From the result, all proposed robust estimators gives the better result for SRR estimating than classical L1 and L2 estimator. The proposed robust estimators result demonstrated the higher resistance to the registration error and noise.

5.3.1.3 Poisson Noise

The original HR image is shown in Fig. 5.9 (g-1) and one of corrupted LR images is shown in Fig. 5.9 (g-2). Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator result have higher PSNR than L1 and L2 estimator result. The result of implementing the SRR algorithm using L1 estimator, L2 estimator, Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator are shown in Figs. 5.9 (g-3) - 5.9 (g-8) respectively.

From the result, all proposed robust estimators gives the better SRR result than L1 and L2 estimators because all proposed robust estimators are more resistant to the registration error and noise error.

5.3.1.4 Salt&Pepper Noise

This experiment is a 3 Salt&Pepper Noise cases at D=0.005, D=0.010 and D=0.015 respectively and the original HR images are shown in Fig. 5.9 (h-1) – Fig. 5.9 (j-1) respectively. The corrupted images at D=0.005, D=0.010 and D=0.015 are showed in Fig. 5.9 (h-2), Fig. 5.9 (i-2) and Fig. 5.9 (j-2) respectively. The results of Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator have higher PSNR than these of L1 and L2 estimator. At D=0.005, D=0.010 and D=0.015, the result of implementing the SRR algorithm using L1 estimator, L2 estimator, Huber estimator, Lorentzian estimator and Tukey estimator are shown in Figs. 5.9 (h-3) - 5.9 (h-8), Figs. 5.9 (i-3) - 5.9 (i-8) and Figs 5.9 (j-4) - 5.9 (j-8) respectively.

From the result, all proposed robust estimators give the better result for SRR estimating than L1 and L2 estimator because all proposed robust estimators are more resistant to the registration error and noise error.

5.3.1.5 Speckle Noise

The last experiment is a 3 Speckle Noise cases for 40th frame Susie sequence at V=0.02 and V=0.03 respectively and the original HR images are shown in Figs. 5.9 (k-1) – 5.9 (l-1) respectively. The corrupted images at V=0.02 and V=0.03 are showed in Fig. 5.9 (k-2) and Fig. 5.9 (l-2) respectively. The Hampel, Andrew's Sine, Geman&McClure and Leclerc give higher PSNR than L1 and L2 estimator results. At V=0.02 and V=0.03, the result of implementing the SRR algorithm using L1 estimator, L2 estimator, Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator are shown in Figs. 5.9 (k-3) - 5.9 (k-8) and Figs. 5.9 (l-3) - 5.9 (l-8) respectively.

From the result, all proposed robust estimators give the better SRR result than L1 and L2 estimator because all proposed robust estimators are more resistance to the registration error. Moreover, L2 estimator can not enhancement the image corrupted by Speckle noise because the L2 norm is very sensitive to outliers (registration error) where the influence function increases linearly and without bound.

Figure 5.9 : The experimental result of the SRR algorithm using proposed robust estimation technique with proposed registration (Susie Sequence: The 40th Frame)

Figure 5.9 : The experimental result of the SRR algorithm using proposed robust estimation technique with proposed registration (Susie Sequence: The 40th Frame) (Con.)

(i-2) Corrupted LR Image (S&P:D=0.010) (PSNR=27.3206dB)
(i-3) L1 SRR Image with Lap Reg. (PSNR=28.7302dB) $(\beta = 1, \lambda = 1)$
(i-4) L2 SRR Image with Lap Reg. (PSNR=27.8977dB) $(\beta = 0.5, \lambda = 1)$
(i-5) Hampel SRR Image with Lap Reg. (PSNR=29.2558dB) $(\beta = 0.5, \lambda = 1, T = 1)$
(i-6) AS. SRR Image with Lap Reg. (PSNR=29.2559dB) $(\beta = 0.5, \lambda = 0.75, T = 1)$
(i-7) G&M SRR Image with Lap Reg. (PSNR=29.2570dB) $(\beta = 0.5, \lambda = 0.5, T = 1)$
(i-8) Lec. SRR Image with Lap Reg. (PSNR=29.2627dB) $(\beta = 0.5, \lambda = 0.5, T = 1)$

(j-2) Corrupted LR Image (S&P:D=0.015) (PSNR=25.5210dB)
(j-3) L1 SRR Image with Lap Reg. (PSNR=27.5187dB) $(\beta = 1, \lambda = 1)$
(j-4) L2 SRR Image with Lap Reg. (PSNR=26.2784dB) $(\beta = 0.5, \lambda = 0.75)$
(j-5) Hampel SRR Image with Lap Reg. (PSNR=28.5041dB) $(\beta = 0.5, \lambda = 1, T = 1)$
(j-6) AS. SRR Image with Lap Reg. (PSNR=28.5054dB) $(\beta = 0.5, \lambda = 1, T = 1)$
(j-7) G&M SRR Image with Lap Reg. (PSNR=28.5107dB) $(\beta = 0.5, \lambda = 0.75, T = 1)$
(j-8) Lec. SRR Image with Lap Reg. (PSNR=28.5065dB) $(\beta = 0.5, \lambda = 0.75, T = 1)$

(k-2) Corrupted LR Image (Speckle:V=0.02) (PSNR=25.2720dB)
(k-3) L1 SRR Image with Lap Reg. (PSNR=27.7187dB) $(\beta = 0.5, \lambda = 1)$
(k-4) L2 SRR Image with Lap Reg. (PSNR=26.6633dB) $(\beta = 0.5, \lambda = 1)$
(k-5) Hampel SRR Image with Lap Reg. (PSNR=28.3637dB) $(\beta = 0.5, \lambda = 1, T = 1)$
(k-6) AS. SRR Image with Lap Reg. (PSNR=28.3635dB) $(\beta = 0.5, \lambda = 1, T = 1)$
(k-7) G&M SRR Image with Lap Reg. (PSNR=28.3684dB) $(\beta = 0.5, \lambda = 0.75, T = 1)$
(k-8) Lec. SRR Image with Lap Reg. (PSNR=28.3642dB) $(\beta = 0.5, \lambda = 0.75, T = 1)$

(l-2) Corrupted LR Image (Speckle:V=0.03) (PSNR=23.9860dB)
(l-3) L1 SRR Image with Lap Reg. (PSNR=27.0925dB) $(\beta = 0.5, \lambda = 1)$
(l-4) L2 SRR Image with Lap Reg. (PSNR=25.5199dB) $(\beta = 0.5, \lambda = 1)$
(l-5) Hampel SRR Image with Lap Reg. (PSNR=28.3637dB) $(\beta = 0.5, \lambda = 1, T = 1)$
(l-6) AS. SRR Image with Lap Reg. (PSNR=28.3635dB) $(\beta = 0.5, \lambda = 1, T = 1)$
(l-7) G&M SRR Image with Lap Reg. (PSNR=28.3684dB) $(\beta = 0.5, \lambda = 0.75, T = 1)$
(l-8) Lec. SRR Image with Lap Reg. (PSNR=28.3642dB) $(\beta = 0.5, \lambda = 0.75, T = 1)$

Figure 5.9 : The experimental result of the SRR algorithm using proposed robust estimation technique with proposed registration (Susie Sequence: The 40th Frame) (Con.)

5.2.2 Experimental Result of Foreman Sequence (The 110th Frame)

5.2.2.1 Noiseless

The original HR image is shown in Fig. 5.10 (a-1) and one of corrupted LR images is shown in Fig. 5.10 (a-2). Next, the result of implementing the SRR algorithm using L1 estimator, L2 estimator, Hampel, Andrew's Sine, Geman&McClure and Leclerc Norm are shown in Figs. 5.10 (a-3) - 5.10 (a-8) respectively. From the results, Huber estimator can reconstruct the noiseless image slightly better than L1 and L2 estimator respectively.

5.2.2.2 AWGN (Additive White Gaussian Noise)

This experiment is a 5 AWGN cases at SNR=25, 22.5, 20, 17.5 and 15dB respectively and the original HR images are shown in Fig. 5.10 (b-1) - Fig. 5.10 (f-1) respectively. The corrupted images at SNR=25, 22.5, 20, 17.5 and 15dB are showed in Fig. 5.10 (b-2) - Fig. 5.10 (f-2) respectively. From the experimental results, the Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator result gives higher PSNR than L1 and L2 estimator result. At SNR=25, 22.5, 20, 17.5 and 15dB, the result of implementing the SRR algorithm using L1 estimator, L2 estimator, Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator are shown in Figs. 5.10 (b-3) - 5.10 (b-8), 5.10 (c-3) - 5.10 (c-8), 5.10 (d-3) - 5.10 (d-8), 5.10 (e-3) - 5.10 (e-8) and Figs. 5.10 (f-3) - 5.10 (f-8) respectively.

From the result, all proposed robust estimators gives the better result for SRR estimating than classical L1 and L2 estimator. The proposed robust estimators result demonstrated the higher resistance to the registration error and noise.

5.2.2.3 Poisson Noise

The original HR image is shown in Fig. 5.10 (g-1) and one of corrupted LR images is shown in Fig. 5.10 (g-2). Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator result have higher PSNR than L1 and L2 estimator result. The result of implementing the SRR algorithm using L1 estimator, L2 estimator, Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator are shown in Figs. 5.10 (g-3) - 5.10 (g-8) respectively.

From the result, all proposed robust estimators gives the better SRR result than L1 and L2 estimators because all proposed robust estimators are more resistant to the registration error and noise error.

