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Objective Evaluation and Suppressing Effects of Noise in Dynamic Image Fusion

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In this paper the results of an investigation into the effects of noise on dynamic (video) image fusion performance are presented. We start by creating an extensive multisensor dataset of noise-corrupted videos. Then, we define an objective metric for the evaluation of noisy dynamic fusion N-DQ$^{AB/F}$ and demonstrate its consistency with visual assessment. The metric to evaluate a wide range of conventional and robust dynamic fusion techniques and strategies for suppressing noise in the fused video on the created dataset is applied. We identify the characteristics of multiresolution pyramid representations and feature selection strategies capable of mitigating the effects of noise on dynamic fusion performance. The paper also shows some relatively simple noise suppression techniques integrated into the fusion process which can yield performance improvements in specially challenging low SNR conditions with very little computational complexity

Key words: **image processing, image quality, image fusion, noie measurement, noise filtering, noise suppression.**

Introduction

MODERN sensing modalities deliver real-time multi-sensor imaging in defence, avionics, medical imaging and surveillance applications to name but a few. Dynamic image fusion, or video fusion, fuses these streams of multisensor data into a single output stream [1-4]. In the process, fusion algorithms generally assume their input data arriving from the sensors to be a faithful representation of the observed scene and attempt to transfer it without loss into the fused stream.

In reality, this is rarely the case as noise corrupts practically all sensed image data. It is particularly so in challenging conditions faced by multisensor imaging systems employing additional sensor modalities such as infrared and light intensified cameras to compensate for low useful signal strength in the visual range. Signal boosting used by many cameras to compensate for low signal power usually results in significant corruption of their imagery by noise. This presents significant problems for fusion algorithms [5-7] aiming to produce a single reliable representation of the scene as noise is treated as a true signal and merely transferred into the fused stream.

This paper presents the results of a systematic investigation into the effects of noise on the performance of multisensor dynamic image fusion. Noise has had considerable research attention in research literature; however, in the context of fusion, it is usually just an application condition [4, 6, 8]. Although a considerable number of noise mitigation strategies have been proposed, even in the domain of image fusion [5, 6, 8], systematic efforts to tackle this issue are largely missing. A thorough investigation into noise in still image fusion was performed by the authors in [9] showing that a careful choice of fusion strategy can yield more robust fusion performance when inputs are corrupted by noise.

An analysis of noisy fusion performance generally relies on visual observation of which algorithms produce the most pleasing images [8]. Apart from being subjective, this approach is highly inefficient as it cannot easily be used for systematic evaluation of multiple fusion alternatives on large datasets. Objective metrics of video fusion performance are the most practical manner to achieve this. In [4] an objective evaluation metric focusing on noisy fusion was defined as the mutual information between inter-frame differences of input and fused sequences. This metric directly measures temporal stability [10], the appearance of motion artifacts produced by inconsistent fusion across the frames, but largely ignores structural information transfer associated withconventional fusion performance.

In this paper, we propose an objective metric to evaluate both the spatial and temporal effects of noise on dynamic image fusion performance. We employ a well-known fusion evaluation framework [10, 11] based on gradient information preservation to derive an absolute measure of fusion performance in the presence of various levels of input noise. We use the metric to evaluate a range of conventional and robust dynamic fusion techniques and strategies for suppressing noise in the fused video on an extensive dataset of noise corrupted multisensor images. We also use this framework to analyse noise mitigation strategies that can be integrated with fusion and identify techniques that improve robustness of dynamic fusion to noise.

In the following Section 2, we introduce and analyse the effects of noise on dynamic image fusion, describe an extensive dataset of noisy input videos and introduce simple noise mitigation strategies that can be used in conjunction with fusion. In Section 3, we define an objective metric for computational assessment of noisy dynamic fusion and an

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automated evaluation framework for testing noisy fusion. The results of our investigation are presented in Section 4 and we give a conclusion in Section 5.

Noise in dynamic image fusion

Noise corrupts all sensor data, and through it fused imagery. This is particularly pertinent in dynamic image fusion. In still image fusion, noise corrupts the spatial signal creating a random pattern over a true image structure. People are known to be able to see "through" noise to a certain degree and this resistance is reflected in a certain tolerance to low noise levels in still fused images [10]. However, in dynamic fusion, the temporal dimension greatly alters the perception of noise signals. Noise is usually random and independent across time and space. Video noise patterns are not static but dynamic: they flicker in front of the eyes of the observer triggering various attention mechanisms of the human visual system (HVS). This gives rise to the distracting effect of dynamic noise as our eyes struggle to stay focused on the true scene structures. For this reason, the effect of noise power on our perceptual experience is greatly exaggerated in the dynamic case and noise becomes a far more serious problem in dynamic fusion.

