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Super-Resolution of Turbulent Video: Potentials and Limitations

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ABSTRACT

A common distortion in videos acquired in long range observation systems is image instability in form of chaotic local displacements of image frames caused by fluctuations in the refraction index of the atmosphere turbulence. At the same time, such videos, which are designed to present moving objects on a stable background, contain tremendous redundancy that potentially can be used for image stabilization and perfecting provided reliable separation of stable background from true moving objects. Recently, it was proposed to use this redundancy for resolution enhancement of turbulent video through elastic registration, with sub-pixel accuracy, of segments of video frames that represent stable scenes. This paper presents results of investigation, by means of computer simulation, into how parameters of such a resolution enhancement process affect its performance and its potentials and limitations.

Keywords: Super-Resolution, Turbulence-Compensation, Optical-Flow

1. INTRODUCTION

The major cause for image distortion in long distance observation systems is the atmospheric turbulence, which causes spatial and temporal random fluctuations in the index of refraction of the atmosphere [1]. At the result, light from each of the points in the scene acquires slightly different tilts and low order aberrations, causing the images of these points to be randomly dislocated from their correct geometrical positions. In acquiring these images by video cameras, the image sampling grid defined by the video camera sensor can be considered to be chaotically moving over a stationary image scene. Therefore, in turbulence-corrupted videos, consequent frames of a stable scene differ only due to atmospheric turbulence-induced local displacements between images. This phenomenon allows generating images of such scenes with larger number of samples than that provided by the camera if consecutive image frames are combined by means of their appropriate re-sampling [2,3,4,5,6,7,8].

Generally, this super-resolution process consists of two main stages. The first is determination, with sub-pixel accuracy, of pixel movements (displacement map). The second is combination of data observed in several frames in order to generate a single combined image with higher spatial resolution. A flow diagram of this stage of processing is shown in Fig 1.

For each current frame of the turbulent video, inputs of the process are: a corresponding reference frame, which represents an estimate of the stable scene, and the current frame displacement map. The latter serves for placing pixels of the current frame, according to their positions determined by the displacement map, into the reference frame. This is implemented by means of its corresponding up-sampling to match the sub-pixel accuracy of the displacement map. As a result, output stabilized and enhanced in its resolution frame is accumulated. In this accumulation process it may happen that several pixels of different frames are to be placed in the same location in the output enhanced frame. In order to make best use of all of them, these pixels must be averaged. For this averaging, the median of those pixels is computed in order to avoid the influence of outliers that may appear due to possible errors in the displacement map.

After all available input frames are used in this way, the enhanced and up-sampled output frame contains, in positions where there were substitutions from input frames, accumulated pixels of the input frames and, in positions where there were no substitutions, interpolated pixels of the reference frame. Substituted pixels introduce to the output frame high frequencies outside the base-band defined by the original sampling rate of the input frames. Those frequencies were lost in the input frames due to the sampling aliasing effects. Interpolated pixels that were not substituted do not contain frequencies outside the base-band. In order to finalize the processing and take full advantage of the super-resolution provided by the substituted pixels, the iterative re-interpolation algorithm can be used akin to the Papoulis-Gershberg algorithm [7,8]. Once iterations are stopped, the output-stabilized and resolution-enhanced image obtained in the previous step is down-sampled to the sampling rate determined by selected enhanced bandwidth and then it can be subjected, when needed, to additional processing aimed at camera aperture correction and, if necessary, denoising.