5.2.2.4 Salt&Pepper Noise

This experiment is a 3 Salt&Pepper Noise cases at D=0.005, D=0.010 and D=0.015 respectively and the original HR images are shown in Fig. 5.10 (h-1) – Fig. 5.10 (j-1) respectively. The corrupted images at D=0.005, D=0.010 and D=0.015 are showed in Fig. 5.10 (h-2), Fig. 5.10 (i-2) and Fig. 5.10 (j-2) respectively. The results of Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator have higher PSNR than these of L1 and L2 estimator. At D=0.005, D=0.010 and D=0.015, the result of implementing the SRR algorithm using L1 estimator, L2 estimator, Huber estimator, Lorentzian estimator and Tukey estimator are shown in Figs. 5.10 (h-3) - 5.10 (h-8), Figs. 5.10 (i-3) - 5.10 (i-8) and Figs 5.10 (j-4) - 5.10 (j-8) respectively.

From the result, all proposed robust estimators give the better result for SRR estimating than L1 and L2 estimator because all proposed robust estimators are more resistant to the registration error and noise error.

5.2.2.5 Speckle Noise

The last experiment is a 3 Speckle Noise cases for 40th frame Susie sequence at V=0.01, V=0.02 and V=0.03 respectively and the original HR images are shown in Figs. 5.10 (k-1) – 5.10 (m-1) respectively. The corrupted images at V=0.01, V=0.02 and V=0.03 are showed in Fig. 5.10 (k-2), Fig. 5.10 (l-2) and Fig. 5.10 (m-2) respectively. The Hampel, Andrew's Sine, Geman&McClure and Leclerc give higher PSNR than L1 and L2 estimator results. At V=0.01, V=0.02 and V=0.03, the result of implementing the SRR algorithm using L1 estimator, L2 estimator, Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator are shown in Figs. 5.10 (k-3) - 5.10 (k-8), Figs. 5.10 (l-3) - 5.10 (l-8) and Figs. 5.10 (m-3) - 5.10 (m-8) respectively.

From the result, all proposed robust estimators give the better SRR result than L1 and L2 estimator because all proposed robust estimators are more resistance to the registration error. Moreover, L2 estimator can not enhancement the image corrupted by Speckle noise because the L2 norm is very sensitive to outliers (registration error) where the influence function increases linearly and without bound.

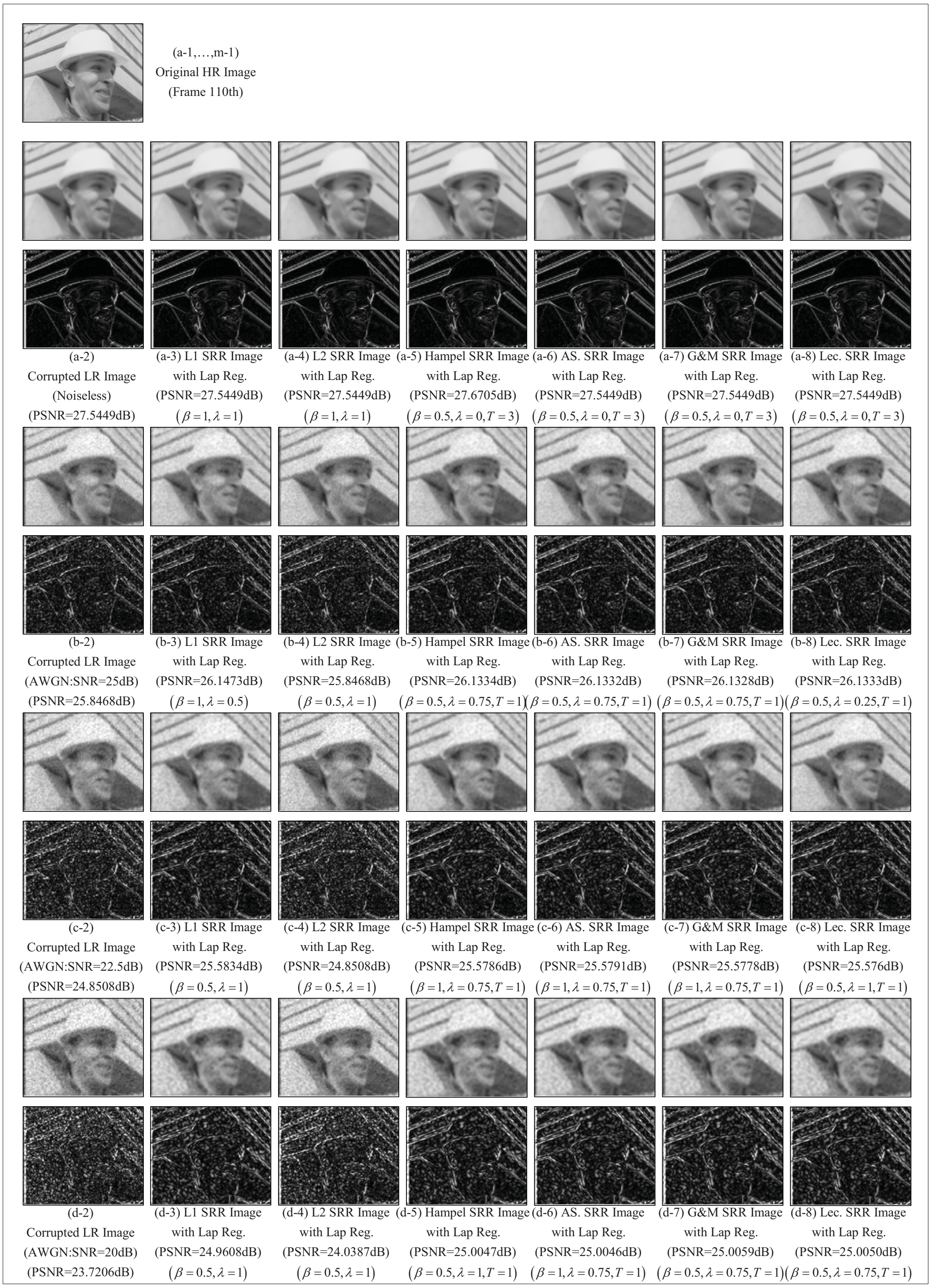
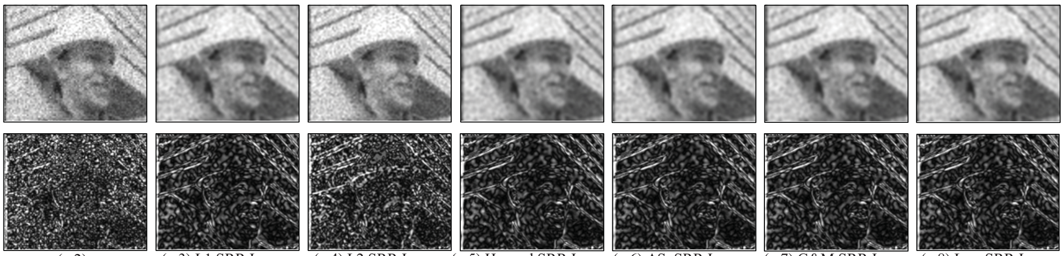
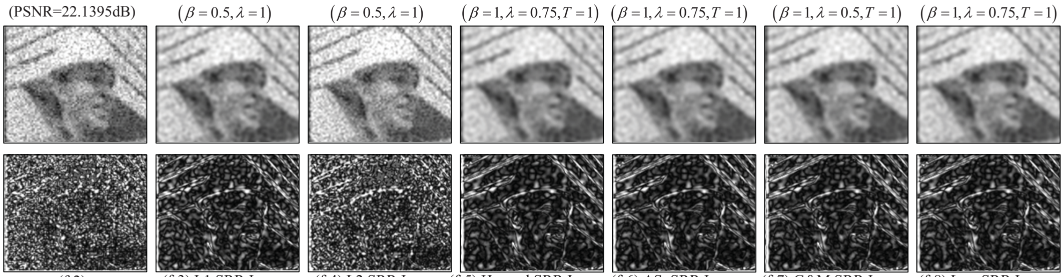


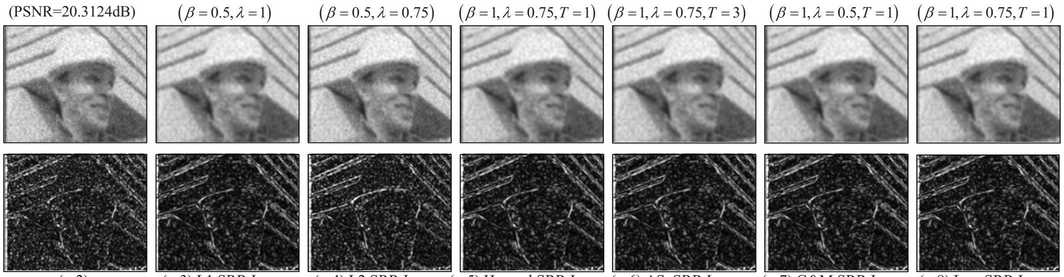
Figure 5.10 : The experimental result of the SRR algorithm using proposed robust estimation technique with classical registration (Foreman Sequence: The 110th Frame)