Noisy Multisensor Data

Sensor noise is the result of several processes associated with the underlying measurement physics [12-14] resulting in several types of noise, such as additive and shot noise that usually combine into more complex noise patterns. Additive noise, such as that caused by the dark (leakage) current and temperature effects in IR sensors, is typically the predominant component. In our early investigation presented here, we focused on this type of noise and built models to corrupt clear videos to produce a noisy multisensor video dataset for evaluation of noisy dynamic fusion.

Additive noise is modeled as a random signal drawn from a specific distribution overlaid over the true scene image. To obtain a noise corrupted version A_{SNR} of our multisensor sequence A , we: (i) generated a noise-seed signal n using a Gaussian distribution with zero mean and unit variance:

$$n(x,y,t) = N(0,1),\ \forall x,y,t \in A \qquad (1)$$

(ii) scaled n by an appropriate factor k_{SNR} to produce a desired signal-to-noise ratio (SNR) given the signal power S_A evaluated directly from A and (iii) added the boosted noise signal to A:

$$A_{SNR} = A + k_{SNR} * n \qquad (2)$$

A noise seed n was generated separately for each input sequence and the SNR level to avoid biasing our measurements.

We used the process above to corrupt the non-visual (thermal) sensor input in a set of 20 spatially registered multisensor sequences. This reflects the realistic situation where thermal sensors are generally much more susceptible to noise, usually boosted by their internal processing seeking to increase signal power.

Thermal sensor sequences were corrupted at six different levels of SNR: 30, 20, 10, 6, 3 and 1dB. They range in content and signal power, which proportionally affects the visibility of noise patterns in the videos. Fig.1 shows an example of noise corruption on a frame from the infrared sensor of the "va1" sequence in the dataset. In this case, important content remains visible even in the presence of heavy noise corruption.

Dynamic Fusion in Noisy Input Conditions

Dynamic or video fusion has been a topic of research for over a decade now with practical fusion systems already used in a number of surveillance applications [1-4]. However, for a range of practical reasons such as (computational) power considerations and low latency requirements, most dynamic fusion methods resemble still image fusion algorithms. Fusion is performed on a frame-by-frame basis, with relatively little consideration for mutual dependence between frames, generally high even in sequences with significant motion.

The most basic manner to fuse two sequences is to take their average – *arithmetic fusion*. Yet the most prevalent and certainly most successful approach to image fusion is the use of multiresolution (MR) techniques. Each input frame is initially transformed using a decomposition algorithm into an MR pyramid representation separating information according to scale and optionally orientation (Laplacian, steerable pyramids, discrete wavelet transform (DWT), dual tree complex wavelet transform (DT-CWT) and others) [4, 5, 8, 15-20]. Input pyramids are then combined, a sub-band at a time, into a new, fused pyramid using a fusion rule that generally selects the most salient features from either input. The fused pyramid is finally reconstructed to produce the fused frame.

In the presence of noise in input images, this approach was found to suffer compared to simpler arithmetic fusion [10]. The feature selection stage treats noise as valid input information and transfers it directly into the fused image. Furthermore, certain methods, such as shift variant DWT and orientation selectivity, produce reconstruction artifacts as selection breaks the continuity of the sub-band signals.

These effects are exacerbated in the dynamic fusion case by noise effects on a feature selection between frames. Flickering artifacts appear in the fused sequence as the selection switches from one to the other input due to noise. Fig.2 illustrates this effect on the consecutive frames of a DWT fused sequence obtained using barely noisy inputs. The effect is highly distracting to observers.

Noise Mitigation Strategies in Fusion

Robustness to noise can be introduced into the fusion process in a number of ways: i) a more suitable MR transform space, ii) more consistent noise-aware feature selection strategies and iii) explicit introduction of noise suppression techniques in the fusion process. In the following, we investigate the effect of each of these strategies on noisy dynamic fusion performance.

Shift invariance is a property of an MR transform space that lends much stability in fusion applications. Multiscale, non-subsampled DWT – SIDWT/DWF was shown to provide better fusion performance [3]. However, this approach is highly impractical due to its computational power requirements. A more efficient shift-invariant approach is Dual-Tree Complex Wavelet Transform (DT-CWT) [16,17]. It produces a real and a complex pyramid for each image, whose magnitude at each location is a better indication of true signal saliency and thus better suited to fusion than DWT [18,19]. We test this transform space against more conventional ones in Section 4.

