An Integrated Interpolation-based Super Resolution Reconstruction Algorithm for Video Surveillance

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Abstract—**This paper aims at implementing an integrated super resolution reconstruction algorithm to interpolate the missing pixels in the grid to create a high resolution image for a specific purpose. One of the most important application areas of super resolution reconstruction is video surveillance for the purpose of public security. Although, the video surveillance technology are going under tremendous transformation from analog generation to IP-based systems. However, their replacement rate is still not encouraging due to installation and operating costs as well as low output video quality. To overcome this problem, we propose a new hybrid model to integrate super resolution reconstruction into video surveillance. Our proposed algorithm is based on interpolation of cropped low resolution frames extracted from a low quality video surveillance sequence for effective and efficient reconstruction of a high resolution license plate recognition image. Our super resolved image utilizing multiple frames provides far more detail information than any interpolated image from a single frame. The proposed algorithm requires a relatively small number of self extracted low resolution frames from a low quality input sequence. This is important for practical applications, because if a large number of low resolution frames were required the accumulation of imaging errors would adversely affect the reconstruction accuracy. We apply our proposed algorithm to a real sequence from video surveillance and compare our results with those obtained via well-established techniques. Experimental results show that the proposed algorithm performs much better than the conventional MISO super resolution techniques. We also noticed significant reduction in the computational cost and memory requirement during the whole reconstruction process.**

Index Terms—**Interpolation, Reconstruction-Based Super Resolution, Video Surveillance**

I. Introduction

In today's environment, virtually every educational institution, financial institution, mass transportation center, medical center, municipality and agency must plan for threats and protect the security of its property, employees, customers, citizens and IT infrastructure. Surveillance techniques may be used to manage security risks and business issues more effectively across a variety of organizations, including public safety, airports, retail stores and financial institutions. Over the past several decades, surveillance techniques have matured dramatically. Analog tapes and security personnel are being replaced with Internet Protocol (IP) technology, leveraging digital video cameras, remote access, and intelligent analytics. This evolution provides organizations with significant opportunities to improve security and reduce operating costs as businesses in every sector face challenges in protecting their customers, employees, and assets. Due to this, the video surveillance becomes a key component of many organizations safety and security system. The three different generations of surveillance systems are often described as analog, digital and Smart or Intelligent video surveillance. Even the emergence of the fourth generation video surveillance is also under way. The First-generation video surveillance systems are entirely analog. Cameras are controlled and transmitted video is an analog format. Analog video surveillance has served as a deterrent to crime, as well as a means to record people, movement and events. However, factors such as high cost, poor image quality, and limited ability to distribute information have contributed to the need for this technology to evolve. Second-generation video surveillance systems are also based on analog camera, fiber or coaxial connectivity, with video switching provided by an analog video matrix switch. However, recording functions are enhanced in this case. It primarily focuses on addressing recording and storage problems. Similarly, DVRs replace analog VCRs as they offer longer operation life than VCRs. So, DVRs convert the analog video feeds into a digital format and save the resulting digitized video on internal hard disk drives. Digital Video Surveillance provides enhanced functionality and business value for clients, enabling them to manage and safeguard their organizations more effectively. In Third-generation systems, the deployments remain the same as with first and second-generation video surveillance systems. However, accessibility of live and recorded video is enhanced with introduction of IP gateway decoders.

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Although, in very short span of time rapid transformation take place in video surveillance systems. However, the deployment of more advanced surveillance system in organizations is still not an easy task for many reasons including high installation and operating costs as well as low output video quality.

Video sequences captured from modern surveillance cameras are normally digitized at smaller resolutions than still pictures in order to reserve system's resources. A frame thus extracted from such video would be of lower quality than desirable for a specific application. On the other hand, high resolution (HR) images are needed for accurate pattern recognition applications. Although, to enhance the visual quality of degraded images, the image processing applications such as image enhancement and image restoration can be applied but the resolution is still limited by the image sensors [1], and that's why they are not able to produce a desirable result. Super resolution (SR) reconstruction is different from what is known as image restoration where a higher resolution image is obtained from a single image. The aim of applying SR technique is to provide more detail by output image than any of the input images. This output image has the combined affect of all the input low resolution (LR) images if it is reconstructed accurately. Similarly, the goal of image restoration is to recover a degraded image but it does not change the size of image. However, SR techniques do increase the size of the image because of image interpolation. Important applications of the image and video SR include but not limited to video surveillance, satellite imaging (such as remote sensing), medical diagnosis (CT, MRI and ultrasound), radar imaging, image compression, computer vision, robotics, digital mosaicing, web cams and mobile camera images (having cheaper sensors).