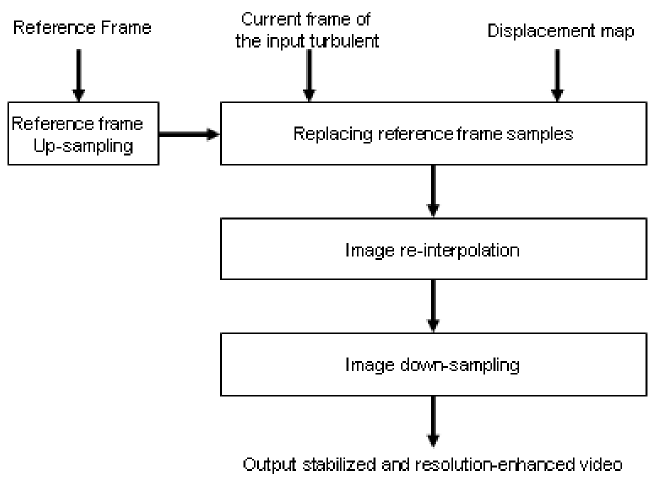


Figure 1 - Flow diagram of the process of generation of stabilized frames with super-resolution

This paper presents results of investigation, by means of computer simulation, into how parameters of atmosphere turbulence, such as variance of turbulence induced image local displacements, fill factor of video camera, the number of frames involved in the process and the number of re-interpolation iterations affect the performance of such a resolution enhancement process.

2. ALGORITHM'S PARAMETERS

2.1. Camera Fill Factor

The camera fill factor is the ratio of the active detection area (the size of the light sensitive photodiode) to the inter pixel distance. Because of the electronics around the pixels, fill factor value is smaller than or equal to 1. Camera photo detectors introduce low pass filtering to the images captured by the camera. Large fill factor means better light energy efficiency of photo detectors and higher degree of low pass filtering, which causes a loss of image high spatial frequencies. Figure 2 illustrates frequency responses of photo detectors with different fill factors. The resolution of images acquired by cameras is ultimately limited by this low pass filtering. Super-resolution methods allow eliminating aliasing effects due to image sampling but not the image low pass filtering by camera photo detectors. The latter can be, at least partially, compensated by means of deblurring through aperture correction. Therefore super-resolution methods are potentially more efficient for images acquired with cameras with small fill factor.

2.2. Turbulence Intensity

Pixel displacements due to atmospheric turbulence are chaotic and therefore can be characterized only statistically. In our study, the intensity of the turbulence was specified by the standard deviation of the motion vector length. Weak turbulence with low standard deviation of the motion vector length causes small shifts. In this case, the low-resolution (LR) video will virtually appear static and the frames will be nearly identical. Intensive turbulence with standard deviation by the order of the inter-pixel distance may cause very substantial aliasing, which might be difficult to measure and compensate. One can expect that standard deviation of motion vector length of about 0.5 is potentially most suitable from the point of view of the super-resolution process.

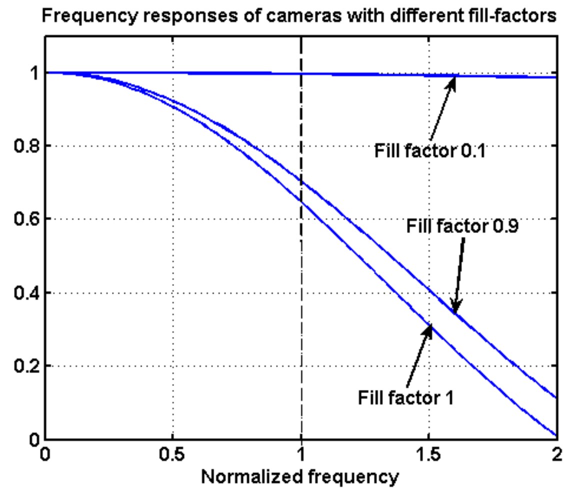


Figure 2 – Camera frequency responses for large and small fill factors. Frequency axis is normalized to the width of the camera base band

2.3. The number of processed low resolution frames

The quality of the resolution-enhanced frames depends on the amount of data used for their formation. More frames can potentially produce better quality. However, when the number of frames is becoming large enough, having more frames will not necessarily supply more (or significantly more) new pixels, while it will require more processing time.