Figure 1. Corruption levels on "va1" sequence, visible reference top left, then from right to left noise free IR and at 10, 6, 3 and 1 dB SNR

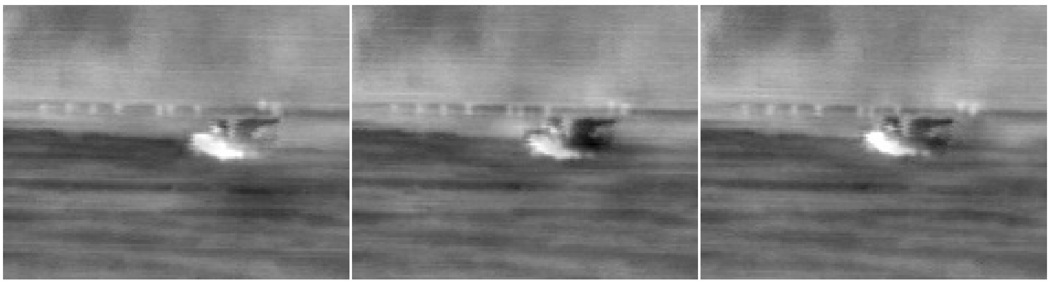

Figure 2. Consecutive frames from a fused sequence showing dynamic flickering induced by inconsistent feature selection

Feature selection, or the pyramid fusion strategy is instrumental in noisy fusion performance. The benchmark approach: abs-max-selection rule that selects the larger of the two input pyramid coefficients for the fused pyramid is directly responsible for maximizing noise signal power in the fused image. More robust fusion strategies, around for a while [8, 18-20], tend to use wider selection support, i.e. they base their selection on blocks of pyramid coefficients, e.g. 3x3 or 5x5 and impose the majority of filtering to selection maps to remove noise-induced inconsistencies (e.g. the Li et. al. rule [8]).

An approach specific to dynamic fusion uses an even broader selection space, including pyramid coefficients from previous and potentially subsequent frames in selecting the feature at each location. The selection block becomes a 3x3x3 which adds complexity to the fusion process but also directly influences the temporal dimension of the noise power and introduces consistency. In its practical, causal application, we used the local maximum in the 3x3x3 window of pixels around the central pixel in the current frame and two previous frames in the sequence to select which pyramid to take the fused coefficient from. We evaluate both the area-based selection of [8] and its dynamic version against the benchmark approaches in Section 4.

Finally, a simple noise suppression strategy that can be efficiently included in the fusion process is the hard and soft threshold method evaluated for image fusion in [9]. Both methods are suitable for the application in an MR pyramid domain and work on the premise that coefficients caused by noise are generally smaller than those caused by salient features and cluster around zero. The hard approach removes coefficients in the pyramid below the threshold by setting them to zero while coefficients above the threshold remain unchanged [21]. The soft threshold additionally reduces coefficients above the threshold by the value of the threshold [22]. This technique is generally restricted to higher resolution levels of the pyramid where noise power is greater compared to the useful signal. Naturally, this type of thresholding also causes losses in the useful parts of the signal which can lead to distortion and information loss. Another very important factor is the choice of the threshold, as it determines the amount of lost data and fused image quality. We look at the effect of these techniques supplied to shift-invariant DT-CWT pyramid fusion of both clear and noisy sequences in Section 4.

Noisy dynamic fusion evaluation

Noisy fusion evaluation is a difficult task [9], made even harder by the temporal dimension which influences human perception greatly. Most fusion assessment metrics are designed for still image fusion and produce reasonable evaluation of spatial information transfer from the inputs into a fused image. Whereas they can be applied on a frame-by-frame basis to video fusion, this means that they would struggle to evaluate effects such as temporal stability and motion smoothness that are greatly affected by noise and are thus unsuitable for our task.

A small number of video fusion assessment techniques have been proposed [4, 10] specifically aimed at evaluating fusion of multisensor sequences. Rockinger and Fechner measured image sequence fusion performance based on mutual information between inter-frame-differences of two input and fused sequences [4]. However, this approach overly focuses on the temporal stability, defined as the consistency that a change in the value of fused grey levels can only be caused by grey level changes in the input sequences as well as a lack of motion artifacts appearing between the frames of the fused sequences.

A video fusion evaluation metric that considers both spatial and temporal information preservation was proposed by the authors in [10]. Based on perceptual models of gradient preservation between input and fused signals, defined in detail in [10, 11] the basic evaluation approach of the $DQ^{AB/F}$ metric is shown in Fig.3. We adopt this metric as a basis for the evaluation of noisy dynamic fusion.