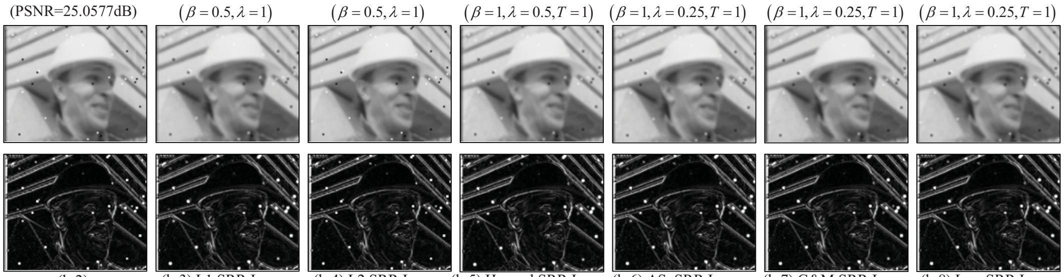
(e-2) Corrupted LR Image (AWGN:SNR=17.5dB) (PSNR=22.1395dB)	(e-3) L1 SRR Image with Lap Reg. (PSNR=24.0890dB) $(\beta=0.5,\lambda=1)$	(e-4) L2 SRR Image with Lap Reg. (PSNR=22.8283dB) $(\beta=0.5,\lambda=1)$	(e-5) Hampel SRR Image with Lap Reg. (PSNR=24.2526dB) $(\beta=1,\lambda=0.75,T=1)$	(e-6) AS. SRR Image with Lap Reg. (PSNR=24.2528dB) $(\beta=1,\lambda=0.75,T=1)$	(e-7) G&M SRR Image with Lap Reg. (PSNR=24.2511dB) $(\beta=1,\lambda=0.5,T=1)$	(e-8) Lec. SRR Image with Lap Reg. (PSNR=24.2479dB) $(\beta=1,\lambda=0.75,T=1)$



(f-2) Corrupted LR Image (AWGN:SNR=15dB) (PSNR=20.3124dB)	(f-3) L1 SRR Image with Lap Reg. (PSNR=23.1151dB) $(\beta=0.5,\lambda=1)$	(f-4) L2 SRR Image with Lap Reg. (PSNR=21.1894dB) $(\beta=0.5,\lambda=0.75)$	(f-5) Hampel SRR Image with Lap Reg. (PSNR=23.4756dB) $(\beta=1,\lambda=0.75,T=1)$	(f-6) AS. SRR Image with Lap Reg. (PSNR=23.4754dB) $(\beta=1,\lambda=0.75,T=3)$	(f-7) G&M SRR Image with Lap Reg. (PSNR=23.4709dB) $(\beta=1,\lambda=0.5,T=1)$	(f-8) Lec. SRR Image with Lap Reg. (PSNR=23.4693dB) $(\beta=1,\lambda=0.75,T=1)$

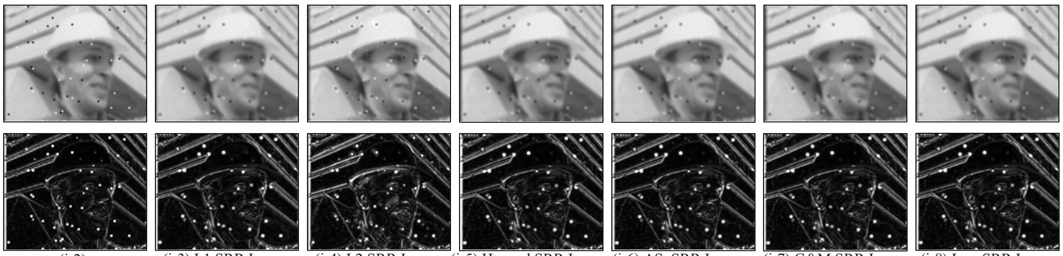


(g-2) Corrupted LR Image (Poisson) (PSNR=25.0577dB)	(g-3) L1 SRR Image with Lap Reg. (PSNR=25.7916dB) $(\beta=0.5,\lambda=1)$	(g-4) L2 SRR Image with Lap Reg. (PSNR=25.1040dB) $(\beta=0.5,\lambda=1)$	(g-5) Hampel SRR Image with Lap Reg. (PSNR=25.7721dB) $(\beta=1,\lambda=0.5,T=1)$	(g-6) AS. SRR Image with Lap Reg. (PSNR=25.7731dB) $(\beta=1,\lambda=0.25,T=1)$	(g-7) G&M SRR Image with Lap Reg. (PSNR=25.7708dB) $(\beta=1,\lambda=0.25,T=1)$	(g-8) Lec. SRR Image with Lap Reg. (PSNR=25.7687dB) $(\beta=1,\lambda=0.25,T=1)$

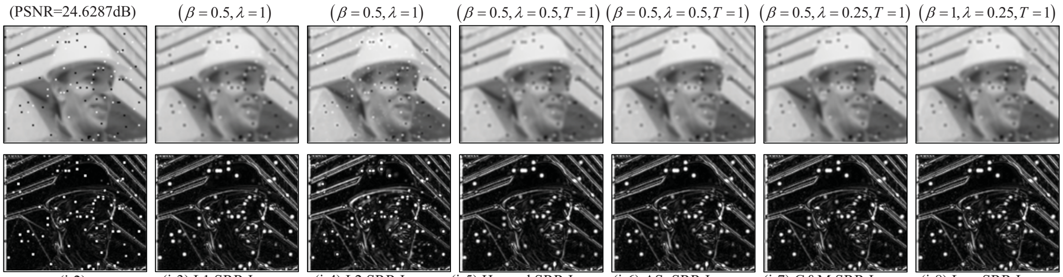


(h-2) Corrupted LR Image (S&P:D=0.005) (PSNR=25.5815dB)	(h-3) L1 SRR Image with Lap Reg. (PSNR=25.9735dB) $(\beta=1,\lambda=0.75)$	(h-4) L2 SRR Image with Lap Reg. (PSNR=25.5815dB) $(\beta=0.5,\lambda=1)$	(h-5) Hampel SRR Image with Lap Reg. (PSNR=25.9684dB) $(\beta=1,\lambda=0.25,T=1)$	(h-6) AS. SRR Image with Lap Reg. (PSNR=25.9680dB) $(\beta=1,\lambda=0.25,T=1)$	(h-7) G&M SRR Image with Lap Reg. (PSNR=25.9606dB) $(\beta=0.5,\lambda=0.25,T=1)$	(h-8) Lec. SRR Image with Lap Reg. (PSNR=25.9607dB) $(\beta=1,\lambda=0.25,T=1)$

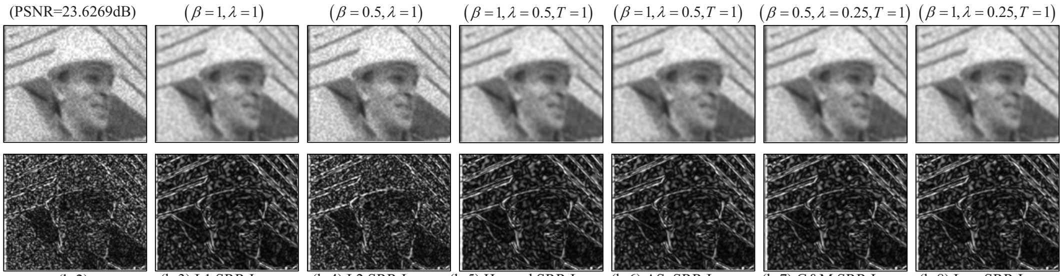
Figure 5.10 : The experimental result of the SRR algorithm using proposed robust estimation technique with classical registration (Foreman Sequence: The 110th Frame) (Con.)



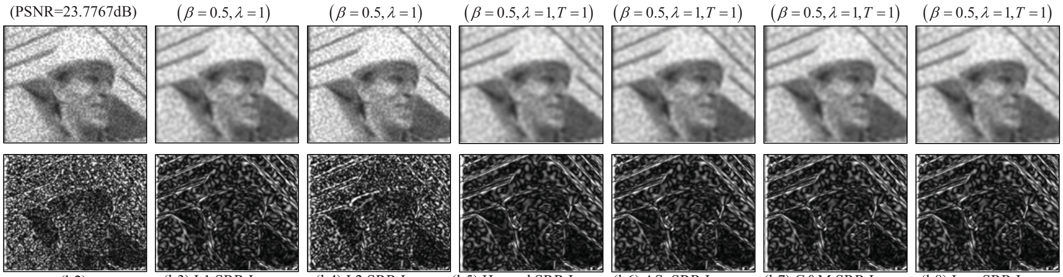
(i-2)	(i-3) L1 SRR Image	(i-4) L2 SRR Image	(i-5) Hampel SRR Image	(i-6) AS. SRR Image	(i-7) G&M SRR Image	(i-8) Lec. SRR Image
Corrupted LR Image	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.
(S&P:D=0.010)	(PSNR=25.3920dB)	(PSNR=24.8303dB)	(PSNR=25.4357dB)	(PSNR=25.4367dB)	(PSNR=25.4344dB)	(PSNR=25.4315dB)
(PSNR=24.6287dB)	$(\beta=0.5,\lambda=1)$	$(\beta=0.5,\lambda=1)$	$(\beta=0.5,\lambda=0.5,T=1)$	$(\beta=0.5,\lambda=0.5,T=1)$	$(\beta=0.5,\lambda=0.25,T=1)$	$(\beta=1,\lambda=0.25,T=1)$



