patch from D_h. We obtain a locally consistent solution by allowing patches to overlap and demanding that the reconstructed high-resolution patches agree on the overlapped areas. We also try to train two over complete dictionaries in a probabilistic model similar to [9]. In this strategy, a local model from the sparse prior is used to recover lost high-frequency for local details. The global model from the reconstruction constraint is then applied to remove possible artifacts from the first step and make the image more consistent and natural.

III. SPARSE REPRESENTATION

Sparse representation is a method which represents all data of a linear signal combination as a small number of atoms in an optimal dictionary. Thus, each signal is shown as a combination of different atoms. Sparse Representation has various applications such as noise reduction, compression, pattern classification and feature extraction. A searching method to find out basic coefficients with a small data size is called Sparse Coding. In other words, decoding needs the related atoms with appropriate weight.

Suppose we are given a dictionary D of generating elements $\{\underline{d}_k\}_{k=1}^{L}$, each one a vector in C^N, which we assume normalized: $\underline{d}_k^H \underline{d}_k = 1$. The dictionary D can be viewed a matrix of size N × L, with generating elements for columns. We do not suppose any fixed relationship between N and L. In particular, the dictionary can be over-complete and contain linearly dependent subsets, while it doesn't need to be a basis.

As examples of such dictionaries, we can mention: wavelet packets and cosine packets dictionaries of Coifman and Meyer [10], which contain L = N log(N) elements, representing transient harmonic phenomena with a variety of durations and locations; wavelet frames, such as the directional wavelet frames of Ron and Shen [11], which contain L = CN elements for various constants C > 1; and the combined Ridgelet/Wavelet systems of Starck, Cand`es, and Donoho [12]. With such variety, individual elements in the dictionary cannot called 'basis elements' ; so the term of atom is used instead [13] for further elaboration on the atoms/dictionary terminology and other examples.

Given a signal $S \in C^N$, we seek the sparsest coefficient vector γ in C_L such that D γ = S. Formally, we aim to solve the optimization problem:

$$\text{Minimize } \|\gamma\|_0 \text{ subject to } \underline{S} = \mathbf{D}\underline{\gamma}. \qquad (2)$$

Here the l_0 norm $\|\gamma\|_0$ is simply the number of non-zero element in γ. While this problem is easily solved if there is a unique solution $D\gamma = S$ among general (not necessarily sparse) vectors γ, such uniqueness does not hold in any of our applications; in fact such cases mostly involve $L >> N$, where such uniqueness is of course impossible. Detecting these coefficients of an optimizing dictionary is an NP-hard problem and needs some methods such as genetic algorithms with ability of solving these types of problems.

A Sparse coding

Suppose to have a training set of image patches shown as: $S = \{s_1, s_2, \ldots, s_N\}$, the problem of dictionary learning from different patches of images can be defined as follows.

$$D = \arg\min_{\{D,\gamma\}} \|S - \mathbf{D}\gamma\|_0 \qquad (3)$$

The optimal dictionary D consists of basic atoms, γ is a N-coefficient vector with minimum number of non-zero components which any vector with combination of different atoms, is able to regenerate the first set of patches used from S.

To have the same sparse representation vector for image patches, with respect to D_h and D_l, the two dictionaries are trained simultaneously by concatenating them with proper normalization. Then in the next step, two dictionaries of D_l and D_h are simultaneously created using genetic algorithm and based on equation 3, they will be training with the same γ vector.

IV. GENETIC ALGORITHM FOR THIS OPTIMIZATION PROBLEM

Since this problem is not a convex one, separation optimizes the dictionary and then the coefficients will be optimized.

B. Genetic algorithm

The genetic algorithm (GA) is a search heuristic that is normally used to generate useful solutions for optimization and settle down the problems that using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover [14]. In general, the genetic algorithm is applied to spaces which are too large to be exhaustively searched.

In genetic algorithm there is an initial population which is created from a random selection of solutions. Then fitness value is assigned according to a criteria defined by the person solving the problem. This fitness is assigned to each solution (chromosome) depending on how close it actually is the solution of problem.

Those chromosomes with a higher fitness value are more likely to reproduce offspring (which can mutate after reproduction). The offspring is a product of the father and mother, whose composition consists of a combination of genes from them (this process is known as "crossing over").

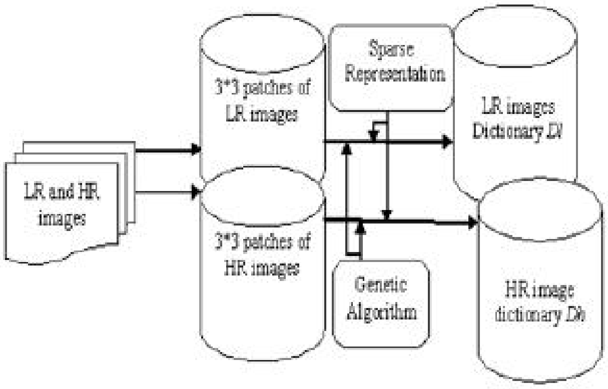

Figure 2. Framework of low resolution and high resolution Dictionaries

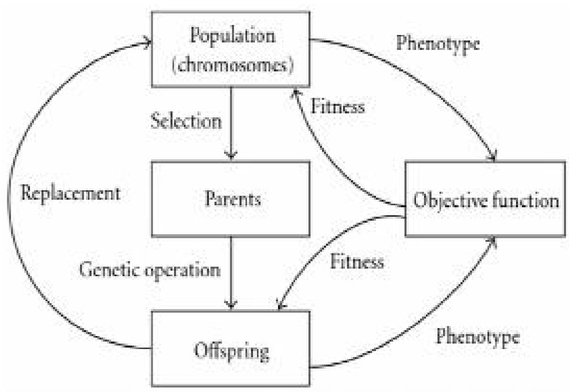

Figure 3. Genetic algorithms flowchart

If the new generation contains a solution that produces an output that is close enough or equal to the desired answer, then the problem has been solved. If this is not the case, then the new generation will go through the same process as their parents have done. One continues this process until a possible solution is reached.