$DQ^{AB/F}$ uses three consecutive frame blocks of all three sequences (2 inputs and fused) to extract spatial and temporal information contained in each sequence. Expressed in terms of gradient parameters, this information is compared between the inputs and the fused signal using perceptual gradient preservation models measuring perceived information loss due to the observed gradient differences. A contribution to the preservation of information is evaluated at each location m, n in each frame. Both sets of estimates, for the spatial and temporal channel, are pooled into a single preservation – performance score for the frame using a weighted summation that takes into account their local perceptual importance. Individual frame results are then pooled to obtain a single measure for the whole sequence [11].

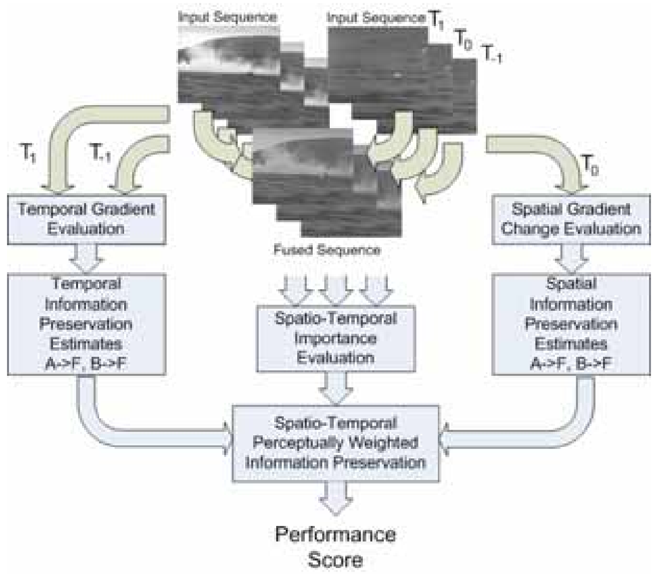

Figure 3. Architecture of the dynamic fusion evaluation metric $DQ^{AB/F}$

To evaluate noisy dynamic fusion, we need to understand what constitutes ideal fusion. $DQ^{AB/F}$ evaluates absolute fusion performance given the input sequences as the accurate transfer of input content into a fused output as faithfully as possible. $DQ^{AB/F}$ increases toward unity as the amount of information loss and artifacts in F decreases. However, when inputs are corrupted by noise, we are not interested in preserving all of the input information. A loss of input “noise information” in fused video is an actual advantage of the underlying fusion algorithm.

In order to measure noisy dynamic fusion, we follow the approach defined in [9]. Direct application of the metric to measure preservation of information from a noisy input A_{SNR} and in the fused video F_{SNR}, $DQ^{A_{SNR}B/F_{SNR}}$ is therefore not subjectively meaningful since the loss of “noise information” in F_{SNR} will yield a reduction in the performance score. Instead, we need to measure only the representation of the “true” scene information in the noisy fused video. The true information is contained in the noise free input sequence A so a meaningful noisy performance assessment can be achieved using the form $DQ^{AB/F_{SNR}}$ of the metric. We call this noisy dynamic fusion evaluation metric the $N\text{-}DQ^{AB/F_{SNR}}$. The value of $N\text{-}DQ^{AB/F_{SNR}}$ increases when the fused output image is a more accurate representation of the noise free input videos A and B, i.e. when there is a reduction of noise in F_{SNR}. $N\text{-}DQ^{AB/F_{SNR}}$ therefore measures the overall, absolute level of fusion success in representing the true scene information in the noisy fused video F_{SNR}. It is a direct estimate of fusion performance under noisy input conditions and is evaluated in exactly the same manner as the noise free fusion metric $N\text{-}DQ^{AB/F}$ described in the previous section and in [10]. Thus for decreasing the SNR values, $N\text{-}DQ^{AB/F_{SNR}}$ should describe the absolute degradation of fusion performance with increasing noise. Notice that $N\text{-}DQ^{AB/F_{SNR}}$ still takes into account the effects of artifacts and distortions introduced by the fusion algorithm itself.

To measure the effects of noise on dynamic fusion performance in a systematic manner, we built an integrated noisy fusion evaluation framework, illustrated in Fig.4. The framework takes as an input a pair of clear input video sequences and measures signal power of the thermal sequence. It creates a noise seed signal n (1) which is linearly scaled to boost noise power to a set SNR level before it is added to the clear video. The noisy video sequence A_{SNR} is then fused with the other input using the specified fusion method. The resulting noisy fused video F_{SNR} is compared to the original, noise free inputs, using the N-DQ$^{AB/F_{SNR}}$ metric.

