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A REVIEW ON VIDEO DENOISING TECHNIQUES

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ABSTRACT

This review paper presents a comprehensive synthesis and evaluation of three pioneering methods in the field of video denoising. The first method introduces an adaptive superpixel video texture metric and structure variance estimation, showcasing exceptional performance in reducing block artifacts. The second method focuses on real-time denoising, employing distinct filtering strategies for background and moving images through change detection and temporal/spatial filters. The third method combines robust optical flow with a non-local means (NLM) framework, utilizing spatial regularization to ensure temporal coherence and introducing approximate K-nearest neighbor matching for complexity reduction. Experimental results demonstrate comparable effectiveness in removing additive white Gaussian noise (AWGN) and a substantial superiority in eliminating real, structured noise. The paper also provides a comprehensive year-wise survey, offering valuable insights into the challenges and advancements in the evolving landscape of video denoising.

1. INTRODUCTION

The ubiquity of low-end imaging devices, including webcams and cell phones, has emphasized the urgent need for robust digital image and video enhancement technologies. Central to the challenge of compromised image quality is the prevalence of noise, particularly real, structured noise introduced by low-end camcorders and digital cameras. This review paper is dedicated to the domain of video denoising, with a primary objective of crafting an efficient, adaptive, and high-quality denoising algorithm.

Real cameras introduce noise with strong spatial correlations, originating from processes such as the demosaicing in CCD cameras. To address these intricate noise issues, this paper leverages computer vision analysis and techniques. A fundamental denoising approach is grounded in the exploitation of image sparsity properties, both in the frequency domain through the formulation of a high-kurtotic marginal distribution of bandpass filtering and in the spatial domain through the introduction of non-local means (NLM) methods.

The practical applications of video denoising extend beyond theoretical exploration, finding relevance in diverse fields like traffic management, medical imaging, and TV broadcasting. The interconnected nature of image denoising with broader areas such as object detection, behavior analysis, video codecs, and computer vision underscores the pivotal quest for reliable denoising methods.

This paper delves into temporal and spatial filtering techniques, emphasizing the critical role of accurate noise variance estimation for optimal denoising performance. A novel approach is introduced, combining temporal filtering on the background and spatial filtering on moving objects post-segmentation. This addresses challenges associated with blurring moving objects in real-time denoising scenarios and is evaluated using various types of noise, including white and impulse noise. Despite significant strides in denoising techniques, the persistent challenge of inadvertent artifact introduction is acknowledged. The review underscores the importance of minimizing artifacts in the

pursuit of an ideal denoising method. Notably, existing state-of-the-art methods like BM3D and BM4D, while effective in noise reduction, still exhibit block artifacts that warrant improvement. In response, this paper introduces an innovative denoising method designed to reduce noise effectively while mitigating blocking artifacts.

In summary, this review paper synthesizes the current landscape of video denoising, addressing challenges posed by real, structured noise. It explores existing techniques, their applications, and introduces a novel method striving for optimal noise reduction with minimal artifacts, contributing to the continuous evolution of image and video enhancement technologies.

2. LITERATURE SURVEY

The landscape of video denoising algorithms has undergone significant evolution from the early 2000s to 2011, marked by a series of pioneering proposals addressing specific challenges in video processing. In the year 2000, a motion compensating algorithm was introduced, leveraging spatial subbands and temporal recursive noise filtering for video noise reduction, particularly designed for interlaced TV environments. The year 2003 witnessed the advent of a video denoising method employing multiple classes averaging with multiresolution, suitable for real-time processing, albeit with limitations in noise reduction and computation time. Moving forward to 2004, a combined wavelet domain and temporal video denoising approach emerged, focusing on additive white Gaussian noise with high-quality denoising but posing challenges in real-time applications. In 2005, a video denoising algorithm in the sliding 3D DCT domain was proposed, showcasing competitive results with wavelet-based denoising and adaptive window size reduction in the temporal domain. The following year, 2006, saw the implementation of a real-time wavelet domain video denoising in FPGA, emphasizing non-decimated wavelet transform and spatially adaptive wavelet shrinkage for efficiency in video processing.