2.4. The number of iterations in the process of re-interpolation

Once the motion vectors for each available low resolution frame are known, pixels in the sub-sampled reference frame are replaced with known pixels from those frames. As a result, an up-sampled reference frame that contains pixels (samples) from all the low resolution images is obtained. At this stage it is required finally to perform image re-interpolation to remove aliasing and to generate the best approximation to the image from the given set of pixels. This is achieved by the iterative interpolation algorithm, which converges to the best band limited approximation of the image. More iterations means that the final image will be closer to the best possible approximation within a given bandwidth. However, iterations consume time, and therefore a compromise should be sought between the resulting image quality and computation time.

3. COMPUTER MODEL

For analyzing the influence of the above mentioned parameters on the performance of the super-resolution algorithm, a computer simulation model has been built (Fig. 3) to generate sequences of low-resolution turbulent degraded frames from a high resolution input test images The input parameters for the simulation were camera fill factor and the frame-wise pixel translation maps for simulating the turbulence effect. The realizations of the motion vector maps were generated in the form of X- and Y-shift arrays of pseudo-random Gaussian random numbers with a given standard deviation. For each realization of the pixel translation map, a corresponding low-resolution frame was produced by means of down-sampling of up-sampled low pass filtered high-resolution image according to the sampling grid specified by the corresponding motion vector map. The up-sampling factor used in the model was 10. Once low-resolution frames were obtained, they were used as an input sequences for the super-resolution algorithm shown in flow diagram of Fig. 1. Fig. 4 illustrates examples of test high-resolution and low-resolution images as well as of a sample map of motion vectors.

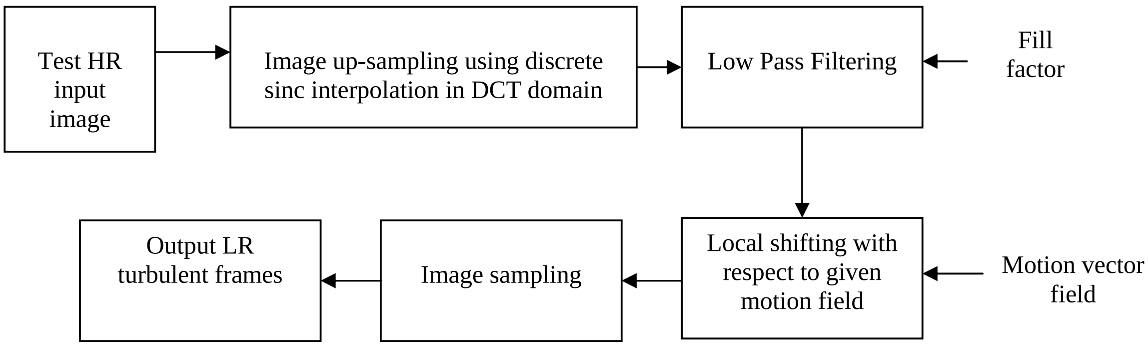
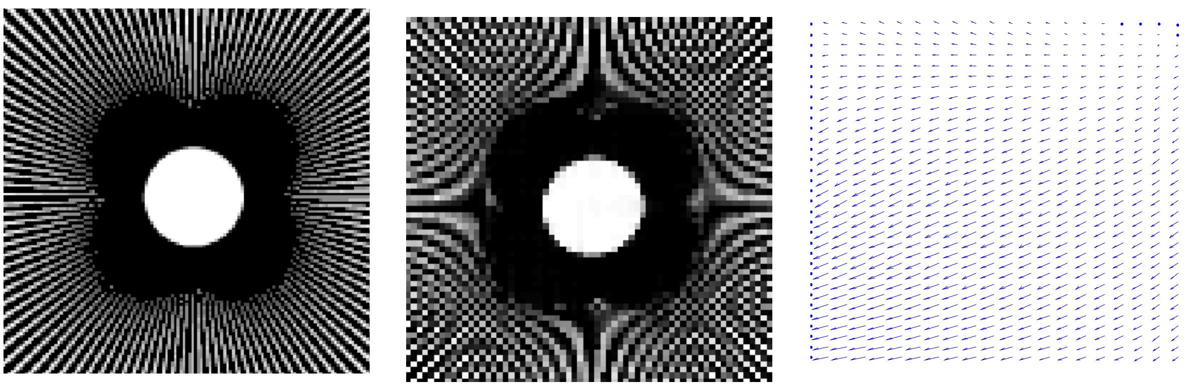


