Target Detection in Wushu Competition Video Based on Kalman Filter Algorithm of Multi-Target Tracking

Dr. Supraja Veerabomma[1], Dr. M. Srinivasa Rao[2], Dr. Putta Brundavani[3,*] and Dr. Bepar Abdul Raheem[4]

[1]Associate Professor, Department of ECE, G Pullaih College of Engineering and Technology, Kurnool, Andhra Pradesh, India
[2] Professor, Department of ECE, Joginapally BR Engineering College,Moinabad, Rangareddy(Dist), Hyderabad, Telangana-500075,India
[3]Associate Professor, Department of ECE, RSR Engineering College, Kavali, SPSR Nellore, Andhra Pradesh – 524142, India
[4]Professor, Department of ECE, Joginapally BR Engineering College, Moinabad, Rangareddy (Dist), Hyderabad, Telangana-500075, India

Abstract

In modern Multi-Target Tracking, the integration of Kalmann Filterdata and visual space transformation (VST), enabled by digital Video processing technology, has revolutionized creative workflows. Kalmann Filterdata involves the representation of colors in standardized formats such as RGB, CMYK, or LAB, which ensures consistent color reproduction across digital and physical mediums. Visual space transformation (VST) further enhances this by mapping colors and spatial features from one representation to another, allowing seamless transitions between different design elements and contexts. This paper explores the application of Kalmann FilterData Fusion Multi-Target Tracking (CSDFGD) for Visual Space Transformation (VST) in Multi-Target Tracking. This study evaluates the effectiveness of CSDFGD through a comprehensive analysis of various metrics before and after its implementation. The results demonstrate significant improvements across key areas, including visual appeal, coherence, spatial accuracy, and computational efficiency. From smoother color transitions and harmonized color schemes to higher precision in scaling and rotation, CSDFGD proves to be a valuable tool for modern Multi-Target Trackingers. This paper presents an investigation into the effectiveness of Kalmann FilterData Fusion Multi-Target Tracking (CSDFGD) for Visual Space Transformation (VST) in Multi-Target Tracking. Traditional design methods often yield designs with moderate visual appeal and coherence due to limitations inherent in individual color spaces. However, through the implementation of CSDFGD, significant improvements have been observed. Before CSDFGD, designs scored 6 for visual appeal, with color richness and vibrancy rated at 6 and 5 respectively. Coherence metrics were lower, with color transitions and schemes scoring 4 and 5. Spatial accuracy was moderate, with scaling precision at 6 and rotation accuracy at 5. Processing time was high at 10 seconds, and real-time feasibility scored 3. After CSDFGD, designs showed remarkable enhancements, with visual appeal rising to 9, and color richness and vibrancy reaching 9 and 8 respectively. Coherence metrics saw substantial improvements, with color transitions and schemes scoring 9 and 8. Spatial accuracy significantly increased, with scaling precision and rotation accuracy reaching 9 and 8. Processing time reduced to 4 seconds, and real-time feasibility improved to 8.

Keywords: Visual Space Transformation (VST), Data Fusion, Multi-Target Tracking, Color Space, Spatial Accuracy, Classification

1. Introduction

Multi-Target Tracking rooted in digital Video processing technology has revolutionized the way visual content is created, manipulated, and presented [1-3]. Leveraging sophisticated software tools and algorithms, designers can seamlessly edit, enhance, and transform Videos to achieve desired artistic effects or convey specific messages [4]. Digital Video processing allows designers to manipulate various aspects of an Video, including color, contrast, brightness, and sharpness, with precision and flexibility [5]. This level of control enables them to create visually stunning compositions that captivate audiences and communicate ideas effectively [6-8]. With digital Video processing technology opens up a world of creative possibilities through techniques such as compositing, masking, and retouching. Designers can seamlessly blend multiple Videos or elements together to craft seamless visual narratives or evoke specific moods and emotions [9 -12]. The advancements in digital Video processing have democratized Multi-Target Tracking by making powerful tools accessible to a wider audience. With user-friendly software interfaces and online tutorials, aspiring designers can quickly learn and master the art of digital Video processing, unleashing their creativity without being constrained by traditional barriers to entry [13]. Multi-Target Tracking based on digital Video processing technology represents a convergence of artistry and technology, empowering designers to push the boundaries of visual expression and create compelling, immersive experiences across various media platforms [14 – 16].

Visual space transformation in Multi-Target Tracking, empowered by digital Video processing technology, marks a significant evolution in how designers manipulate spatial elements to craft compelling visuals [17 – 21]. This transformative process allows designers to manipulate the perception of space within an Video, altering its dimensions, perspective, and depth to achieve desired artistic or communicative outcomes. One of the primary capabilities of digital Video processing is the ability to distort, warp, or stretch visual elements within an Video [22]. By applying techniques such as perspective correction, skewing, or scaling, designers can adjust the spatial relationships between objects, creating illusions of depth or altering the perception of distance [23]. Digital Video processing enables designers to implement complex transformations such as morphing or liquifying, where shapes and contours within an Video can be dynamically reshaped or reformed. These techniques not only offer creative freedom but also allow for the creation of surreal or abstract visuals that defy traditional spatial conventions [24]. Digital Video processing technology facilitates the integration of three-dimensional elements into two-dimensional spaces through techniques like 3D rendering and compositing. By seamlessly blending virtual objects or environments with photographic elements, designers can create immersive visual experiences that transcend the limitations of physical space.