SR reconstruction uses information from several LR images in order to generate one HR image. During the reconstruction process, it involves two important image processing techniques namely registration and interpolation. The purpose of registration is to accurately align individual LR frames with sub-pixel precision. Frame alignment is very critical step in SR reconstruction process, which is achieved by effective estimation of motion parameters. If multiple objects moving in different direction are captured by a video camera, these object's movement can be described only by terms of local motion. But in the case of a non-stationary camera, which means that the camera moves during the capture such as track and zoom, it can be generally described by global motion. This is why it is necessary to estimate first camera movement then to compensate it and finally to recomputed local motion vectors by considering the estimated camera motion. Mainly, the camera motion constitutes global motion whereas local motion concerns object motion. Local or object motion is the movement of some pixels or blocks in the frame and not all of the pixels of the image. Also, pixels in the frames may not have only global motion but both global and local motion vectors if the scene contains moving objects. Image registration deals with that issue of aligning the LR images by computing such motion vectors. Though the original images were taken from approximately the same location, they are likely to be subjected to slightly different rotation and zoom. These images are registered or aligned appropriately before the reconstruction of a HR image. That's why image registration is considered as a significant intermediate process in achieving accurate SR from a sequence of aliased and under-sampled LR frames. On the other side, interpolation is a process of comparing the LR pixel values to generate new pixel values for a HR image. Currently, there are two different approaches for image SR: (i) The classical reconstruction-based SR and, (ii) example-based SR. A detail of further classification among those approaches can be found in [2]-[6]. Despite depending upon the size of available database, example-based algorithms have been more developed recently, giving the possibility of using high frequency information embedded in HR image databases.

Also, the optimal number of images to be used when reconstructing a HR image depends on many parameters, such as the registration accuracy, imaging model and so on. Obviously, the more images used in the reconstruction process, the better the resultant HR image should be. However this is not always true in practical scenario as there is a limit to the improvement that can be obtained. Blur, noise, and inaccuracies in the imaging model limit the increase in resolving power that can be obtained otherwise. So even given a very large number of LR images, it will not be possible to reconstruct a sharp HR image. In other words, a HR image should contain details of the contents, i.e. high frequency components such as edges and texture areas. However, these details are suppressed by single image interpolation process, consequently, preserving these extra details is the key issue in SR research as natural images are not random signals, but redundant, i.e., pixels are statistically dependent on each other. However, there is a key benefit of using the interpolation process in our algorithm as it has a very low computational cost in terms of both time and memory utilization since it is implemented at some intermediate step in a system. So, a new algorithm based on interpolation for the SR reconstruction of the images inference from a sequence of continuous (but not necessary) LR frames is proposed. The basic idea is to use the information gathered from the LR frames extracted from a video sequence to obtain a HR image by eliminating or minimizing image distortion due to various degradation factors. Our approach handles the problem of visible artifacts in effective way and improves the quality of the HR image.

The rest of this paper is organized as follows: Section II provides the motivation behind our work. In Section III, we briefly explain the core concept of MISO image SR. Section IV highlights the importance of video surveillance in today scenario. Section V discusses in detail the possible role of SR enhancement in the field of video surveillance. Section VI briefly describes the main steps of our proposed integrated algorithm. Next, Section