Figure 3– Flow diagram of the computer model



a) b) c)

Figure 4 – a) Original high resolution test image, b) a turbulent low resolution frame (output), c) a sample of a motion vector map

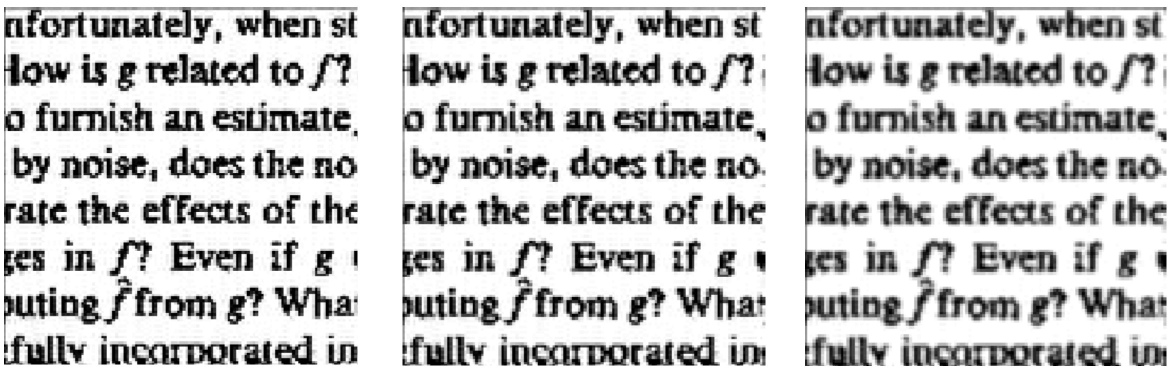
4. SIMULATION RESULTS

4.1. Camera Fill Factor

As it was already mentioned, camera fill factor determines the degree of low pass filtering of images acquired by the camera. Fig. 5 illustrates results of generating super-resolved images from sequences of turbulence distorted low-resolution images acquired with cameras with fill-factors 0.05, 0.5 and 0.95. In all cases, the number of low-resolution frames used was 30, the standard deviation of the motion vector length was 0.5 pixels and 50 iterations were used for re-interpolation. It can clearly be seen from the figure, that cameras with small fill factor produce better results. Spectra of the corresponding images shown in Figs. 5, d) through f), also demonstrate that images acquired with larger fill factor have less high frequencies.

4.2. Turbulence intensity

Results of studying influence of turbulence intensity on the efficiency of image resolution recovery through the super-resolution process are illustrated in Figs. 6 and 7. Super-resolved images shown in Fig. 6 were obtained from 30 low resolution frames, the camera fill factor was 0.05 and 100 iterations were used in the interpolation. One can see from these images that turbulence with standard deviation of motion vector lengths of about 0.5 inter-pixel distance creates a sort of optimal conditions for image resolution recovery.