(j-2)	(j-3) L1 SRR Image	(j-4) L2 SRR Image	(j-5) Hampel SRR Image	(j-6) AS. SRR Image	(j-7) G&M SRR Image	(j-8) Lec. SRR Image
Corrupted LR Image	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.
(S&P:D=0.015)	(PSNR=24.8592dB)	(PSNR=24.2964dB)	(PSNR=25.0201dB)	(PSNR=25.0199dB)	(PSNR=25.0202dB)	(PSNR=25.0170dB)
(PSNR=23.6269dB)	$(\beta=1,\lambda=1)$	$(\beta=0.5,\lambda=1)$	$(\beta=1,\lambda=0.5,T=1)$	$(\beta=1,\lambda=0.5,T=1)$	$(\beta=0.5,\lambda=0.25,T=1)$	$(\beta=1,\lambda=0.25,T=1)$

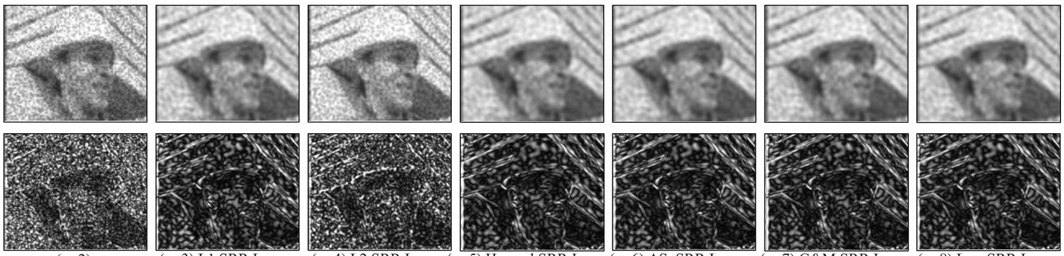


(k-2)	(k-3) L1 SRR Image	(k-4) L2 SRR Image	(k-5) Hampel SRR Image	(k-6) AS. SRR Image	(k-7) G&M SRR Image	(k-8) Lec. SRR Image
Corrupted LR Image	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.
(Speckle:V=0.01)	(PSNR=25.0185dB)	(PSNR=24.1172dB)	(PSNR=25.0509dB)	(PSNR=25.0505dB)	(PSNR=25.0538dB)	(PSNR=25.0537dB)
(PSNR=23.7767dB)	$(\beta=0.5,\lambda=1)$	$(\beta=0.5,\lambda=1)$	$(\beta=0.5,\lambda=1,T=1)$	$(\beta=0.5,\lambda=1,T=1)$	$(\beta=0.5,\lambda=1,T=1)$	$(\beta=0.5,\lambda=1,T=1)$



(l-2)	(l-3) L1 SRR Image	(l-4) L2 SRR Image	(l-5) Hampel SRR Image	(l-6) AS. SRR Image	(l-7) G&M SRR Image	(l-8) Lec. SRR Image
Corrupted LR Image	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.	with Lap Reg.
(Speckle:V=0.02)	(PSNR=24.0958dB)	(PSNR=22.7284dB)	(PSNR=24.2254dB)	(PSNR=24.2250dB)	(PSNR=24.2254dB)	(PSNR=24.2258dB)
(PSNR=21.8538dB)	$(\beta=0.5,\lambda=1)$	$(\beta=0.5,\lambda=1)$	$(\beta=1,\lambda=0.5,T=1)$	$(\beta=1,\lambda=0.5,T=1)$	$(\beta=1,\lambda=0.25,T=1)$	$(\beta=1,\lambda=0.25,T=1)$

Figure 5.10 : The experimental result of the SRR algorithm using proposed robust estimation technique with classical registration (Foreman Sequence: The 110th Frame) (Con.)



(m-2) Corrupted LR Image (Speckle:V=0.03) (PSNR=20.5570dB)

(m-3) L1 SRR Image with Lap Reg. (PSNR=23.3854dB) $(\beta = 0.5, \lambda = 1)$

(m-4) L2 SRR Image with Lap Reg. (PSNR=21.7708dB) $(\beta = 0.5, \lambda = 1)$

(m-5) Hampel SRR Image with Lap Reg. (PSNR=23.6247dB) $(\beta = 1, \lambda = 0.75, T = 1)$

(m-6) AS. SRR Image with Lap Reg. (PSNR=23.6246dB) $(\beta = 1, \lambda = 0.75, T = 1)$

(m-7) G&M SRR Image with Lap Reg. (PSNR=23.6239dB) $(\beta = 1, \lambda = 0.25, T = 1)$

(m-8) Lec. SRR Image with Lap Reg. (PSNR=23.6223dB) $(\beta = 1, \lambda = 0.75, T = 1)$

Figure 5.10 : The experimental result of the SRR algorithm using proposed robust estimation technique with classical registration (Foreman Sequence: The 110th Frame) (Con.)

6. CONCLUSIONS

6.1 Conclusion

This paper presents four robust norm estimators for the SRR framework and presents four robust regularized functions. Several images and noise models were tested for their effectiveness. The performance was analyzed both in terms of the PSNR and visually appealing results.

This paper propose an novel approach using a novel robust estimation norm function (Hampel, Andrew's Sine, Geman&McClure and Leclerc) for SRR and the proposed robust SRR can be effectively applied on the images that are corrupted by various noise models. Therefore, this experiment is examined how the estimation techniques impact to the SRR performance by ignoring the registration error. (All corrupted low resolution images are synthesized from the same original high resolution image.) From the experimental result, the SRR algorithm using Hampel, Andrew's Sine, Geman&McClure and Leclerc norm gives the highest PSRN especially for high power noise. For Salt&Pepper Noise cases, the Hampel, Andrew's Sine, Geman&McClure and Leclerc estimator give the far better reconstruction than L1 and L2 estimator because these robust estimators are designed to be robust and reject outliers. The norms are more forgiving on outliers; that is, they should increase less rapidly than L2. Next, Finally, The SRR algorithm using L1 norm gives the lowest PSRN because the L1 norm is excessively robust against the outliers.

Later, this paper examines the performance of the SRR algorithm using proposed estimation norms (Hampel, Andrew's Sine, Geman&McClure and Leclerc norm function) when the SRR algorithm is used for the real image sequence. The 38^{th}- 42^{nd} frame Susie sequence and the 108^{th}- 112^{th} frame Foreman sequence are used in these experiments to generate the super-resolution image. Hence, the SRR algorithm for this experiment is used the COM (Classical Observation Model or translational block-based). From the experimental result, the SRR algorithm using Hampel, Andrew's Sine, Geman&McClure and Leclerc norm with the classical registration gives the highest PSRN because these robust estimators are designed to be robust and reject outliers (registration error). The norms are more forgiving on outliers; that is, they should increase less rapidly than L1 and L2. Next, The SRR algorithm using L1 norm gives the higher PSRN than the SRR algorithm using L2 norm because L2 norm is more sensitive the outliers such as the registration error (and the L2 influence function increases linearly and without bound) than L1 norm. Finally, L2 estimator fails to enhance the image in the inaccurate registration because the L2 norm is very sensitive to outliers (registration error) where the influence function increases linearly and without bound.

Finally, this paper examines the performance of the SRR algorithm using proposed estimation norms (Hampel, Andrew's Sine, Geman&McClure and Leclerc norm function) with proposed registration (GOM) when the SRR algorithm is used for the real image sequence. The 38^{th}- 42^{nd} frame Susie sequence and the 108^{th}- 112^{th} frame Foreman sequence are used in these experiments to generate the super-resolution image. Hence, the SRR algorithm for this experiment is used the GOM (General Observation Model or fast affine block-based). From the experimental result, the SRR algorithm using Hampel, Andrew's Sine, Geman&McClure and Leclerc norm with the proposed registration gives the highest PSRN because these robust estimators are designed to be robust and reject outliers (registration error).

6.2 Future Research on SRR algorithms

The high accuracy and fast registration must be developed to incorporate with SRR framework to cope with the real sequence or standard sequence.

Several parameters (such as Regularized Parameter, step size, norm constant parameter) are still manually specified. The optimal values are found by experiments for most visually appealing results with highest PSNR. Automatic parameter specification is necessary for the practical SRR algorithms in the future research.

6.3 Lists of Publication (from this research project) (29 papers)

6.3.1 Research Articles (International Journal and Transactions)

1. **Vorapoj Patanavijit**, Supatana Auethavekiat and Somchai Jitapunkul, Video Enhancement Based on A Robust Hampel Iterative SRR with A General Observation Model, ECTI Transactions on EEC (Electrical Engineering/Electronics and Communications), ECTI Association, Thailand, Aug. 2011, pp. 223-235. (Indexed by CHE (Commission on Higher Education) of Thailand and Indexed by TRF (Thai Research Fund))
2. **Vorapoj Patanavijit**, A Robust Iterative Multiframe Super-Resolution Reconstruction based on Hampel Stochastic Estimation with Hampel-Tikhonov Regularization, Pattern Recognition ISBN 978-953-307-014-8, IN-TECH, Kirchengasse 43/3, A-1070 Vienna, Austria, Oct. 2009 pp. 99-113. (intechweb.org).