An automated evaluation can be performed by the framework where a matrix of noisy video fusion performance scores is obtained for a whole range of noise corruption levels (σ) including noise free cases, $\sigma = 0$.

Finally, an important and often overlooked aspect of dynamic fusion evaluation is computational requirements of algorithms. However, measuring it accurately requires actual real-time implementations of different fusion algorithms usually not available. At this early stage of our investigation, we will provide a broad overview of relative complexity of the evaluated fusion methods in Section 4.

Results

We applied the noisy fusion evaluation framework on the 20 multisensor video sequences in our database using the six defined noise power (SNR) levels. Here we show visual examples of fused noisy sequences and provide the mean objective results for the alternative fusion noisy fusion algorithms obtained on the entire multisensor dataset.

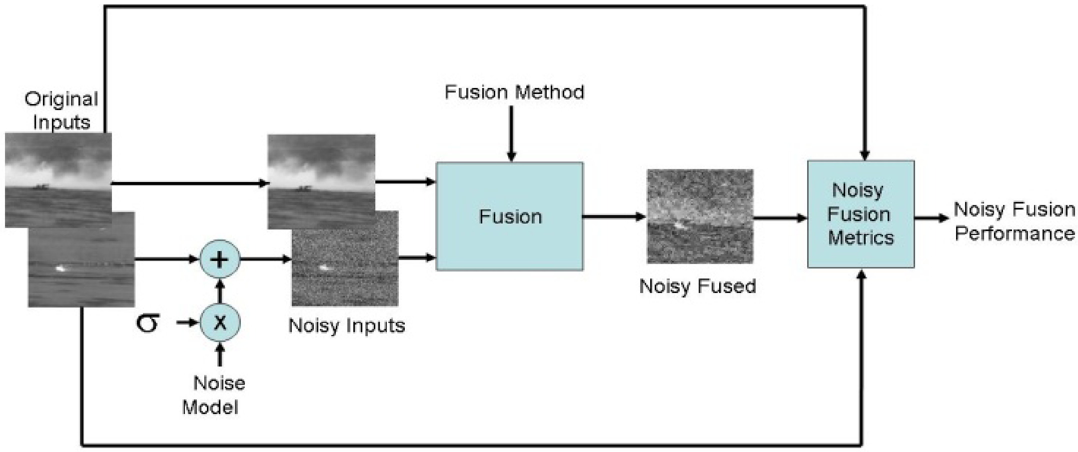

Figure 4. Noisy fusion performance evaluation framework

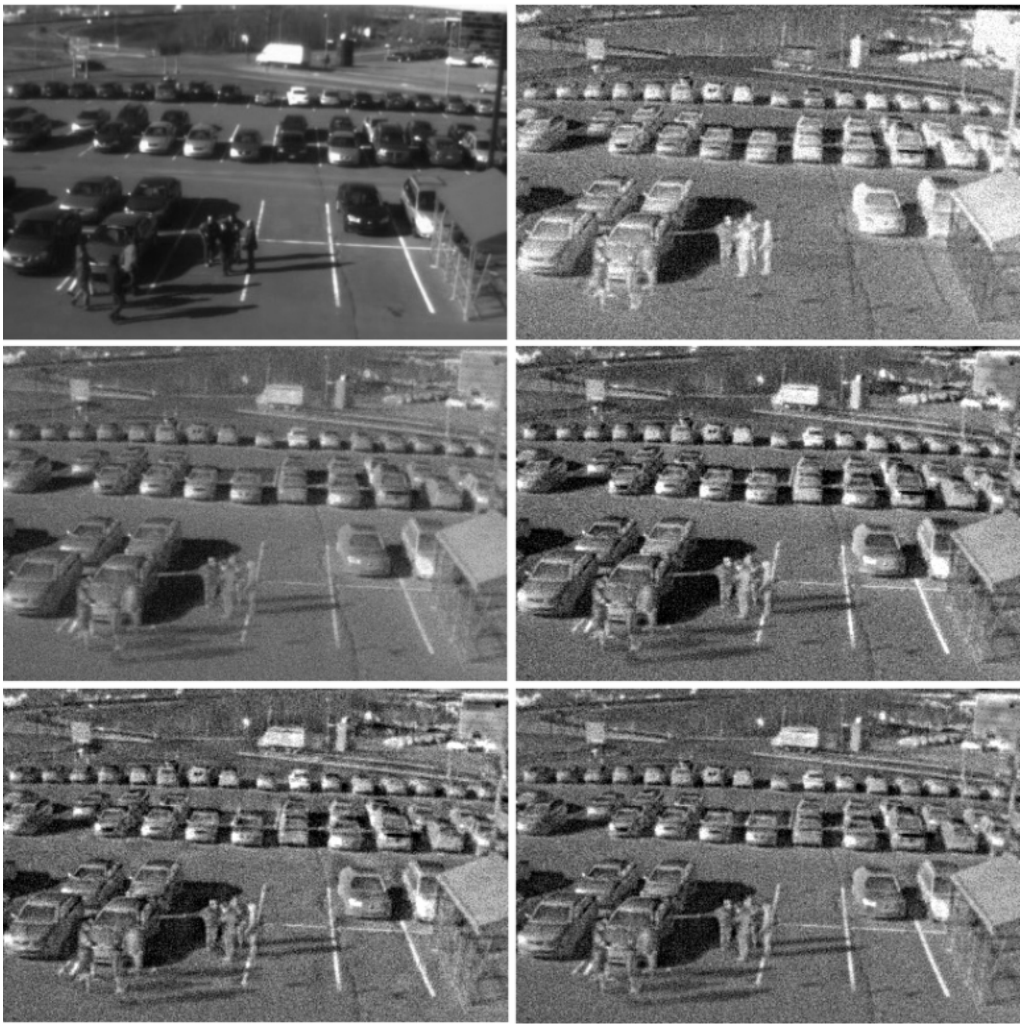

Figure 5. Noisy fusion example: source frames top; averaging and laplacian pyramid fusion middle; DWT and DT-CWT fusion with abs max selection

Fig.5 shows the example frames from the "Fight" sequence at 6 dB SNR. The arithmetic fusion (middle left) produces lowest contrast but also, by the same method, low noise power in the fused frame. The positive effect of shift invariance is visible in the lack of "ringing" artifacts visible in the DWT (bottom left) compared to the DT-CWT space fusion (bottom right), note the halo around the van in the background. Laplacian fusion produces perhaps the clearest fused image with good contrast and low artifacts all over the scene, even if it maintains relatively high noise power.