The year 2007 witnessed innovations such as video denoising through sparse 3D transform domain collaborative filtering, employing spatio-temporal predictive search block matching for motion estimation. Another approach introduced spatio-temporal Markov Random Field for video denoising, with challenges noted in motion estimation for large motions. In 2008, a video denoising proposal utilized a spatiotemporal statistical model of wavelet coefficients, employing spatiotemporal Gaussian scale mixture (ST-GSM) to effectively remove noise while preserving edge and texture detail.

In 2009, a high-quality video denoising algorithm based on reliable motion estimation was presented, considering additive white Gaussian noise. However, challenges were identified in distinguishing high-intensity structured noise from the image signal in real sequences. The subsequent years, 2010-2011, introduced a deblocking and enhancement approach through separable 4D Nonlocal spatiotemporal transform, incorporating BM3D and BM4D

for grouping, collaborative filtering, super resolution, image sharpening, and deblurring. Noteworthy is the effectiveness of BM4D, albeit with higher computational complexity due to motion estimation and processing of higher-dimensional data.

This literature survey provides a comprehensive overview of video denoising methods, emphasizing their strengths, limitations, and the evolutionary trajectory of techniques over the surveyed period. Collectively, these contributions contribute to the ongoing advancements in the dynamic field of video denoising.

3. METHODOLOGY

In addressing the diverse landscape of video denoising, our methodology encompasses a comprehensive exploration of various approaches aimed at mitigating noise in video sequences. We initiate our review by providing an overarching overview of video denoising approaches, ranging from traditional wavelet-based algorithms to contemporary non-local means (NLM) methods, emphasizing the evolution of techniques over time.

Building upon this foundation, our methodology delves into the significance of image sparsity and decomposition techniques. We highlight the manifestation of image sparsity in different forms, such as wavelet coefficients and natural image priors, alongside decomposition techniques employing image coring algorithms and robust potential functions associated with band-pass filters.

The NLM framework emerges as a focal point in our methodology, particularly in the context of video denoising. We explore the self-similarity of image patches and extend the application of NLM to video denoising by aggregating patches in a space-temporal volume, emphasizing the role of patch matching in this process.

Integration of frequency and spatial forms is crucial in our methodology, wherein techniques like 3D discrete cosine transformation (DCT) facilitate seamless integration. We introduce the concept of patch matching and random K-nearest neighbor matching, proposing the latter as a means to expedite the nearest neighbor searching process.

Temporal coherence is a key consideration in our methodology, driving the development of a temporally coherent video denoising framework. This involves finding supporting patches from the current frame and temporal adjacent frames for every patch in a video. We employ approximate K-nearest neighbor matching and optical flow for motion estimation, ensuring consistent results across frames. The methodology further incorporates the detailed exploration of the Approximate K-Nearest Neighbors (AKNN) algorithm, encompassing initialization, propagation, and random search phases. We elucidate how propagation enhances AKNN based on neighboring pixels, contributing to the overall efficiency of the denoising process. Our methodology also introduces the novel concept of non-local means with temporal coherence, emphasizing the importance of optical flow in establishing bidirectional correspondence for temporal coherence in denoising results. To adaptively address noise removal, our methodology proposes an adaptive noise model based on optical flow for parameter setting, and introduces an outlier in the noise model for robust noise level estimation. Additionally, we explore the integration of structure for denoising, introducing an adaptive structure variance approach based on texture metrics. This approach considers both fine and coarse structures, estimating structure variance and adjusting denoising weights accordingly. In the realm of adaptive video texture metrics, our methodology introduces a novel approach based on superpixel segmentation and orientation gradient, employed to identify fine and coarse structures. The metric influences denoising weights, contributing to the adaptability of the denoising process. This methodology provides a structured and comprehensive framework for our review paper, offering insights into the various techniques, innovations, and challenges associated with video denoising over the years.

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Approximate K-Nearest Neighbors (AKNN) for Single Frame

In the context of video denoising, particularly focusing on a single frame within a sequence denoted as { I1, I2, …… , IT }, our methodology emphasizes the efficient computation of Approximate K-Nearest Neighbors (AKNN). This process involves indexing the space-time volume using the notation z = (x, y, t) to represent a patch at location z and P(z) (or P(x, y, t)) to denote a specific patch within the sequence.