6.3.2 Research Articles (International Proceeding and Conference)

1. Pham Hong Ha, Wilaiporn Lee and **Vorapoj Patanavijit**, The Novel Frequency Domain Tikhonov Regularization for an Image Reconstruction Based on Compressive Sensing with SL0 Algorithm, Proceeding of The Ninth Annual International Conference of Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON 2012), ECTI Association Thailand, Hua Hin, Thailand, May 2012. (IEEE Xplore) (Accepted)
2. **Vorapoj Patanavijit**, A Nonlinear Myriad Filter For A Recursive Video Enhancement Using a Robust SRR Based On Stochastic Regularization, Proceeding of IEEE International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS 2011), ISBN: 978-1-4577-2164-9, Chiang Mai, Thailand, Dec. 2011. (IEEE Xplore)
3. Kornkamol Thakulsukanant and **Vorapoj Patanavijit**, A Performance Comparison Of Single Image Reconstruction Techniques Under Several Noisy Environments, The 7th International Conference on Signal Image Technology & Internet Based Systems (SITIS 2011), ISBN 978-0-7695-4635-3, Dijon, France, Nov 2011. (IEEE Xplore)
4. **Vorapoj Patanavijit**, A Recursive Resolution-Enhancement using Multiframe SRR based on Meridian Filter with Meridian-Tikhonov Regularization, Proceeding of The Eighth Annual International Conference of Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON 2011), ECTI Association Thailand, Khon Kaen, Thailand, May 2011. (IEEE Xplore)
5. **Vorapoj Patanavijit**, A Leclerc Bayesian Approach for Video Reconstruction Based on A Robust Iterative SRR and A General Observation Model, Proceeding of IEEE International Symposium on Communications and Information Technologies 2010 (ISCIT 2010), Tokyo, Japan, Oct. 2010. (IEEE Xplore)
6. **Vorapoj Patanavijit**, Video Enhancement Using A Robust Iterative SRR Based On A Geman&McClure Stochastic Estimation With A General Observation Model, Proceeding of The Seventh Annual International Conference of Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON 2010), ECTI Association Thailand, Chiang Mai, Thailand, May 2010. (IEEE Xplore)
7. Pham Hong Ha and **Vorapoj Patanavijit**, Performance Evaluation of L1, L2 and SL0 on Compressive Sensing based on Stochastic Estimation Technique, Proceeding of The Seventh Annual International Conference of Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON 2010), ECTI Association Thailand, Chiang Mai, Thailand, May 2010. (IEEE Xplore)
8. **Vorapoj Patanavijit**, Video Enhancement Using A Robust Iterative SRR Based On Andrew's Sine Regularization Technique, Proceeding of IEEE International Symposium

on Intelligent Signal Processing and Communication Systems (ISPACS 2009), Kanazawa, Japan, Dec. 2009. (IEEE Xplore)

9. **Vorapoj Patanavijit**, Video Enhancement Using A Robust Iterative SRR Based On Leclerc Stochastic Estimation, Proceeding of IEEE International Symposium on Communications and Information Technologies 2009 (ISCIT 2009), Incheon, Korea, pp. 370–375, Sep. 2009. (IEEE Xplore)
10. **Vorapoj Patanavijit**, Video Enhancement Using A Robust Iterative SRR Based On A Geman&McClure Stochastic Estimation, Proceeding of IEEE International Conference on Signal Processing System (ICSPS 2009), Singapore, pp. 330–333, May 2009. (IEEE Xplore)
11. **Vorapoj Patanavijit**, Video Enhancement Using A Robust Iterative SRR Based On A Hampel Stochastic Estimation, Proceeding of The Sixth Annual International Conference of Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON 2009), ECTI Association Thailand, Pattaya, Thailand, May 2009. (IEEE Xplore)
12. **Vorapoj Patanavijit**, A Robust Iterative Multiframe SRR based on Andrew's Sine Stochastic Estimation with Andrew's Sine-Tikhonov Regularization, Proceeding of IEEE International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS 2008), Bangkok, Thailand, Feb. 2009. (IEEE Xplore)
13. **Vorapoj Patanavijit** and Somchai Jitapunkul, General Observation Model for an Iterative Multiframe Regularized Super-Resolution Reconstruction for Video Enhancement, Proceeding of IEEE International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS 2008), Bangkok, Thailand, Feb. 2009. (IEEE Xplore)
14. **Vorapoj Patanavijit**, Geman&McClure Stochastic Estimation for a Robust Iterative Multiframe SRR with Geman&McClure-Tikhonov Regularization, Proceeding of IEEE International Conference on Computer and Electrical Engineering (ICCEE 2008), Phuket Island, Thailand, pp. 502–506, Dec. 2008. (IEEE Xplore)
15. **Vorapoj Patanavijit**, A Robust Iterative Multiframe SRR based on Hampel Stochastic Estimation with Hampel-Tikhonov Regularization, Proceeding of IEEE 19th International Conference on Pattern Recognition (ICPR 2008), Florida, USA, Dec. 2008. (IEEE Xplore)
16. **Vorapoj Patanavijit**, Andrew's Sine Estimation for a Robust Iterative Multiframe Super-Resolution Reconstruction using Stochastic Regularization Technique, Proceeding of IEEE Northeast Workshop on Circuits And Systems (IEEE-NEWCAS-TAISA'08), Montreal, Canada, pp. 145–148, June 2008. (IEEE Xplore)
17. **Vorapoj Patanavijit**, A Robust Iterative Multiframe SRR using Stochastic Regularization Technique based on Hampel Estimation, Proceeding of The Fifth Annual International Conference of Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON 2008), ECTI Association Thailand, Krabi, Thailand, pp. 473–476, May 2008. (IEEE Xplore)

6.3.3 Research Articles (National Proceeding and Conference)

1. **Vorapoj Patanavijit**, The Empirical Performance Study of a Super Resolution Reconstruction Based on Frequency Domain from Aliased Multi-Low Resolution Images, Proceeding of The 34th Electrical Engineering Conference (EECON-34), Ambassador City Jomtien Hotel, Pataya, Chonburi, Thailand, Dec. 2011. (CD-ROM)
2. **Vorapoj Patanavijit**, A Robust Recursive SRR Based On Andrew's Sine Stochastic Estimation With Fast Affine Block-Based Registration for Video Enhancement, Proceeding of The 34th Electrical Engineering Conference (EECON-34), Ambassador City Jomtien Hotel, Pataya, Chonburi, Thailand, Dec 2011. (CD-ROM)

3. Pham Hong Ha and **Vorapoj Patanavijit**, A Novel Iterative Robust Image Reconstruction Based on SL0 Compressive Sensing using Huber Stochastic Estimation Technique in Wavelet Domain, Proceeding of The 34th Electrical Engineering Conference (EECON-34), Ambassador City Jomtien Hotel, Pataya, Chonburi, Thailand, Dec. 2011. (CD-ROM)
4. **Vorapoj Patanavijit**, A Robust Resolution-Enhancement using Recursive Multiframe Super Resolution Reconstruction based on Myriad Norm Estimation Technique with Myriad-Tikhonov Regularization, Proceeding of The 33nd Electrical Engineering Conference (EECON-33), Centara Duangtawan Hotel, Chiang Mai, Thailand, Dec. 2010.
5. Pham Hong Ha and **Vorapoj Patanavijit**, A Novel Robust Compressive Sensing Based Maximum Likelihood with Myriad Stochastic Norm, Proceeding of The 33nd Electrical Engineering Conference (EECON-33), Centara Duangtawan Hotel, Chiang Mai, Thailand, Dec. 2010.
6. **Vorapoj Patanavijit**, Multiframe Resolution-Enhancement using A Robust Iterative SRR based on Leclerc Stochastic Technique, Proceeding of The 32nd Electrical Engineering Conference (EECON-32), Prachinburi, Thailand, Oct. 2009.
7. **Vorapoj Patanavijit**, A Robust Iterative Multiframe SRR using Stochastic Regularization Technique Based on Geman & Mcclure Estimation, Proceeding of The National Conference on Information Technology 2008 (NCIT 2008), Bangkok, Thailand, pp. 241-247, Nov. 2008.

6.3.4 Academic Articles (International Journal and Transactions)

1. **Vorapoj Patanavijit**, Tutorial of Image Reconstruction Based on Weighted Sum (WS) Filter Approach: From Single Image to Multi-Frame Image, AU Journal of Technology (AU J.T.), Assumption University (ABAC), Bangkok, Thailand, Oct. 2009. (www.journal.au.edu)
2. **Vorapoj Patanavijit**, Mathematical Analysis of Stochastic Regularization Approach for Super-Resolution Reconstruction, AU Journal of Technology (AU J.T.), Assumption University (ABAC), Bangkok, Thailand, pp. 235–244, April 2009. (www.journal.au.edu)
3. **Vorapoj Patanavijit**, Super-Resolution Reconstruction and its Future Research Direction, AU Journal of Technology (AU J.T.), Assumption University (ABAC), Bangkok, Thailand, pp. 149–163, Jan. 2009. (www.journal.au.edu)