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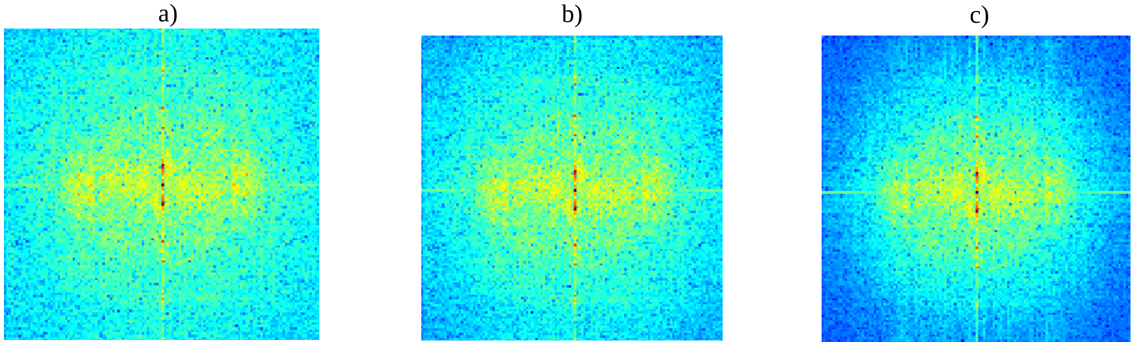
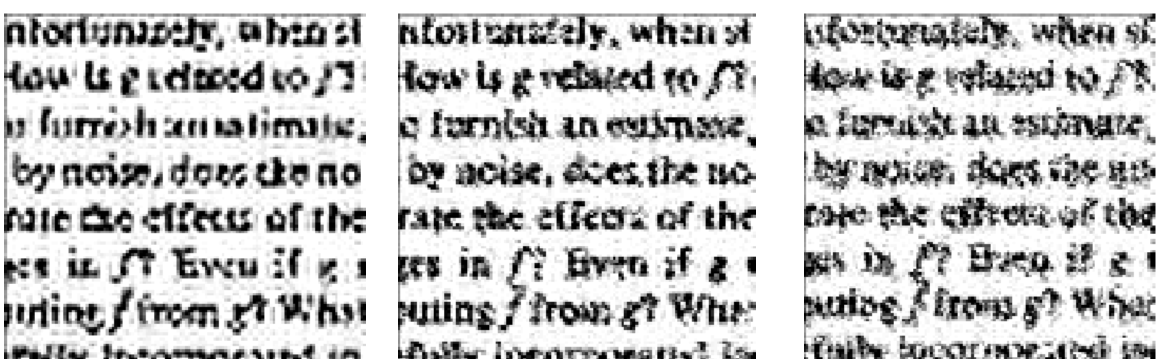


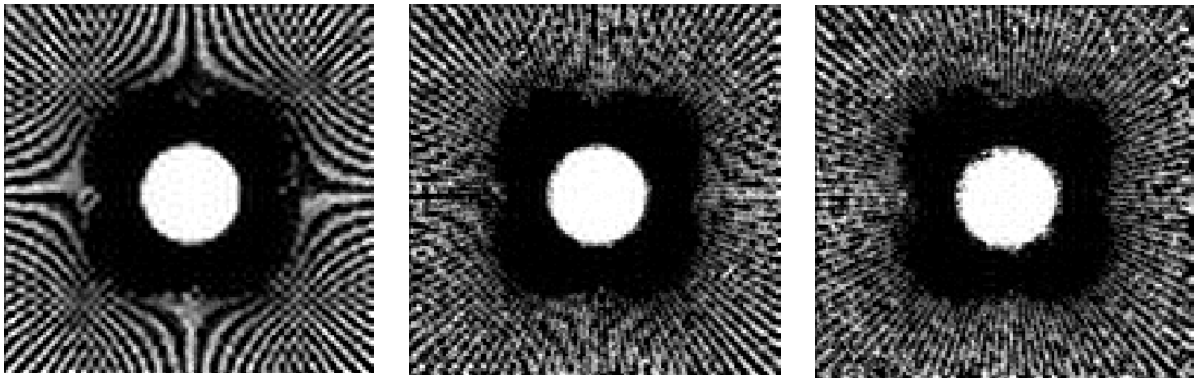
d) e) f)

Figure 5– Super-resolved images obtained from low resolution images acquired by cameras with different fill factors: a) - fill factor 0.05; b) - fill factor 0.5; c) - fill factor 0.95. Figures d)-f) show corresponding image spectra intensities displayed in pseudo colors.



a) b) c)

Figure 6 – Super-resolution results obtained from low resolution images distorted by atmospheric turbulence with different intensity: (a) standard deviation (STD) of motion vector length 0.1 of inter-pixel distance; (b) STD 0.4 of inter-pixel distance; (c) STD of 0.8 of inter-pixel distance.