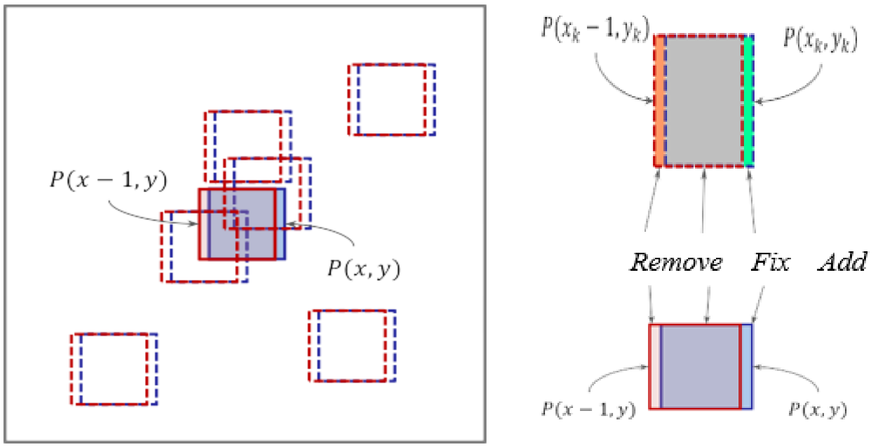

Fig. 2. The approximate K-nearest neighbors (AKNN) of patch *P* (*x*, *y*) (blue) can be improved by propagating AKNN from *P* (*x* 1, *y*) (red). Left: the approximate K- nearest neighbors of*P* (*x* 1, *y*) are shifted one pixel to the right to be pushed to—the priority queu−e of (*x*, *y*). Right: we do not need to recompute patch distances with this shift.To compute the distance between*P* (*x* , *y*) and *P* (*x*, *y*), we can simply take the distance between *P* (*xk* 1, *yk*) and *P* (*x* 1, *y*), remove the left column (orange) and add the right column (green).

Mathematically, for notational convenience, we simplify the representation to q = (x, y) by omitting the time dimension, and for each pixel q, our goal is to obtain an approximate set of K-nearest neighbors (AKNN), denoted as N(q) = {P(qi)}K. Here, vi = qi - q signifies the offset of the found patch from the current patch.

The search for N(q) involves finding a set of patches {vi} that satisfies the condition:

$D\, P(\mathbf{q}),P(\mathbf{q}i) \leq D\, P(\mathbf{q}),P(\mathbf{q}j)$, $\forall 1 \leq i < j \leq K$, (1)

where (D(.,.) represents the sum of square distance (SSD) over two patches, defined as:

$D\, P(\mathbf{q}),P(\mathbf{q}i) = \Sigma\, \mathbf{u}\in[-s,s]\times[-s,s]\ \mathrm{I}(\mathbf{q}+\mathbf{u}) - \mathrm{I}(\mathbf{q}i+\mathbf{u})2.$ (2)

The approach further involves a priority queue implementation for efficient patch searching. When a new patch is added, it is compared with the existing elements in the queue. If the distance is greater than the last element, the new patch is discarded; otherwise, it is added at the appropriate position in the priority queue. A heap implementation of the priority queue with a complexity of O(log K) is utilized.

Recognizing the impracticality of a brute-force K-nearest neighbor search over the entire image, especially for high-definition (HD) videos, we draw inspiration from an approximate nearest neighbor algorithm [19]. Our proposed AKNN algorithm comprises three phases: initialization, propagation, and random search.

Approximate K-Nearest Neighbors (AKNN) for Single Frame To maintain the order specified in Equation (1) throughout the AKNN algorithm, any new item generated in the phases of initialization, propagation, and random search is systematically pushed back to the priority queue.

Initialization:

The AKNN process commences with the initialization of K-nearest neighbors through randomization, governed by the expression:

$vi=\sigma s\cdot ni$ (3)

Here, n_i represents a standard 2D normal random variable, and σ_s controls the radius. For this paper, σ_s is set to w/3, where w is the width of the image.