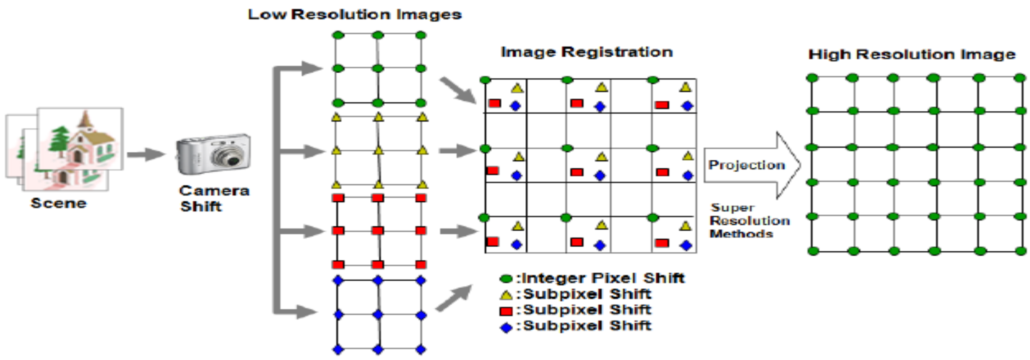

Figure 1. Basic concept of MISO image super resolution

VII gives the analysis of simulation results in terms of qualitative assessment, carried out on real videos to validate the effectiveness of our proposed model. The concluding remarks as well as some useful future directions in the light of our performed work are given in Section VIII.

II. MOTIVATION

One of the most practical application of video surveillance is License plate number recognition or License Plate Recognition (LPR), which is now a fairly well explored problem with many successful solutions. However, a distant license plate number in existing surveillance video may be unrecognizable at the current resolution. This is true because of the distance to the surveillance camera, position, inclination and other variables that affect the video quality. To overcome this problem, specific-purpose cameras i.e., license plate capture cameras may be installed in special places. Which is a specialized form of Close-Circuit Television (CCTV) camera that has built in software that helps to identify and capture license plates on still or moving vehicles. Its most common use is the control of parking areas and traffic monitoring. Although, the intelligent traffic modes built into these cameras allows the camera to compensate for speed, weather, and headlight issues. However, the replacement of such specialized cameras everywhere is not an easy task due to high installation and operating costs. Similarly, it becomes more challenging to capture a usable video from the existing surveillance cameras that identifies vehicle license plate. That is the motivation behind our work to use the existing video surveillance system and at the same time by exploiting the SR enhancement technology to generate a HR image from real-time video as produced by a special purpose surveillance camera.

III. CONCEPT OF MISO IMAGE SUPER RESOLUTION

The basic principle of SR imaging is that changes in the LR images caused by the degradation factors such as blur and the scene motion provides additional data that can be exploited to reconstruct a single HR image from the set of LR observations. This process has been also referred as Multi Input Single Output (MISO) reconstruction-based SR. The SR problem has been an active area of research for more than two decades now. The core idea behind a MISO SR process is very simple. Basically the non-redundant information from the given LR images is used to generate a HR image. So, multi-frame analysis provides the basis for SR reconstruction. The whole process of SR is summarized in Figure (1) [2]. As seen, a general framework for MISO image SR for a given bunch of LR images typically involves two crucial steps. i.e., image registration and projecting LR image values onto HR grid. Thus, the key to a comprehensive analysis of the classical SR problem is to formulate the problem and to model it as simply and as efficiently as possible. However, there are a few pitfalls that should be avoided when dealing with the SR problem, as they are potential risks for the SR algorithms. For example, although there are a lot of SR techniques available now-a-days, however every technique didn’t provide the better results for every application. Therefore, an appropriate technique must be choose before it would apply to the given data. Moreover, the algorithm performance depends significantly on the appropriate choice of parameters, such that generally a long supervised process is needed to obtain useful results. Also, most of the SR methods employ a number of parameters that need to be tuned. This tuning process can be time-consuming since the parameter values have to be chosen differently for each image and degradation condition. Similarly, if the objects in image are completely still or only move a little, the SR image could not be well reconstructed for the lack of sub-pixels shifts. Since, SR methods critically depend on the accuracy of image registration. The only way to improve the resolution is the correct utilization of sub-pixel shifts between images. Without sub-pixel accuracy, we only have shifted copies of the same image, which gives no extra information to recover the lost information. Again, if the original images were captured with much noise or overexposure, we could not reconstruct the good HR images for the error prone image registration.