REFERENCES

1. A. M. Thompson, J. C. Brown, J. W. Kay and D. M. Titterington, A Study of Methods of Choosing the Smoothing Parameter in Image Restoration by Regularization, IEEE Transactions on Pattern Analysis and Machine Intelligence 13, 4 (April 1991) : 326-339.
2. A. J. Patti and Y. Altunbasak, Artifact Reduction for Set Theoretic Super Resolution Image Reconstruction with Edge Constraints and Higher-Order Interpolation, IEEE Transactions on Image Processing 10, 1 (Jan. 2001) : 179–186.
3. A. W. Fitzgibbon, Stochastic Rigidity : Image Registration for Nowhere-Static Scenes, Researching Report, Robotics Research Group, Department of Engineering Science, University of Oxford, 2001 : 1-8.
4. B. Bascle, A. Blake and A. Zisserman, Motion Deblurring and Super-Resolution from an Image Sequence, Researching Report, Robotics Research Group, Department of Engineering Science, University of Oxford, 1996 : 1-10.
5. B. Anconelli, Method and Software for Deconvolution of Interferometric Images, Thesis Proposal of PhD Program in Computer Science, University of Genova, Dec. 2003 : pp. 1–25.
6. B. Zitova and J. Flusser, Image Registration Method: a Survey, Elsevier Image and Vision Computing 21, (June 2003) : 977-1000.
7. B. K. Gunturk, Y. Altunbasak and R. M. Mersereau, Color Plane Interpolation Using Alternating Projections, IEEE Transactions on Image Processing 11, 9 (Sep. 2002) : 997-1013
8. B. K. Gunturk, Y. Altunbasak and R. M. Mersereau, Super-Resolution Reconstruction of Compressed Video Using Transform-Domain Statistics, , IEEE Transactions on Image Processing 13, 1, (Jan. 2004) : 33–43
9. C. A. Segall, R. Molina and A. K. Katsaggelos, High-resolution Images from Low-Resolution Compressed Video, IEEE Signal Processing Magazine 20, 3 (May 2003) : 37-48.
10. C. Bouman and K. Sauer, A Generalized Gaussian Image Model for Edge-Preserving MAP Estimation, IEEE Transactions on Image Processing 2, 3 (July 1993) : 293-310.
11. C. Stiller and J. Konrad, Estimating Motion in Image Sequences, IEEE Signal Processing Magazine 15, 4 (July 1999) : 70-91.
12. D. B. Bradshaw and N. G. Kingsbury, Combined Affine and Translational Motion Compensation Scheme Using Triangular Tessellations, Proceeding of the 1997 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP '97), 1997 : 2645-2648.
13. D. Capel and A. Zisserman, Super-Resolution from Multiple Views using Learnt Image Models, Researching Report, Robotics Research Group, Department of Engineering Science, University of Oxford, 2001 : 1-8.
14. D. Geman and C. Yang, Nonlinear Image Recovery with Half-Quadratic Regularization, IEEE Transactions on Image Processing 4, 7 (July 1995) : 932-946.
15. D. Kundur and D. Hatzinakos, Blind Image Deconvolution, IEEE Signal Processing Magazine 13, 5 (May 1996) : 43–64.
16. D. Kundur and D. Hatzinakos, Blind Image Deconvolution Revisited, IEEE Signal Processing Magazine 13, 11 (Nov. 1996) : 61– 63.
17. D. Kundur and D. Hatzinakos, A Novel Blind Deconvolution Scheme for Image Restoration Using Recursive Filtering, IEEE Transactions on Signal Processing 46, 2 (Feb. 1998) : 375–390.

18. D. Lim, Achieving Accurate Image Registration as the Basis for Super-Resolution, Master Thesis, School of Computer Science and Software Engineering, The University of Western Australia, 2002.
19. D. P. Capel, Image Mosaicing and Super-Resolution, Doctoral Dissertation, Robotics Research Group, Department of Engineering Science, University of Oxford, 2001.
20. D. Rajan, S. Chaudhuri and M. V. Joshi, Multi-Objective Super Resolution Concepts and Examples, IEEE Signal Processing Magazine 20, 3 (May 2003) : 49-61.
21. D. Rajan and S. Chaudhuri, Simultaneous Estimation of Super-Resolution Scene and Depth Map from Low Resolution Defocuses Observations, IEEE Transactions on Pattern Analysis and Machine Intelligence 25, 9 (Sep. 2003) : 1102-1117.
22. D. Schilling and P. C. Cosman, Preserving Step Edges in Low Bit Rate Progressive Image Compression, IEEE Transactions on image processing, 12 (Dec. 2003) : 1473-1484.
23. E. Shechtman, Y. Caspi and M. Irani, Space-Time Super-Resolution, IEEE Transactions on Pattern Analysis and Machine Intelligence 27, 4 (April 2005) : 531-545.
24. G. Demoment, Image Reconstruction and Restoration: Overview of Common Estimation Structures and Problems, IEEE Transactions on Acoustics, Speech and Signal Processing 37, 12 (Dec. 1989) : 2024-2036.
25. G. Rochefort, F. Champagnat, G. L. Besnerais and Jean-François Giovannelli, An Improved Observation Model for Super-Resolution Under Affine Motion, IEEE Transactions on Image Processing 15, 11 (Nov. 2006) : 3325-3337.
26. G. M. Callico, A. Nunez, R. P. Llopis and R. Sethuraman, Low-cost and real-time super-resolution over a video encoder IP, Proceedings of the Fourth International Symposium on Quality Electronic Design (ISQED'03), IEEE Computer Society, 2003.
27. H. Hasegawa, T. Ono, I. Yamada and K. Sakaniwa, An Iterative MPEG Super-Resolution with an Outer Approximation of Framewise Quantization Constraint, IEICE Trans. on Fundamentals E88-A, 9 (Sep. 2005).
28 Hua-Mei Chen, S. Lee, R. M. Rao, Mohamed-Adel Slamani and P. K. Varshney, Imaging for Concealed Weapon Detection : A tutorial overview of development in imaging sensors and processing, IEEE Signal Processing Magazine, 5 (Mar. 2005) : 16-24.
29. Hu He, L. P. Kondi, Resolution Enhancement of Video Sequences with Adaptively Weighted Low-Resolution Images and Simultaneous Estimation of the Regularization Parameter, Proceeding of IEEE International Conference on Acoustics, Speech and Signal Processing, Montreal, Canada, III (May 2004) : 213-216.
30. Hu He, L. P. Kondi, Resolution Enhancement of Video Sequences with Simultaneous Estimation of the Regularization Parameter, SPIE Journal of Electronic Imaging 13, 3 (July 2004) : 586-596.
31. Hu He, L. P. Kondi, A Regularization Framework for Joint Blur Estimation and Super-Resolution of Video Sequences, Proceeding of the 2005 International Conference on Image Processing (ICIP '05), Genova, Italy, Sep. 2005.
32. Hu He and Lisimachos P. Kondi, An Image Super-Resolution Algorithm for Different Error Levels Per Frame, IEEE Transactions Image Processing 15, 3 (March 2006) : 592-60.

33. H. Lanteri, M. Roche, O. Cuevas and C. Aime, A General Method to devise Maximum-Likelihood Signal Restoration Multiplicative Algorithms with Non-Negativity Constraints, Elsevier Science B.V., (Nov. 2000) : 945–974.
34. H. Nagahara, Y. Yaji and M. Yachida, Super-Resolution Modeling, IEEE Conference on Multisensor Fusion and Integration for Intelligent Systems 2003, 2003 : 215-221.
35. I. M. Elfadel and R. W. Picard, Miscibility Matrices Explain the Behavior of Grayscale Textures Generated by Gibbs Random Field, SPIE Intelligent Robots and Computer Vision IX, Boston, USA, (Nov. 1990) : 524-535.
36. I. M. Elfadel and R. W. Picard, Gibbs Random Fields, Cooccurrences, and Texture Modeling, Perceptual Computing Group Technical Report #204, Media Laboratory, MIT, USA, (Jan. 1993) : 1-34.

37. I. M. Elfadel and R. W. Picard, Gibbs Random Fields, Cooccurrences, and Texture Modeling, IEEE Transactions on Pattern Analysis and Machine Intelligence 16, 1 (Jan. 1994) : 24-37.
38. I. M. Elfadel and R. W. Picard, On the Structure of Aura and Co-occurrence Matrices for the Gibbs Texture Model, Perceptual Computing Group Technical Report #160, Media Laboratory, MIT, USA, (June 1994) : 1-24.
39. I. Patras and M. Worring, Regularized Patch Motion Estimation, Proceeding of the 16th International Conference on Pattern Recognition (ICPR'02), 2002.
40. J. Wegger, Estimation of Motion in Image Sequences, Master Thesis, Department of Electrical Engineering, Institution of Technology, Linkopings University, Sweden, 2000.
41. J. Sun, N. N. Zheng, H. Tao and H. Y. Shum, Image Hallucination with Primal Sketch Priors, Proceedings of the 2003 IEEE Computer Society Conferences on Computer Vision and Pattern Recognition (CVPR'03), 2003
42. J. Y. A. Wang and E. H. Adelson, Spatio-Temporal Segmentation of Video Data, Proceedings of the SPIE : Image and Video Processing II 2182, San Jose, USA, (Feb. 1994).
43. K. Popat and R. W. Picard, Gibbs Random Fields : Temperature and Parameter Analysis, IEEE International on International Conference on Acoustics, Speech and Signal Processing (ICASSP), Adelaide, Australia, (April 1994).
44. K. Popat and R. W. Picard, Cluster-Based Probability Model Applied to Image Restoration and Compression, IEEE International on International Conference on Acoustics, Speech and Signal Processing (ICASSP), Adelaide, Australia, (April 1994).
45. K. R. Namuduri, Motion Estimation Using Spatio-Temporal Contextual Information, IEEE Transactions on Circuits and Systems for Video Technology 14, 8 (Aug. 2004) : 1111-1115.
46. L. P. Kondi, D. A. Scribner, J. M. Schuler, A Comparison of Digital Image Resolution Enhancement Techniques, Proceeding on SPIE AeroSense Conference (Infrared and Passive Millimiter-wave Imaging Systems: Design, Analysis, Modeling, and Testing), Orlando, FL, (April 2002) : 220-229.
47. M. A. Robertson, Computationally-Efficient Post-Processing of Compressed Video Streams, Master Thesis, Electrical Engineering, The University of Notre Dame, Indiana, USA, March 1998.
48. M. Ben-Ezra and S. K. Nayar, Motion-Based Motion Deblurring, IEEE Transactions on Pattern Analysis and Machine Intelligence 26, 6 (June 2004) : 689-698.