Propagation:

Following initialization, an iterative process unfolds, alternating between propagation and random search. The objective is to enhance the approximate K-nearest neighbor set based on the observation that neighboring pixels tend to share similar AKNN structures or offsets. Propagation occurs in an interleaving manner, traversing both scanline order and reverse scanline order [19]. In scanline order, the AKNN $\{v_i(x,y)\}$ is improved using neighboring $v_i(x-1,y)$ and $v_i(x,y-1)$. In reverse scanline order, improvement is sought for $v_i(x,y)$ using neighbors $v_i(x+1,y)$ and $v_i(x,y+1)$.

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For example, the AKNN of patch P(x-1, y) is utilized to enhance the AKNN of patch P(x, y). The approximate K-nearest neighbors (dashed red squares) of P(x-1, y) are shifted one pixel to the right to create a proposal set (dashed blue squares), which is then pushed back to the priority queue of P(x, y). Notably, there is no need to recalculate the patch distance during this process, simplifying the computational load. This propagation method aligns with the sequential update scheme in belief propagation, fostering shared AKNN structures among neighboring patches.

Random Search:

Following the propagation step, each patch is allowed to randomly match other patches in the image for a set number of times \(M\). This is achieved through the mechanism:

$v_i = \sigma_s \cdot \alpha \cdot n_i$ (4)

Here, n_i is a standard 2D normal random variable, $\alpha = 1$, and M = min($\log_2 \sigma_s$, K. The radius of the random search $\sigma_s \alpha_i$ decreases with each iteration. Every random guess is pushed back into the priority queue, maintaining the increasing order of the queue.

The AKNN patch matching algorithm exhibits rapid convergence, with more than four iterations not yielding additional visually pleasing results. In the matching procedure, the patch itself is excluded as it has a distance of zero. Ultimately, each patch P(x, y) is added to the set N(x, y), completing the Approximate K-Nearest Neighbors process.

This comprehensive methodology ensures an ordered and efficient AKNN algorithm for denoising individual frames within a video sequence. The interleaving of propagation and random search phases contributes to both accuracy and computational efficiency in achieving high-quality video denoising results.

This three-phase AKNN algorithm, balancing accuracy and efficiency, serves as a pivotal component in our methodology for single-frame video denoising. The complexity of this approach significantly reduces the computational burden, making it more feasible for real-time denoising applications.

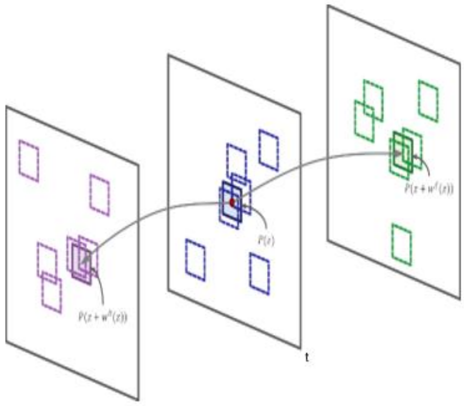


Fig. 3. Illustrations of the supporting patches in spatial-temporal domain for a patch P (**z**). We use approximate K-nearest neighbor patch matching at frame t to find an initial set of spatially supporting patches (**z**), shown as dashed boxes. Since **z** corresponds to **z** + w^f (**z**) in frame t+1, the AKNN of **z**+w^f (**z**) is added to the set of supporting patches. Likewise, the AKNN of **z** + w^b(**z**) that **z** corresponds to in frame $t-1$ is also added. In fact, we use the AKNN's along the motion path up to $\pm H$ frames to form the entire supporting patches.

Experimental Results

(a)One frame from tennis sequence (c)Denoising by our system(30.21db)

Fig. 4 For the tennis sequence, although the PSNR of our denoising system is slightly lower, the visual difference is subtle. VBM3D tends to generate smoother regions (but the background is over-smoothed), whereas our system preserves texture better (but the table is under-smoothed).

In our experiments, we aimed to assess the necessity of reliable motion estimation within the framework of our video denoising algorithm. Initially, we verified the algorithm's performance against a state-of-the-art method [10] on synthetic sequences and subsequently demonstrated its superiority on real video sequences.