The objective N-DQ$^{AB/F_{SNR}}$ metric reveals how the performance of the different fusion approaches is affected by varying levels of noise. Fig.6 shows the mean N-DQ$^{AB/F_{SNR}}$ scores of five different fusion algorithms over the dataset described corrupted to 6 different levels of SNR. At no noise corruption, arithmetic fusion is the worst as expected, see Fig.5. Laplacian pyramid fusion and DT-CWT are the best; however, their performance degrades significantly along that of the other methods as SNR decreases. Even though the advantage in performance of these two methods gets smaller, it persists across the noise corruption range showing that the MR space has an effect on noisy dynamic fusion performance. At low SNR, arithmetic fusion catches up with other methods as its inherent noise power halving makes more of an effect. In fact, at very low SNR, fusion performance of all the methods converges and no method provides significantly better performance.

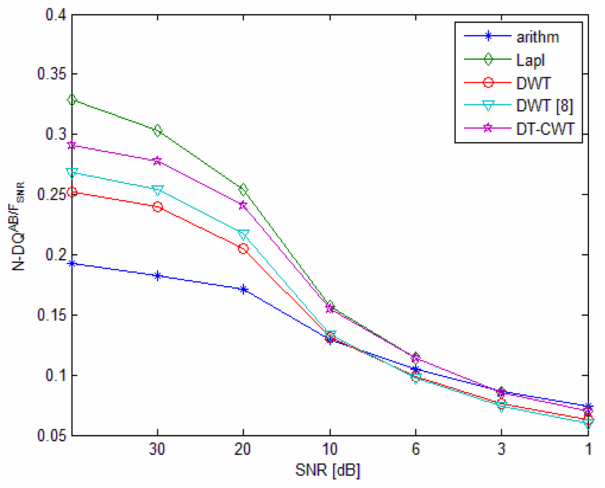

Figure 6. Absolute noisy fusion performance of standard video fusion for a range of noise corruption levels on the 20 multisensor video sequences

A wider support feature selection, using Li et al's method [8], produces an improvement in DWT fusion performance in the noise-free and high SNR case. However, as the noise power increases, even such an area-based selection and majority filtering are overwhelmed and its performance advantage over benchmark DWT select-abs-max fusion disappears.