IV. VIDEO SURVEILLANCE AND IT'S IMPORTANCE

As security risks increases, the need to visually

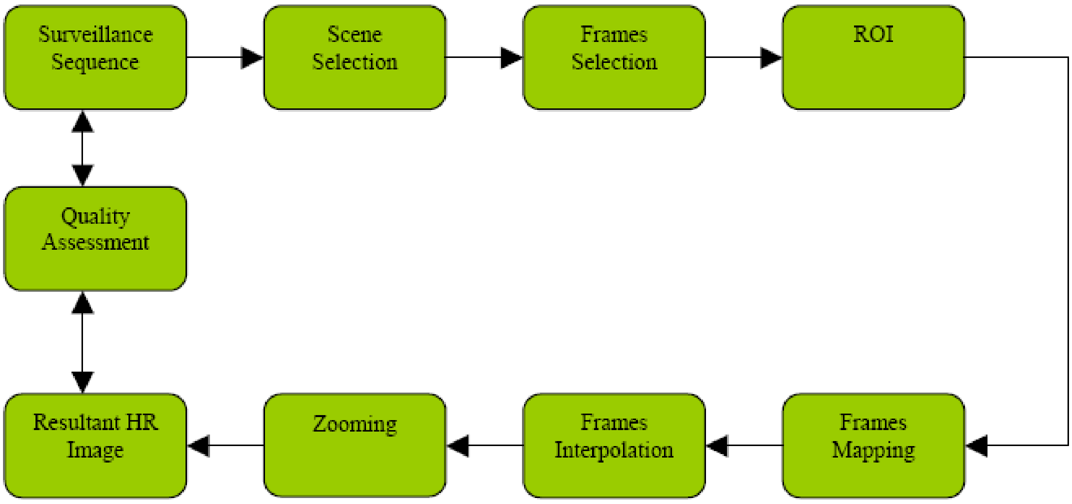

Figure 2. Simplified Block diagram of Proposed SRVS model

monitor and record events in an organization's environment has been become more important. The aim of deploying CCTV surveillance system is to provide real-time monitoring and protection to the general public, or recording events for subsequent investigation. Because of the technological advances, declining costs, and heightened security concerns have led to rapid diffusion of both CCTV surveillance and biometric technologies (For example, facial recognition systems). CCTV cameras have grown significantly from being used both by government as well as by private sector companies. CCTV video surveillance is widely used in public universities and colleges to monitor student movement and detect illegal activity. Also, used at street intersections to catch cars running red lights or for street crime prevention. Similarly, private sector applications greatly exceed those in the public sector, including in the workplace, apartment buildings, garages, stores, banks, and restaurants. Although, video surveillance is not the only an effective remedy for crime prevention and deterrence. However, it is an appropriate security measure in terms of public's demand for security. Most public and business-related CCTV video surveillance systems are actively monitored by security personnel in a centralized setting, remotely monitored, monitored over the Internet through video streaming, or passively taped for future viewing if needed (such as in the event of a bank robbery). Relatively new features in CCTV surveillance technology that considerably enhance its power and scope include night vision cameras, computer assisted operations, and motion detectors that allow an operator to instruct a system to go on "red alert" when anything moves in view of the cameras. According to a survey, video surveillance is more prevalent in Europe than it is in the United States [7]. The trend of deploying surveillance cameras is also growing in the major cities of China. In short, CCTV surveillance increases the "eyes" of law enforcement authorities.

V. ROLE OF SUPER RESOLUTION IN VIDEO SURVEILLANCE

Due to increased security challenges in today world, the accurate identification of desired object is of great importance. One cannot afford any visible artifacts in the image used by security agencies in their investigation such as face of a criminal or the license plate of a car in our case. Therefore, the surveillance applications often need a very HR image in order to obtain an accurate result. A lot of research is in progress to explore new techniques in this regard. For example, the biometric techniques have of great importance. Though most of these solutions are reasonably fast and no doubt provides new dimensions for object identification. However, there are some basic limitations related to these techniques. For instance, these algorithms can hardly improve the quality of their inputs by factors bigger than two. Also, applying them to real video sequences usually produces unstable and noisy output. This is due to the unavoidable registration errors of video sequences.

SR imaging is one of the topics having attracted many research activities in the field of image and video processing. Every time, upgrading or replacing the existing a video surveillance system for a specific application is not a feasible solution. Therefore, SR algorithms are necessary for improving the quality of LR video sequences from surveillance cameras. SR, when used in conjunction with CCTV video surveillance, offers an accurate means to fulfill the purpose of improving the resolution of input frames. So in our opinion, using SR techniques is an integral part in a modern surveillance system. The specific use of SR reconstruction for surveillance application in this paper is to obtain a clearer and more detailed zoom of a vehicle number plate. The proposed algorithm in this paper deals with the above-mentioned problems and result in accurate object identification.