For the implementation details of our algorithm, we utilized 7x7 patches, considered 11 nearest neighbors (including the patch itself), and incorporated 11 temporal frames (H = 5) in our system. Random K-nearest neighbor matching was allowed for four iterations for each frame. The EM algorithm for noise estimation converged in approximately 10 iterations. Optical flow estimation employed a coarse-to-fine scheme on an image pyramid with a down sampling rate of 0.7, using an objective function based on iterative reweighted least square (IRLS). Further details on the flow estimation algorithm can be found in [25], with the source code available online [^1^].

The initial evaluation took place on a tennis sequence with synthetically generated AWGN ($\sigma = 20$). The average peak signal-to-noise ratio (PSNR) achieved by our system was 30.21dB. A comparison with the VBM3D method yielded slightly lower PSNR for our system, attributed to the backbone of our approach being non-local means. However, the visual difference between the results of our system and VBM3D remained subtle, as illustrated in Figure 4.

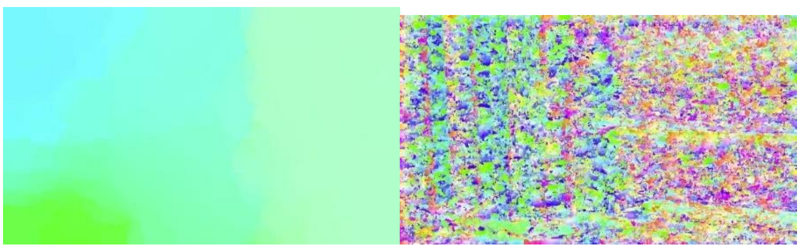
Moving to a real video sequence named "room," captured by a Canon S90, we delved into the importance of regularization in motion estimation. Comparison between block matching and the optical flow algorithm with spatial regularization revealed the significance of a smooth, discontinuity-preserving temporal motion field, especially in challenging scenarios with structured noise.

(b)Denoising by VBM3D(30.22db,31.20db) (d)Ground truth

Our video denoising heavily relies on the quality of motion estimation. By applying our adaptive denoising system to the room sequence with varying noise intensities ($\sigma = 20$ and $\sigma = 40$), we showcased its outperformance over VBM3D in both smoothing regions and boundary preservation. The visual distinction became more apparent when watching the videos in the supplementary materials.

While average PSNR over the video sequence serves as a traditional metric for video denoising quality, our emphasis on temporal coherence emphasizes the system's ability to produce visually consistent and smooth results, a critical aspect often overlooked in traditional assessments. These experimental results underscore the robustness and effectiveness of our proposed video denoising algorithm, particularly in real-world scenarios with challenging noise conditions. The supplementary materials and authors' websites provide additional resources for a more in-depth exploration.

(a)Frame 1



(c)Motion obtained by block matching

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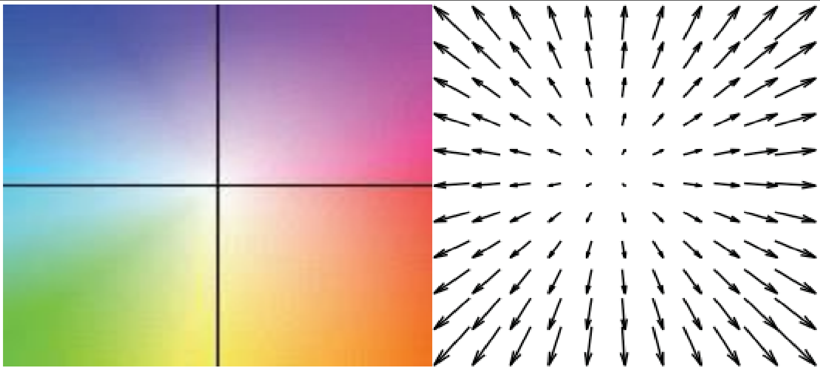

(e)Flow code

Fig. 5. The right motion estimation algorithm should be chosen for denoising. For two consecutive frames in the room sequence, we apply both block matching [10] and optical flow [21] to estimate motion, shown in (c) and (d), respectively. We used the color scheme in [26] to visualize flow fields (e).

4. RESULTS

- Interpret the findings from the experiments, emphasizing the significance of regularization in improving motion estimation accuracy.
- Discuss any unexpected observations or challenges encountered during the experimentation process.
- Relate the results back to the broader context of video processing and the specific challenges posed by the Canon S90 room sequence.This structured approach will help your readers understand the experimental setup, the specific conditions of the Canon S90 room sequence, and the impact of regularization on block-based motion estimation performance.