Fusion integrated noise suppression techniques and noise mitigation pyramid fusion strategies were evaluated on both noise-free and noisy sequences. Noise-free dynamic fusion using these approaches is illustrated on the "mso1" sequence in Fig.7. Soft and hard thresholding applied on the DT-CWT pyramids produce clear detail rich images (top row). Dynamic 3x3x3feature selection on the Laplace pyramid is compared to the benchmark select-abs-max along the bottom row of Fig.7. DT-CWT methods using soft and hard thresholds produce images with lower overall contrast much like the dynamic feature selection fusion (bottom right). A significant result of the dynamic selection that cannot be illustrated easily in still figures is added temporal stability that this sequence exhibits, in particular when noise corruption is present in the inputs.

Figure 7. Hard and soft thresholding on the DT-CWT pyramid (top row) and dynamic 3x3x3-max and select-abs-max feature selection on the Laplacian pyramid (bottom row) applied to noise free images

Noise suppression performance of the two thresholding approaches is illustrated on the frame from the "Visitor Parking" sequence in Fig.8. There are no thresholding predictable results in considerable noise power in the fused frame (top right). Hard threshold produces a limited improvement while soft threshold (bottom left) clearly suppresses noise in the fused signal. Note that the baseline select-abs-max feature selection is used to fuse the two pyramids prior to thresholding. In both thresholding cases, we used a fixed threshold value of 0.05 applied to two highest resolution levels. This corresponded to about 15% of the dynamic range of the coefficients in the pyramid.

Figure 8. Input noisy thermal image at 1dB SNR and fused images using DT-CWT with select-abs-max feature selection followed (clockwise) by no, hard and soft thresholding

The visual findings from Fig.8 are confirmed by the objective scores of the N-DQ$^{AB/F_{SNR}}$ metric applied to the fused sequences produced using these methods on the multisensor dataset corrupted to various SNR levels, Fig. 9. As a reference these methods the figure includes the scores obtained using benchmark select-abs-max feature selection on DT-CWT pyramids, equivalent fusion on the Laplacian pyramid and strategies for suppressing effects of noise in video fusion.

Performance advantage gained from integrating noise suppression into pyramid fusion is realized even for relatively high SNR. Both thresholding methods outperform other fusion algorithms for SNR of 20 dB and below. This advantage remains constant throughout the SNR range. Out of the two approaches, the soft threshold clearly gives the best noisy dynamic fusion results. It outperforms the hard threshold significantly over all SNR levels, confirming the visual example in Fig.8.

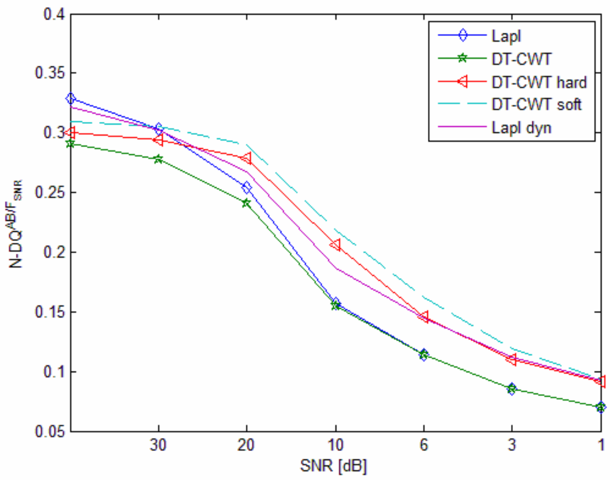

Figure 9. Absolute noisy fusion performance of standard and fusion integrated noise suppression methods for video fusion for a range of noise corruption levels on the multisensor dataset

Finally, in terms of computational complexity, threshold methods, particularly the soft threshold, clearly provide the best noisy performance advantage for the additional computational cost. They require a marginal increase, basically a thresholding operation and perhaps a subtraction on only one, fused pyramid. The DT-CWT space, however, has an additional computational cost and is twice as expensive as the simpler but more noise susceptible standard DWT pyramid.

Conclusion

This paper presented the results of an investigation into the effects of noise on dynamic (video) image fusion. We created an extensive, varied multisensor dataset of noise corrupted videos at 6 levels of SNR and used it to evaluate a wide range of conventional and dynamic noisy fusion techniques. We defined an objective metric for the evaluation of noisy dynamic fusion N-DQ$^{AB/F}$ and showed it produces objective fusion performance scores consistent with a less practical visual assessment. We used the metric as a basis for an automated noisy fusion evaluation framework, which we used to investigate a number of processing concepts and fusion strategies aimed at reducing the effects of noise on performance of dynamic image fusion.