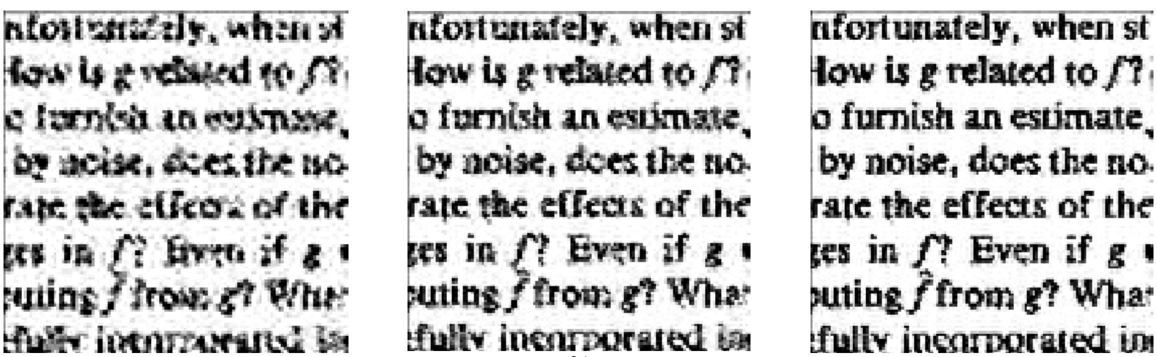


a) b) c)

Figure **7**. Super-resolution results obtained from low resolution images distorted by atmospheric turbulence with different intensity: d) standard deviation (STD) of motion vector length 0.1 of inter-pixel distance; e) STD 0.45 of inter-pixel distance; f) STD 0.9 of inter-pixel distance.

4.3. The number of processed frames

Obviously, the number of processed low-resolution frames directly affects the super-resolution performance as more frames provide more additional samples to form denser sample grid. The question is how many frames are needed to enable resolution improvement for a given turbulence intensity? Ideally, to obtain two times higher resolution one needs to supply 3 additional samples for each initial low resolution sample which means 3 additional frames for each low resolution frame. Our simulation, however, has shown that in reality the number of additional frames must be much larger. This finding is illustrated in Figs. 8 and 9 for two test images. In these experiments, camera fill factor was 0.05, standard deviation of motion vector length was 0.5 and 50 interpolation iterations were used.

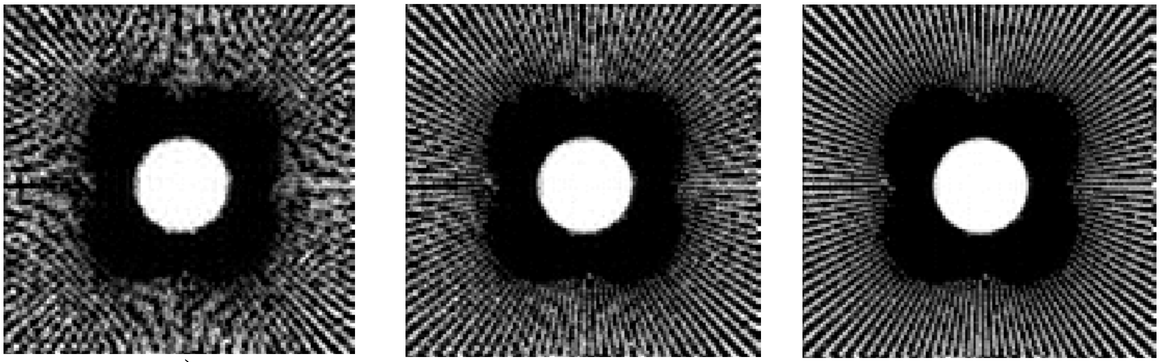


a) b) c)

Figure 8, a) – c). Results of image resolution recovery from 5, 15, and 30 low resolution turbulent images, correspondingly