49. M. Elad and A. Feuer, Restoration of a Single Superresolution Image from Several Blurred, Noisy and Undersampled Measured Images, IEEE Transactions on Image Processing 6, 12 (Dec. 1997) : 1646-1658.
50. M. Elad and A. Feuer, Superresolution Restoration of an Image Sequence: Adaptive Filtering Approach, IEEE Transactions on Image Processing 8, 3 (Match 1999) : 387-395.
51. M. Elad and A. Feuer, Super-Resolution Reconstruction of Image Sequences, IEEE Transactions on Pattern Analysis and Machine Intelligence 21, 9 (Sep. 1999) : 817-834.
52. M. Elad and Y. Hecov Hel-Or, A Fast Super-Resolution Reconstruction Algorithm for Pure Translational Motion and Common Space-Invariant Blur, IEEE Transactions on Image Processing 10, 8 (Aug. 2001) : 1187-1193.
53. M. Elad and A. Feuer, Super-Resolution Restoration of Continuous Image Sequence – Adaptive Filtering Approach, Technical Report, The Technion, The Electrical Engineering Faculty, Israel Institute of Technology, Haifa, 1-12
54. M. Elad, On the Original of the Bilateral Filter and Ways to Improve It, IEEE Transactions on Image Processing 11, 10 (Oct. 2002) : 1141-1151.
55. M. G. Kang and A. K. Katsaggelos, General Choice of the Regularization Functional in Regularized Image Restoration, IEEE Transactions on Image Processing 4, 5 (May 1995) : 594-602.
56. M. G. Kang and A. K. Katsaggelos, Simultaneous Multichannel Image Reconstruction and Estimation of the Regularization Parameter, IEEE Transactions on Image Processing 6, 5 (May 1997) : 774-778.
57. M. G. Kang and S. Chaudhuri, Super-Resolution Image Reconstruction, IEEE Signal Processing Magazine 20, 3 (May 2003) : 19 – 20.
58. M. J. Black, A. Rangarajan, On The Unification Of Line Processes, Outlier Rejection and Robust Statistics with Applications in Early Vision, International Journal of Computer Vision 19, 1 (July 1996) : 57-92.
59. M. J. Black, G. Sapiro, D. Marimont, D. Heeger, Robust Anisotropic Diffusion: Connections Between Robust Statistics, Line Processing and Anisotropic Diffusion, Scale-Space Theory in Computer Vision, Scale-Space'97, B. ter Haar Romeny, L. Florack, J. Koenderink, and M. Viergever (Eds.), Springer Verlag, LNCS 1252, Utrecht, the Netherlands, July 1997 : 323-326.
60. M. J. Black, G. Sapiro, D. H. Marimont and D. Herrger, Robust Anisotropic Diffusion, IEEE Transactions on Image Processing 7, 3 (March 1998).
61. M. J. Black and G. Sapiro, Edges as Outliers: Anisotropic Smoothing Using Local Image Statistics, Scale-Space Theories in Computer Vision, Second International Conference on Scale-Space '99, Corfu, Greece, LNCS 1682, Springer, (Sep. 1999) : 259-270.
62. M. K. Ng and N. K. Bose, Analysis of Displacement Error in High-Resolution Image Reconstruction With Multisensors, IEEE Transactions on Circuits and systems : Fundamental Theory and Application 49, 6 (June 2002) : 806-813.
63. M. K. Ng and Nirmal K. Bose, Mathematical analysis of super-resolution methodology, IEEE Signal Processing Magazine 20, 3 (May 2003) : 62 – 74.
64. M. R. Banham and A. K. Katsaggelos, Digital Image Restoration, IEEE Signal Processing Magazine 14, 2 (March 1997) : 24–41.
65. M. Trimeche, R. C. Bilcu and J. Yrjanainen, Adaptive Outlier Rejection in Image Super-Resolution, EURASIP Journal on Applied Signal Processing, Article ID 38052, Hindawi Publishing Corporation, 2006 : 1-12.
66. M. Victor, W. Zibetti and J. Mayer, Simultaneous Super-Resolution for Video Sequences, Proceeding of the 2005 International Conference on Image Processing (ICIP ’05), Genova, Italy, Sep. 2005.

67. M. Vega, R. Molina and A. K. Katsaggelos, A Bayesian Super-Resolution Approach to Demosaicing of Blurred Image, EURASIP Journal on Applied Signal Processing, Article ID 25072, Hindawi Publishing Corporation, 2006 : 1-12.
68. N. C. Gallagher, JR. Gary L. Wise, A Theoretical Analysis of the Properties of Median Filters, IEEE Transactions on Acoustics, Speech and Signal Processing ASSP-29, 6 (Dec. 1981) : 1136-1141.
69. N. K. Bose, M. K. Ng and A. C. Yau, A Fast Algorithm for Image Super-Resolution from Blurred Observations, EURASIP Journal on Applied Signal Processing, Article ID 35726, Hindawi Publishing Corporation, 2006 : 1-14.
70. N. Nguyen, P. Milanfar and G. Golub, A Computationally Efficient Superresolution Image Reconstruction Algorithm, IEEE Transactions on Image Processing 10, 4 (Apr. 2001) : 573-583.
71. N. X. Nguyen, Numerical Algorithms for Image Superresolution, Doctoral Dissertation, Department of Scientific Computing and Computational Mathematics, Stanford University, 2000.
72. P. L. Combettes and M. R Civanlar, The Foundations of Set Theoretic Estimation, IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 1991), 1991 : 1921-1924.
73. P. L. Combettes, The Foundations of Set Theoretic Estimation, Proceedings of the IEEE 81, 2 (Feb.1993) : 182-208.
74. P. Milanfar, A Model of the Effect of Image Motion in the Radon Transform Domain, IEEE Transactions on Image Processing 8, 9 (Sep. 1999) : 1276-1281.
75. P. Vandewalle, S. Susstrunk and M. Vetterli, Double Resolution from a Set of Aliased Images, Proceeding IS&T/SPIE Electronic Imaging 2004: Sensors and Camera Systems for Scientific, Industrial, and Digital Photography Applications V 5301, 1 (Jan. 2004) : 374-382.
76. P. Vandewalle, S. Susstrunk and M. Vetterli, A Frequency Domain Approach to Super-Resolution Imaging from Aliased Low Resolution Images, Technical Journal, Department of Electrical Engineering and Computer Science, UC Berkeley, USA, May, 2004 : 1–21.
77. P. Vandewalle, L. Sbaiz, M. Vetterli and S. Susstrunk, Super-Resolution from Highly Undersampled Images, Proceeding of the 2005 International Conference on Image Processing (ICIP ’05), Genova, Italy, Sep. 2005.
78. P. Vandewalle, S. Susstrunk and M. Vetterli, A Frequency Domain Approach to Registration of Aliased Images with Application to Super Resolution, EURASIP Journal on Applied Signal Processing, Article ID 71459, Hindawi Publishing Corporation, 2006 : 1-14.
79. P. Marziliano and M. Vetterli, Reconstruction of Irregularly Sampled Discrete-Time Bandlimited Signals with Unknown Sampling Locations, IEEE Transactions on Signal Processing 48, 12 (Dec. 2000) : 3462-3471.
80. R. C. Gonzalez and R. E. Woods, Digital Image Processing, Addison-Wesley Publishing Company, 1992
81. R. Kimmel, Demosaicing: Image Reconstruction from Color CCD Samples, IEEE Transactions on Image Processing 8, 9 (Sep. 1999) : 1221-1228.
82. R. L. Stevenson, B. E. Schmitz and E. J. Delp, Discontinuity Persevering Regularization of Inverse Visual Problems, IEEE Transactions on Systems, Man and Cybernetics 24, 3 (March 1994).
83. R. Molina, J. Nunez, F. Cortijo and J. Mateos, Image Restoration in Astronomy : A Bayesian Perspective, Technical Report, Department of Computer Science, University of Granada, Espana.