We found that the multiresolution analysis strategy has an effect on noisy dynamic fusion performance. The shift-invariant representation (DT-CWT) provides an advantage over shift-variant methods such as DWT at a cost of additional computational complexity. A wider spatial support feature selection used in pyramid fusion is also capable of mitigating the effects of noise on fusion performance but only at high SNR levels. We also found that at low SNR, fusion performance converges and no method provides significantly better performance.

Nevertheless, improved fusion performance can be achieved even at low SNR by integrating relatively simple noise suppression techniques into the fusion process. Both soft and hard thresholding of pyramid coefficients at a cost of a small complexity increase and drop in performance at no-noise levels provide better performance at low SNR with soft thresholding producing the highest N-DQ$^{AB/F}$ scores and kinder looking fused images.

Producing dynamic fusion algorithms robust to noise using these suppression principles but also able to adapt to noise levels encountered in the input data is the natural extension of the work presented in this paper, in addition to currently running subjective trials on noisy dynamic fusion aimed at better understanding of perceptual effects of noise in dynamic fusion.

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Objektivna procena i smanjenje efekta šuma u dinamičkom sjedinjavanju slika

U radu smo predstavili istraživanje vezano za uticaj šuma na sjedinjavanje dinamičkih (video) slika. Na samom početku rada napravljena je baza multisenzorskih video sekvenci, koja je proširena sa dodavanjem različitih nivoa šuma na izvorne video sekvence. Definisali smo objektivnu meru za procenu uspešnosti sjedinjavanja u prisustvu šuma N-DQ$^{AB/F}$ i dali njenu usaglašenost sa vizuelnom predstavom. Mera za procenu uspešnosti sjedinjavanja primenjena je na većem broju metoda za sjedinjavanje dinamičkih slika i strategija za smanjenje efekta šuma u video sjedinjavanju na kreiranoj bazi. Prepoznate su karakteristike multirezolucione piramide i mogućnosti smanjenja efekta šuma u dinamičkom sjedinjavanju slika. Prikazali smo i veoma jednostavne tehnike za smanjenje šuma ugrađene u sam proces fuzije koje daju dobre rezultate pri malim vrednostima SNR uz veoma malo uvećanje računarske zahtevnosti.

Ključne reči: **obrada slike, kvalitet slike, sjedinjavanje slike, merenje šuma, filtriranje šuma, potiskivanje šuma.**

Объективная оценка и снижение эффекта шума в динамическом слиянии изображений

В этой статье мы представили исследование о влиянии шума на слияние динамических (видео) изображений. В самом начале работы произведена база мультисенсорных видеорядов, которая была расширена с добавлением различных уровней шума на исходные видео-последовательности. Мы определили объективную меру для оценки успешного слияния в присутствии шума N-DQAB/F и дали её соответствие с визуальным представлением. Мера по оценке успешного слияния была применена в ряде методов для слияния динамических изображений и стратегий по снижению влияния шума в видео унификации на созданной базе данных. Признаны характеристики кратномасштабной пирамиды и возможности уменьшения влияния шума в динамическом слиянии изображений. Мы представили очень простые методы для снижения уровня шума, встроенные в процесс слияния, которые дают хорошие результаты при низких значениях SNR с очень малым увеличением вычислительной требовательности.

Ключевые слова: **обработка изображения, качество изображения, слияние изображений, измерение шума, фильтрация шума, подавление шумов.**

Evaluation objective et suppression des effets du bruit dans la fusion dynamique des images

Dans ce papier on a présenté la recherche liée à l'effet du bruit sur la fusion des images dynamiques (vidéo). Au tout début du travail on a créé une base de séquences multi sensorielles vidéo qui a été complétée par les différents niveaux de bruit ajoutés aux séquences vidéo originales. On a défini la mesure objective pour l'évaluation de la réussite de fusion en présence du bruit N-DQAB /F et on a présenté son accord avec la représentation visuelle. La mesure pour l'estimation de la fusion a été appliquée chez un grand nombre de méthodes pour la fusion des images dynamiques et des stratégies pour la diminution des effets de bruit dans la fusion vidéo sur la base créé. On a identifié les caractéristiques de la pyramide multi résolution ainsi que les possibilités de diminuer les effets de bruit dans la fusion dynamique des images. On a présenté aussi les techniques très simples pour la suppression du bruit intégré dans le processus même de la fusion qui donnent bons résultats lorsque les valeurs de SNR sont petites et avec une petite augmentation de l'exigence informatique.

Mots clés: **traitement d'image, qualité d'image , fusion d'image, mesurage de bruit, filtrage de bruit, suppression de bruit.**