VI. THE PROPOSED INTEGRATED SRVS ALGORITHM

The proposed model assumes that the original video sequence comes from a video surveillance camera. SR technique will be then used to take advantage of relative scene motions existing from frame to frame of the video sequence. Our proposed SR reconstruction algorithm is based on interpolation technique. Which estimates the SR image after cropping the set of observed LR frames obtained from a selected scene. Although, creating a robust SR algorithm in a surveillance system is much difficult task. However, our proposed algorithm is computationally very efficient due to the fact that only part of the image is super resolve instead of the whole image. The simplified block diagram of our proposed integrated SR Video Surveillance (SRVS) model is shown in Figure (2). The main steps of our proposed algorithm are described in detail as follows.

Proposed Algorithm:
Input: A real-world LR video sequence captured by a surveillance camera
Output: Reconstructed HR image from input video sequence for LPR application

Step 1. The first step of our proposed algorithm is the acquisition of a real-time video sequence using existing video CCTV camera. The captured video sequence will serve as an input to our proposed model. This captured video sequence is a series of many rapid snapshots of a scene and is composed by a continuation of frames.

Step 2. Select a particular scene of interest in a given video sequence, if needed. For instance, the selected scene in our case is a moving car in which we are interested to recognize its license plate. This is important in order to avoid any unnecessary processing and will save the system's resources. However, existing datasets for action recognition are unrealistic for real-world surveillance because they consist of short clips showing one action by one individual. In such scenario, this step may be avoided. On the other hand, in real life video sequences, the scene selection is important step since the installed video surveillance cameras are capturing the continuous scene all the time.

Step 3. Discard the frames with no significant movements from the selected scene while only extract the frames with useful information. This is because the frames with little motion didn't have any additional information and thus will not contribute in the reconstruction of final HR image. At the same time, the frame selection also helps to conserve hard disk space. We accomplished this task by using VirtualDub. However, any other tool can be used to extract the desired frames from the selected scene of a video sequence. Generally, consecutive frames may be picked from a selected scene but it is not necessary. Figures 3 and 4 show one of the selected input LR frame along with their frame number obtained from the video sequence for our experiments. Frames 2 to 5 (for the first experiment) and 4,6,7,9,10 (for the second experiment) were selected for further processing due to the favorable conditions as these frames have a direct line of sight to vehicle number plate.

Step 4. Crop the selected frames by selecting an appropriate $M \times N$ window. This would enable us to select a region of interest (ROI) in the LR frames and hence removing the background clutter. For instance, in our case part of the frames that features only the moving car were selected while isolating the remaining portion of the frames. It is necessary in order to minimize SR computation and make the processing more efficient. The cropped images are then fed to the next step in order to register them accurately.

Step 5. Map the cropped frames on a HR grid in frequency domain by computing the corresponding motion parameters between the reference frame and each of the other frames. If the registration can accurately estimate the translational or rotational motion, the align LR frames can produce an enhanced image. That's why registration is a crucial step for the reconstruction of an accurate HR image. We adapted Vandewalle et al. frequency domain approach [8] to register the set of aliased cropped images.

Step 6. Interpolate the missing pixels using cubic convolution on the HR grid to generate an initial HR image.

Step 7. Zoom a portion of the intermediate HR image as required for a specific application in order to make it clearer and more recognizable.

Step 8. Display the resultant zoomed portion of a HR reconstructed image obtained from multiple cropped images.

Step 9. At last stage, perform quality assessment of the reconstructed image either by subjective means or objective using any well-known method.