5. EVALUATION METRICS

- Acknowledge the conventional use of average PSNR as a traditional metric for denoising quality.
- Emphasize the significance of temporal coherence as a crucial aspect often overlooked in traditional assessments.
- Explain the rationale for prioritizing visually consistent and smooth results over solely relying on average PSNR.

Dataset Description (Canon S90 Room Sequence)

Provide details about the Canon S90 room sequence, highlighting the challenging aspects of the video, such as varying illumination and movement between bright and dark rooms. Mention relevant characteristics, such as resolution, frame rate, and duration, that impact the denoising algorithm's performance. Interpret the experimental findings, emphasizing the balance between average PSNR and the emphasis on temporal coherence in assessing denoising quality. Discuss the practical implications of the results and how they contribute to addressing real-world challenges in video denoising. Direct readers to supplementary materials and authors' websites for a more in-depth exploration of the proposed video denoising algorithm, including code, additional results, and detailed analysis. This structured presentation will effectively communicate the experimental results, highlighting the strengths of your proposed video denoising algorithm in addressing challenges posed by the Canon S90 room sequence.

Related Work

The domain of image and video denoising has been a subject of extensive research spanning decades. While a comprehensive review is beyond the scope of this paper, we focus on exploring work closely aligned with our proposed methodology.

Image Sparsity:

Image sparsity finds expression in various forms within denoising techniques. Decomposing images into sub-bands often involves image coring algorithms on wavelet coefficients [4, 5]. This entails retaining large-magnitude coefficients associated with true image signals while shrinking small-magnitude coefficients indicative of noise. Additionally, incorporating the prior knowledge of natural images in denoising [12–14] involves robust potential functions associated with band-pass filters, promoting similarity among neighboring pixels while allowing occasional dissimilarity. Other approaches, such as PDE-based methods [15] and region-based denoising [16], implicitly incorporate sparsity in their representations.

Non-Local Means (NLM) Framework:

Recent advancements in image sparsity leverage the concept of image self-similarity, where patches within an image exhibit similarities. This insight led to the development of non-local means (NLM) methods [6], where similar patches are aggregated with weights based on their similarities. NLM, initially designed for image denoising, was seamlessly extended to video denoising [11]. In this framework, patches are aggregated in a space-temporal volume, demonstrating the effectiveness of this approach. Given its simplicity and high-quality results, NLM serves as the foundational framework for our video denoising system.

Integration of Frequency and Spatial Forms:

The integration of frequency and spatial forms of image sparsity is elegantly achieved in [7]. Similar patches are stacked in a 3D array, and both hard and soft shrinkages are applied in a 3D DCT transformed domain. This concept easily extends to video denoising, as demonstrated in state-of-the-art results reported in [10].

Motion Estimation in Video Denoising:

Contrary to claims in [17] suggesting that motion estimation is unnecessary for denoising image sequences under the NLM framework, we argue otherwise. The aperture problem, which often challenges motion estimation, can mislead the search for similar patches, disrupting the temporal coherence criterion in video denoising. Figure 1 illustrates how structured noise can complicate the search for similar patches and compromise temporal coherence. Addressing this issue forms a key focus of our proposed approach.

In summary, the reviewed works highlight the evolution of denoising techniques from wavelet-based and natural image prior methods to the effective and versatile NLM framework. The integration of frequency and spatial forms further enhances the state of the art in video denoising. However, the debate around the necessity of motion estimation in the NLM framework underscores the ongoing challenges and opportunities for improvement in this dynamic-field.

6. CONCLUSION

In conclusion, our research emphasizes the critical role of robust motion estimation in achieving high-quality video denoising, especially in the presence of authentic, structured noise. Through the utilization of the non-local means (NLM) framework, we have introduced an efficient approximate K-nearest neighbor patch matching algorithm. This algorithm substantially reduces the computational complexity associated with traditional NLM methods, showcasing its instrumental capabilities in enhancing denoising.