C. Using Genetic algorithm for construction Dictionaries

In this study, 3*3 patches are shown as a 9 triplet arrays and dictionaries illustrate as a 9*n two-dimensional arrays where n is the number of atoms and 9 is the length of each patch. Genetic algorithm is used to build dictionaries for two generations of chromosomes; for each D_l and D_h dictionaries are considered as three-dimensional and another three-dimensional array as a coefficients.

After generating the original population, the most suitable individuals are chosen to survive. Then the suitable ones will mutate and survive.

Meanwhile, the unsuitable ones will compete to survive between every two of them rather than being abandoned. Then the winners will take the crossover to generate the individuals that survive to the next generation. As a result, we will find the global optimized solutions.

V. Image de-blurring by using of dictionaries Dl and Dh

After creating an optimal dictionary, the system can de-blur the images as shown in figure 4. The procedure is that, the input file (blurred image) y is divided to3*3 patches and each patch is separately passed to the system to find the high resolution equivalent of the patch itself.

First of all, the coefficient vector γ for the patch is calculated according to equation (2), and Dl is found based on genetic algorithm. Since D_l and D_h were trained with the same coefficients vector, by applying γ to Dh, the high resolution equivalent patch will be obtained.

Finally, by putting together these patches, the entire image will be created. The flowchart of image de-blurring method is sketched.
In order to increase the speed of the construction algorithm, it is possible to consider the number of non-zero elements coefficient of γ equal to one.

As a result, The Euclidean distance can be used for de-blurring and finding the nearest atoms are found very quickly. In figure 4, the flowchart of used method is shown.

Our de-blurring method's process is shown as pseudo code in figure 5.

VI. Experimental results

In this research, different images of a vehicle are utilized as training data. Since in order to train and test the system, a set of blurred images and their high resolution equivalent set and Gaussian function are applied. Then, a set of features are extracted in terms of patches with size of 3 x 3 for both sets of low resolution Y and high resolution S images.

The number of 170 different blurred images and 170 high resolution equivalent sets are utilized as the database and some of them are shown in Fig 6, all of the images get the same size to be used. In this project, each low resolution and high resolution image is divided into 272000 patches of size 3x3.

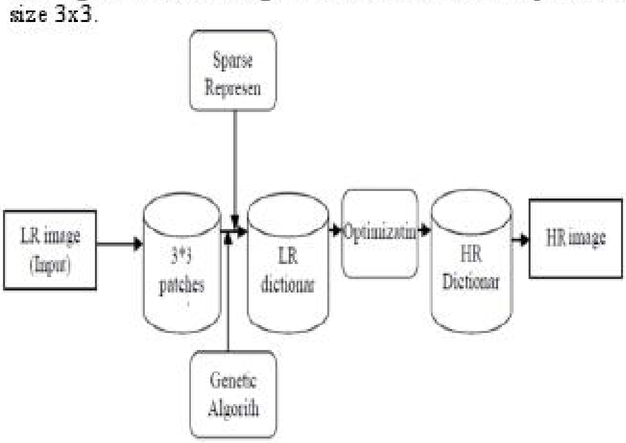

figure 4. Flowchart of image de-blurring method.

Input: *training dictionaries* $\mathbf{D}_h$ *and* $\mathbf{D}_l$, *a low-resolution image* $\mathbf{Y}$.
1: Create 3 × 3 patches y of Y.
2: Solve the optimization problem (1) with genetic algorithm to find best γ *vector.*
3: Reconstruct SR image by using γ *vector and* $\mathbf{D}_h$
4: ***Output****: super-resolution image X*

Figure 5. Pseudo code of de-blurring

The results of our proposed method are shown in fig 7, which shows acceptable result of the method. The middle and right column are shown first and second iteration of de-blurring algorithm, respectively. Regarding to experimental result the second iteration is efficient, and the performance of next iterations is not appropriate.

Experimental results demonstrate the effectiveness of the sparsity as a condition for patch-based super-resolution and the significant performance of proposed approach for plate images. Also, experimental results show that the dictionary size is related to accurateness of algorithm.

Larger dictionaries should process more expressive power and thus may yield more accurate results, while increasing the computation cost.

Most single input super-resolution algorithms assume that the input images are clean and free of noise, an assumption which is likely to be violated in real applications. To deal with noisy data, previous algorithms usually divide the recovery process into two disjoint steps: first denoising and then super resolution. However, the results of such a strategy depend on the specific denoising technique, and any artifacts during denoising on the low-resolution image will be kept or even magnified in the latter super-resolution process. Here we demonstrate that by formulating the problem into our sparse representation model, our method is much more robust to noise with input and thus can handle super-resolution and denoising simultaneously.

Figure 6. Illustration some of data Set (Left, high and right, low resolution)

Figure 7. Final result (Left column: Input images. Two next column are output of first and second iteration of de-blurring)

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