VII. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

We made use of two different video sequences in order to evaluate the performance of our proposed algorithm. For this purpose, we conducted two different experiments. In the first experiment, the video sequence is captured under uncontrolled environment and is especially used to test the performance of our proposed SR reconstruction algorithm for vehicle license plate number. However, the nature of this video sequence is unknown to us. The input to other experiment is also a real video sequence captured from a surveillance camera and showing only a slow-moving car. This video sequence is captured under controlled environment from a surveillance camera mounted on a top of pole overlooking stop signs. This kind of camera, along with others at different locations are normally set up in the university campus to monitor and improve students and general public safety through remote surveillance activities. A portion of video sequence in both cases is selected for our experiments. We refer to them as the 'Carwide' and the 'Car' video sequences respectively. In both the experiments the analyzed frames concerned mainly of LR images of license plate recognition problem. Due to the different hardware and different spatial positions of the cameras, both of the selected video sequences have different characteristics. The CCTV camera in the 'Carwide' video sequence is mounted at a much greater distance from the stop sign, while the 'Car' video sequence is captured at much closer distance and is set to its full optical zoom. The spatial resolution of the video stream captured by a surveillance camera in both cases is very low, i.e., 256 × 236 (at the sampling rate of 30 frames per second), and 72 × 121 (at the sampling rate of 8 frames per second), for 'Carwide' and 'Car' video sequences respectively. However, it is visually more pleasing to set the sampling rate to the most minimum which is 25 frames per second in order to avoid a jerking sensation in the capture video and also to minimize any motion blurring in fast moving objects. Our proposed algorithm consists of manually extracted license plate images and selected frames from a video captured from a surveillance camera. We used VirtualDub to extract selected frames from a video sequence for both the experiments. The frame selection was characterized by a fair amount of motion. After cropping, the resolution of the frames showing the license plate number becomes only 172 × 114 and 48 × 72 pixels. Here, the car license plate is selected as our ROI. We performed this task using Microsoft Office Picture Viewer, however, any other picture viewer software like ImageGrab can be used for this task. In both the experiments, the noisy and blurry 172 × 114 and 48 × 72 pixel license plate images made it very difficult to read the text on the plates. To overcome this problem, we employed second-order interpolation (cubic convolution) during the reconstruction process in our algorithm as it provides smoother and high quality accurate image compare to other. To support our position, we provide comparison of our proposed algorithm with well-established techniques like IBP and POCS in particular. Figures 3 and 4 show a typical frame of a video sequence captured from a surveillance camera in both cases along with the reconstructed images using our proposed algorithm (with varying number of input frames) and other well-established techniques. We used up to five LR frames in the reconstruction process in order to obtain a resolution enhancement factor up to 4. To further support our position, we also apply our proposed algorithm on different kind of simulated images and again we obtain promising results. For this purpose a synthetic set of four shifted and aliased LR images were artificially generated from a HR image 'Cab' (captured at university west gate) by applying different translations. The whole process is summarized (neglecting unnecessary steps) in Figure 5. The proposed algorithm is implemented on a Pentium IV, 2 GHz notebook machine with 2 GB RAM. MATLAB has been used for implementation of proposed hybrid algorithm.

Since, quality assessment is an important task in the field of image and video processing. In most scenarios, performance of algorithms is evaluated automatically without human's interference using objective metrics or through subjective testing. However, objective metrics can only serve as an estimation of the real quality of video, which is the subjective opinion of actual viewers. Since, there is no 'true' HR image available for comparison so only the practical mode for performance evaluation are considered and verified on the original test video sequences in our paper. From the experimental results, we can subjectively find the improvement in the quality of the reconstructed image using original LR frames compared to other SR reconstruction techniques. Also, computation time is greatly reduced because only region of interest in the frames are processed provided by cropping the larger image. So as seen from the results there is a good cut off between image quality and computational constraints. Our proposed algorithm is robust and high efficient in nature. Although, there is no unique definition of robustness in the literature. In general an algorithm is said to be robust when it gives similar estimation even if outliers such as noise, local motion and background motion affect the input frames as in our case. Similarly, the simulation results show that more the number of frames used in the reconstruction, the better the quality of the reconstructed image will be. However, it is not always true as evident from Figure 4. The model is tested using real world videos from different environments and the results are promising.

VIII. CONCLUSIONS

In this paper, we introduce new dimensions of SR technology regarding video surveillance. A novel and hybrid reconstruction scheme has been proposed for SR reconstruction that focuses mainly on one of its most important application area, i.e., LPR. The proposed algorithm integrated the advantages of existing video surveillance system and image SR to overcome the drawbacks in existing video surveillance system. We applied the second-order interpolation scheme in our proposed model to generate a HR reconstructed image using LR input frames extracted from a sequence of aliased and under-sampled, low limited quality video sequence. The proposed algorithm is an effective way to super resolves license plate number in a video sequence. Experimental results demonstrate that the proposed algorithm has better visual quality and produces excellent reconstruction results in comparison to state-of-the-art methods. Experiments with different kind of real world video sequences from uncontrolled environments show promising results in terms of visual quality. At the same time, the new method utilizes less computational time and achieves better performance.