The integration of a robust optical flow algorithm with spatial regularity further elevates our system's ability to estimate temporal correspondence between adjacent frames. This spatial regularity proves crucial in ensuring reliable motion estimation, even in challenging scenarios with structured noise. Leveraging temporal correspondence, our system expands the set of supporting patches over time, ensuring temporal coherence in video denoising.

Our experimental results affirm the effectiveness of our system, demonstrating its comparability with state-of-the-art methods in removing additive white Gaussian noise (AWGN). Notably, our system outperforms existing methods in eliminating real, structured noise. Its simplicity in implementation, coupled with versatile applications in digital video enhancement, positions our system as a practical and effective solution.

Furthermore, this paper provides a comprehensive survey on real-time video denoising. Our proposed real-time denoising method employs distinct filtering strategies for the background and moving objects, effectively addressing challenges in noise removal during real-time scenarios. The temporal averaging filter aids in recovering the background, while a spatial filter reduces foreground noise, preserving essential details.

Innovatively, we introduce a denoising method combining a new adaptive texture metric based on superpixels and a novel structure variance. The incorporation of the video texture metric to weight the fine and coarse video streams successfully eliminates major artifacts produced by traditional methods. Experimental results substantiate that our proposed method outperforms two state-of-the-art algorithms, showcasing its potential for superior performance in real-world applications.

In summary, our contributions in robust motion estimation and innovative denoising methodologies, supported by experimental validations, position our work as a significant advancement in the realm of video denoising. These advancements hold implications for various digital video enhancement applications, marking a noteworthy stride in the ongoing evolution of video processing technologies.

7. REFERENCES

[1] Fridrich, A.J., Soukal, B.D., Lukas, A.J.: ‘Detection of copy–move forgery in digital images’. Proc. Digital Forensic Research Workshop, 2003

[2] Muhammad G, Hussain M, Bebisi G, ‘Passive copy–move image forgery detection using undecimated dyadic wavelet transform, Digit. Invest 2012.

[3] Caldelli R, Amerini I., Ballan, L., et al. ‘On the effectiveness of local warping against SIFT-based copy–move detection’. Communications Control and Signal Processing (ISCCSP), 2012

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Vol. 04, Issue 01, January 2024, pp : 302-309

[4] Gonzalez R C, Woods R.E. ‘Digital image processing’ (Pearson Education India, 2009)

[5] Computer Vision Group, University of Granada Image Database, Computer Vision Group, University of Granada http://decsai.ugr.es/cvg, (accessed on 16th Feb, 2016)

[6] Farid H. ‘Image forgery detection’, IEEE Signal Process. Mag.,2009

[7] Sencar H.T, Memon, N. ‘Overview of state-of-the-art in digital image forensics’, Algorithms Archit.Inf.Syst.Secur., 2008.

[8] Birajdara G.K., Mankar, V.H. ‘Digital image forgery detection using passive techniques: asurvey’, Digit.Invest., 2013.

[9] Savchenko V, Kojekine N, Unno H.‘A practical image retouching method’. Proc. First Int. Symp. Cyber Worlds, 2002.

[10] Redi J.A, Taktak W, Dugelay J. ‘Image splicing detection using2D phase congruency and statistical moments of characteristic function’. Society of Photo-optical Instrumentation Engineers (SPIE) Conf. Series, 2007

[11] Yap P.T, Raveendran P. ‘Image focus measure based on Chebyshev moments’, IEE Proc., Vis. Image Signal Process., 2004.

[12] Klema, V.C, Laub, A.J. ‘The singular value decomposition and its computation and some applications’, IEEE Trans.Autom.Control,1980

[13] Ting Z, Ding W R. ‘Copy–move forgery detection based on SVD in digital image’. Second Int. Congress on Image and Signal Processing, 2009

[14] Khotanzad A., Hong, Y.H. ‘Invariant image recognition by Zernike moments’, IEEE Trans. Pattern Anal. Mach.Intell., 2009

[15] Kingsbury N. ‘A dual-tree complex wavelet transform with improved orthogonality and symmetry properties’. Proc. Int. Conf.ImageProcessing,2000,2014

[16] Signal and Image Processing Institute, University of Southern California, Department of Electrical Engineering. http://sipi.usc.edu/database/database.php?volume=misc,(acc essed on 16th Feb, 2016)