4.4. The number of iterations in the process of re-interpolation

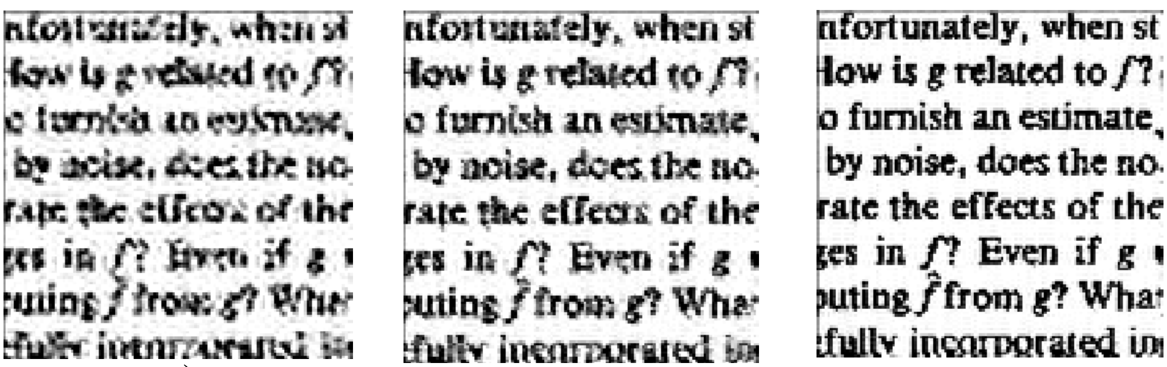
Image re-interpolation is the final stage of the super-resolution process aimed at recovery of those samples in the dense sampling grid that were not obtained from the accumulated low resolution frames. As it was mentioned, it is implemented through an iterative interpolation algorithm, which converges to the best band limited approximation of



a) b) c)

Figure 9, a) – c). Results of image resolution recovery from 5, 15, and 30 low-resolution turbulent images, correspondingly

the image. Figs. 10 a) – c) show how the number of iterations influences the quality of final super-resolved image. In this experiment, camera fill factor was 0.05, standard deviation of vector motion lengths was 0.5 of inter-pixel distances and 30 low resolution frames were used. Fig. 11 illustrates the iteration process. It shows a typical dependence of the energy of the difference between subsequent images in course of iterations from the number of interpolation iterations. From these figures one can see that the number of iterations is a quite critical parameter of the restoration process and that, to achieve a good restoration quality, one needs to use about 100 iterations.



a) b) c)

Figure 10– a)-c) SR image with 5, 20 and 100 iterations, respectively.

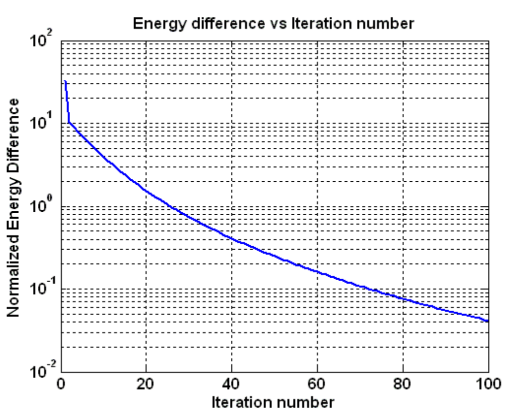


Figure 11. Energy of the difference between subsequent images in course of iterations as a function of the number of interpolation iterations

5. CONCLUSION

A computer model for studying the performance of the algorithm for generating super-resolved images from sequences of low resolution images distorted by the atmospheric turbulence and obtained results of the study are described. The study has shown that

- Image local instabilities in video sequences distorted by atmospheric turbulence can be compensated and utilized for increasing image resolution beyond the limits defined by the camera sampling rate.
- Camera fill factor limits potential image resolution enhancement that can be achieved by means of fusion several low-resolution images. Cameras with smaller fill factor are better suited for the super resolution process. In this respect, color cameras with separate RGB sensors are most promising.
- Most suitable for super resolution are turbulent videos in which standard deviation of pixel displacement due to turbulence is of the order of 0.5 of the inter-pixels distance.
- Several tens of image frames with low inter-frame correlations of pixel displacements are required to achieve substantial resolution enhancement.
- Good re-interpolation of images fused from a set of low-resolution turbulent images is essential for achieving good quality of the resolution enhancement.

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