84. R. Molina, On the Hierarchical Bayesian Approach to Image Restoration Applications to Astronomical Images, IEEE Transactions on Pattern Analysis and Machine Intelligence 16, 11 (Dec. 1995) : 1122-1128.
85. R. Molina, A. K. Katsaggelos and J. Mateos, Bayesian and Regularization Methods for Hyperparameter Estimation in Image Restoration, IEEE Transactions on Image Processing, 8, 2 (Feb. 1999) : 231-246.
86. R. Molina, M. Vega, J. Abad and A. K. Katsaggelos, Parameter Estimation in Bayesian High-Resolution Image Reconstruction With Multisensors, IEEE Transactions on Image Processing 12, 12 (Dec. 2003) : 1655-1667.
87. R. Pan and S. J. Reeves, Efficient Huber-Markov Edge-Preserving Image Restoration, IEEE Transactions on Image Processing 15, 12 (Dec. 2006) : 3728-3735.
88. R. R. Schultz and R. L. Stevenson, A Bayesian Approach to Image Expansion for Improved Definition, IEEE Transactions on Image Processing 3, 3 (May 1994) : 233-242.
89. R. R. Schultz and R. L. Stevenson, Extraction of High-Resolution Frames from Video Sequences, IEEE Transactions on Image Processing 5, 6 (June 1996) : 996-1011.
90. R. W. Picard, I. M. Elfadel and A. P. Pentland, Markov/Gibbs Texture Modeling : Aura Matrices and Temperature Effects, Proceeding of the IEEE Conference on Computer Vision and Pattern Recognition, Maui, June 1991 : 371-377.
91. R. W. Picard, Gibbs Random Fields : Temperature and Parameter Analysis, IEEE International on International Conference on Acoustics, Speech and Signal Processing (ICASSP), San Francisco, USA, March 1992 : 45-48.
92. S. Baker and T. Kanade, Limits on Super-Resolution and How to Break Them, IEEE Transactions on Pattern Analysis and Machine Intelligence 24, 9 (Sep. 2002) : 1167-1183.
93. S. Borman, Topics in Multiframe Superresolution Restoration, Doctoral Dissertation, Electrical Engineering, The University of Notre Dame, Indiana, USA, April 2004.
94. S. Chaudhuri and D. Rani Taur, High-Resolution Slow-Motion Sequencing, IEEE Signal Processing Magazine 20, 3 (Mar. 2005) : 16-24.
95. S. C. Park, M. K. Park and M. G. Kang, Super-Resolution Image Reconstruction : A Technical Overview, IEEE Signal Processing Magazine 20, 3 (May 2003) : 21 - 36.
96. S. C. Park, M. G. Kang, A. Segall and A. K. Katsaggelos, Spatially Adaptive High-Resolution Image Reconstruction of DCT-Based Compressed Images, IEEE Transactions on Image Processing 13, 4 (April 2004) : 573-585.
97. S. Farsiu, M. D. Robinson, M. Elad and P. Milanfar, Advances and Challenges in Super-Resolution, International Journal of Imaging Systems and Technology 14, 2 (2004) : 47–57.
98. S. Farsiu, M. D. Robinson, M. Elad and P. Milanfar, Fast and Robust Multiframe Super Resolution, IEEE Transactions on Image Processing 13, 10 (Oct 2004) : 1327-1344.
99. S. Farsiu, M. Elad and P. Milanfar, Multiframe Demosaicing and Super-Resolution of Color Images, IEEE Transactions on Image Processing 15, 1 (Jan. 2006) : 141-159.
100. S. Farsiu, M. Elad and P. Milanfar, Video-to-Video Dynamic Super-Resolution for Grayscale and Color Sequence, EURASIP Journal on Applied Signal Processing, Article ID 61859, Hindawi Publishing Corporation, 2006 : 1-12.
101. S. Haykin, Adaptive Filter Theory, Fourth Edition, Prentice Hall Information and System Science Series, 2002.

102. S. P. Kim, N. K. Bose, and H. M. Valenzuela, Recursive Reconstruction of High Resolution Image from Noisy Undersampled Multiframes, IEEE Transactions on Acoustic, Speech, Signal Processing 38 (1990) : 1013–1027.
103. S. P. Kim and Wen-Yu Su, Recursive High-Resolution Reconstruction of Blurred Multiframe Images, IEEE Transactions on Image Processing 2, 4 (Oct. 1993) : 534-539.
104. S. S. Beauchemin and J. L. Barron, The Computation of Optical Flow, ACM Computing Surveys 27, 3 (Sep. 1995) : 433-467.
105. S. V. Vaseghi, Advanced Signal Processing and Digital Noise Reduction, John Wiley & Sons Ltd., 1996.
106. S. Zhu and Kai-Kuang Ma, A New Diamond Search Algorithm for Fast Block-Matching Motion Estimation, IEEE Transactions on Image Processing 9, 2 (Feb. 2000) : 287-290.
107. T. S. Huang and R. Y. Tsan, Multiple frame image restoration and registration, Advances in Computer Vision and Image Processing 1, T. S. Huang, Ed. Greenwich, CT: JAI, 1984 : 317-339.
108. Viet-Nam Dang, Abdol-Reza Mansouri and Janusz Konrad, Motion Estimation For Region-Based Video Coding, Proceeding of the 1995 International Conference on Image Processing (ICIP ’95), 1995 : 189-192.
109. V. Patanavijit and S. Jitapunkul, A Modified Three-Step Search Algorithm for Fast Affine Block Base Motion Estimation, International Workshop on Advanced Image Technology 2006 (IWAIT 2006), Okinawa, Japan, Jan. 2006 : 99-104.
110. V. Patanavijit and S. Jitapunkul, An Iterative Super-Resolution Reconstruction of Image Sequences using a Bayesian Approach with BTV Prior and Affine Block-Based Registration, IEEE Canadian Conference on Computer and Robot Vision 2006 (CRV 2006), Quebec City, Canada, June 2006.
111. V. Patanavijit and S. Jitapunkul, An Iterative Super-Resolution Reconstruction of Image Sequences using Affine Block-Based Registration, ACM International Symposium on Multimedia Over Wireless (IWCMC 2006), Vancouver, Canada, July 2006 : 51–56.
112. V. Patanavijit and S. Jitapunkul, An Iterative Super-Resolution Reconstruction of Image Sequences using a Bayesian Approach and Affine Block-Based Registration, 14th European Signal Processing Conference (EUSIPCO 2006), Florence, Italy, Sep. 2006.
113. V. Patanavijit and S. Jitapunkul, A Lorentzian Bayesian Approach for Robust Iterative Multiframe Super-Resolution Reconstruction with Lorentzian-Tikhonov Regularization (The Best Paper Award), IEEE International Symposium on Communications and Information Technologies 2006 (ISCIT 2006), Bangkok, Thailand, Oct. 2006 : 1–6 (F3A-4).
114. V. Patanavijit and S. Jitapunkul, A Robust Iterative Multiframe Super-Resolution Reconstruction using a Huber Statistical Estimation Technique, IEEE International Conference on Communications and Networking in China 2006 (CHINACOM 2006), Beijing, China, Oct. 2006.
115. V. Patanavijit and S. Jitapunkul, A Robust Iterative Multiframe Super-Resolution Reconstruction using a Bayesian Approach with Lorentzian Norm, Tenth IEEE International Conference on Communication Systems (ICCS 2006), Singapore, Oct. 2006.
116. V. Patanavijit and S. Jitapunkul, A Lorentzian Stochastic Estimation for an Robust and Iterative Multiframe Super-Resolution Reconstruction, The Annual International Technical Conference of IEEE Region 10 (IEEE TENCON 2006), Wan Chai, Hong Kong, Nov. 2006.

117. V. Patanavijit and S. Jitapunkul, A Robust Iterative Multiframe Super-Resolution Reconstruction using a Bayesian Approach with Tukey's Biweigth, IEEE International Conference on Signal Processing 2006 (ICSP 2006), Guilin, China, Nov. 2006.
118. V. Patanavijit and S. Jitapunkul, An Iterative Super-Resolution Reconstruction of Image Sequences using Fast Affine Block-Based Registration with BTV Regularization, IEEE Asia Pacific Conference on Circuits and System (APCCAS 2006), Singapore, Dec. 2006 : 1746-1749.
119. V. Patanavijit and S. Jitapunkul, A Robust Iterative Multiframe Super-Resolution Reconstruction using a Huber Bayesian Approach with Huber-Tikhonov Regularization, IEEE International Symposium on Intelligent Signal Processing and Communication System (ISPACS 2006), Tottori, Japan, Dec. 2006.
120. V. Patanavijit and S. Jitapunkul, A Lorentzian Stochastic Estimation for A Robust Iterative Multiframe Super-Resolution Reconstruction with Lorentzian-Tikhonov Regularization, EURASIP Journal on Applied Signal Processing (EURASIP JASP) : Special Issue on Super-Resolution Enhancement of Digital Video, Hindawi Publishing Corporation, May 2007.
121. V. Patanavijit, P. Sermwuthisarn and S. Jitapunkul, A Robust Iterative Super-Resolution Reconstruction of Image Sequences using a Tukey's Biweigth Bayesian Approach with Fast Affine Block-Based Registration, IEEE International Conference on Multimedia & Expo (ICME 2007), Beijing, China, July 2007.
122. V. Patanavijit, S. Tae-O-Sot and S. Jitapunkul, A Robust Iterative Super-Resolution Reconstruction of Image Sequences using a Lorentzian Bayesian Approach with Fast Affine Block-Based Registration, IEEE International Conference on Image Processing (ICIP 2007), San Antonio, Texas, USA, Sep. 2007.
123. V. Z. Mesarovic, N. P. Galatsanos and A. K. Katsaggelos, Regularized Constrained Total Least Squares Image Restoration, IEEE Transactions on Image Processing 4, 8 (Aug 1995) : 1096-1108.
124. X. Jing adn Lap-Pui Chau, An Efficient Three-Step Search Algorithm for Block Motion Estimation, IEEE Transactions on Multimedia 6, 3 (June 2004) : 435-438.
125. Y. Wang, J. Osterman and Ya-Qin Zhang, Video Processing and Communication, Prentice Hall, Inc., 2001.
126. Y. Altunbasak, A. J. Patti and R. M. Mersereau, Super-Resolution Still and Video Reconstruction from MPEG-Coded Video, IEEE Transactions on Circuits and Systems for Video Technology 12, 4 (April 2002) : 217–226.
127. Z. Lin and Heung-Yeung Shum, Fundamental Limits of Reconstruction-Based Superresolution Algorithms under Local Translation, IEEE Transactions on Pattern Analysis and Machine Intelligence 26, 1 (Jan. 2004) : 83-97.
128. Z. Jiang, Tien-Tsin Wong and H. Bao, Practical Super-Resolution from Dynamic Video Sequences, Proceedings of the 2003 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'03), 2003