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(a)

(b)

(c)

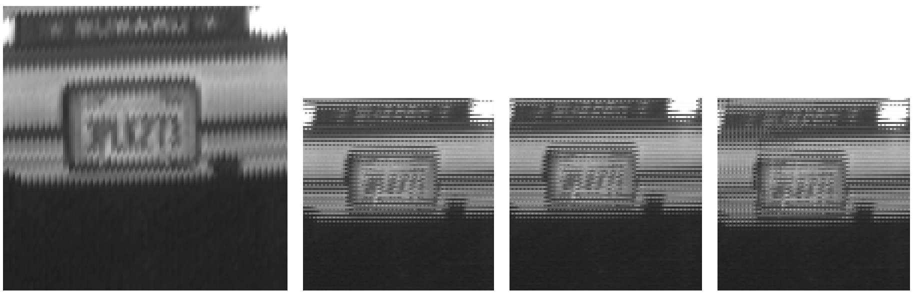
(d)

(e)

(f)

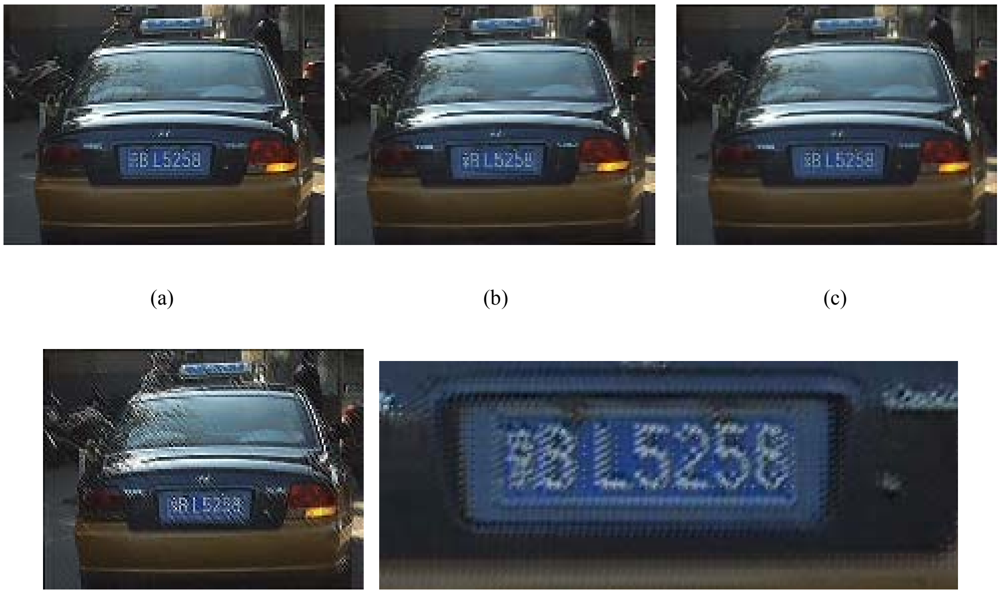
Figure 3. Experimental Results of super resolution reconstruction using different techniques : (a) one of the LR input frame of 'carwide' test sequence (Frame # 3) (b) superresolved using POCS method (c) superresolved using IBP method (d) superresolved using our proposed algorithm (LR frames=2, IF=2) (e) superresolved using our proposed algorithm (LR frames=3, IF=3) (f) superresolved using our proposed algorithm (LR frames=4, IF=4)

(a) (b) (c)



(d) (e) (f) (g)

Figure 4. Experimental Results of super resolution reconstruction using different techniques : (a) one of the LR input frame of 'car' test sequence (Frame # 9) (b) superresolved using POCS method (c) superresolved using IBP method (d) superresolved using our proposed algorithm (LR frames=2, IF=3) (e) superresolved using our proposed algorithm (LR frames=3, IF=3) (f) superresolved using our proposed algorithm (LR frames=4, IF=4) (g) superresolved using our proposed algorithm (LR frames=5, IF=2)



(a) (b) (c)

(d) (e)

Figure 5. Experimental Results of super resolution reconstruction using different techniques : (a) High resolution ‘Cab’ image (640 × 480) (b) one of the artificially generated LR input image from ‘Cab’ image (c) superresolved using POCS method (d) superresolved using IBP method (e) superresolved using our proposed algorithm (LR images=4, IF=4)