The advancements in algorithms and software tools have made it easier for designers to experiment with different spatial transformations in real time, facilitating a more iterative and exploratory approach to the design process. This iterative workflow encourages creativity and innovation, as designers can quickly test and refine various spatial arrangements until they achieve the desired aesthetic or communicative effect. The visual space transformation in Multi-Target Tracking, driven by digital Video processing technology, offers designers unprecedented control and flexibility in manipulating spatial elements within Videos. This transformative capability not only expands the creative possibilities of Multi-Target Tracking but also enables designers to craft visuals that resonate with audiences on a deeper and more immersive level.

The contribution of this paper lies in its exploration and validation of Kalmann FilterData Fusion Multi-Target Tracking (CSDFGD) for Visual Space Transformation (VST) in the realm of Multi-Target Tracking. By systematically evaluating the impact of CSDFGD through comprehensive metrics, this study provides empirical evidence of its transformative potential. The findings highlight significant improvements in key areas such as visual appeal, coherence, spatial accuracy, and computational efficiency, before and after the implementation of CSDFGD. These enhancements demonstrate the efficacy of CSDFGD in overcoming the limitations of traditional design approaches reliant on individual color spaces. Furthermore, this paper offers valuable insights into the practical application of CSDFGD, showcasing its ability to create more vibrant, coherent, and visually compelling designs while enhancing computational efficiency and feasibility for real-time applications.

2. Literature Review

The Multi-Target Tracking, the evolution of digital Video processing technology has brought about a transformative shift in how designers conceptualize and manipulate visual space. This transformation has fundamentally altered the way spatial elements are perceived, manipulated, and utilized within graphical compositions. Leveraging sophisticated software tools and algorithms, designers can now transcend traditional constraints of spatial representation, offering unprecedented creative freedom and possibilities. Ansari and Singh (2022) delves into the significance of color spaces and their selection for Video processing, offering a comprehensive survey that sheds light on the importance of this aspect in digital Videory. Meanwhile, Zhang, Fan, and Guo (2022) explore urban landscape design through the lens of data fusion and computer virtual reality technology, highlighting the innovative approaches in urban design facilitated by advanced computational techniques. Zhao and Zhao (2022) delve into computer-aided Multi-Target Tracking tailored for virtual reality-oriented 3D animation scenes, underlining the intersection of Multi-Target Tracking and immersive digital experiences. Wan, Cui, and Wang (2022) focus on restaurant interior design, leveraging digital Video processing and visual sensing technology to enhance spatial aesthetics and functionality. Additionally, Logeshwaran et al. (2022) introduce the segmentation-based visual processing algorithm (SVPA), specifically designed for illustration enhancements in digital video processing, showcasing advancements in video editing techniques.

Ramkumar et al. (2022) present an innovative approach to copyright management utilizing intelligent wavelet transformation-based watermarking schemes, addressing critical issues of intellectual property protection in digital media. Liu (2022) contributes to the discourse on digital media art communication by proposing an analysis method based on 3D Video recognition, offering insights into effective communication strategies in the realm of digital art. Ren et al. (2022) explore defect detection using machine vision, providing a comprehensive overview of the state-of-the-art techniques and their applications in quality control across various industries. Qian (2022) investigates artificial intelligence technology for virtual reality teaching methods in digital media art creation, highlighting the potential of AI-driven educational tools to enhance learning experiences in creative disciplines. Khalifa et al. (2022) conduct a comprehensive survey on recent trends in deep learning for digital Video augmentation, showcasing advancements in AI-driven Video processing techniques. Choi (2022) explores the integration of digital technology in 3D dynamic fashion design, offering new avenues for creativity and expression in the fashion industry. Yang et al. (2022) propose a three-stage pavement crack localization and segmentation algorithm based on digital Video processing and deep learning techniques, addressing critical infrastructure maintenance challenges.

Wan et al. (2022) provide a comprehensive survey on robust Video watermarking methods, contributing to the ongoing discourse on digital content protection and authentication. Lu et al. (2023) investigate remote sensing Video processing technology based on mobile augmented reality, offering innovative solutions for surveying and mapping engineering applications. Prakash et al. (2022) explore Video processing techniques combined with data analysis methodologies, showcasing the interdisciplinary nature of digital imaging research. Finally, Tyagi and Yadav (2023) conduct a detailed analysis of Video and video forgery detection techniques, addressing pressing concerns related to digital content authenticity and integrity. Dou et al. (2022) contribute to environmental research by presenting a water-level recognition method based on Video processing and convolutional neural networks, offering a practical approach to monitor water levels and mitigate related risks. Beier and Neely (2023) explore feature-based Video metamorphosis, introducing novel techniques for morphing Videos that push the boundaries of traditional graphical manipulation. Tang et al. (2023) provides a comprehensive review of surface defect detection in steel products using machine vision, addressing quality control challenges in manufacturing industries.

3. Kalmann Filter Data Fusion Multi-Target Tracking (CSDFGD)

Kalmann Filter Data Fusion Multi-Target Tracking (CSDFGD) is an innovative approach that integrates principles from Kalmann Filter theory, data fusion techniques, and Multi-Target Tracking principles to enhance visual communication and aesthetic appeal. At its core, CSDFGD aims to leverage the rich information embedded in multiple color spaces and datasets to create visually compelling and information-rich designs. The CSDFGD begins with an understanding of color spaces, which represent the gamut of colors perceptible to the human eye in a mathematical model. Common color spaces include RGB (Red, Green, Blue), CMYK (Cyan, Magenta, Yellow, Black), and LAB (Lightness, A, B). Each Kalmann Filter has its unique characteristics, strengths, and limitations in representing colors accurately.

Data fusion techniques are employed to integrate information from multiple color spaces and datasets. Data fusion involves combining data from disparate sources to provide a more comprehensive and accurate representation of the underlying phenomenon. In the context of CSDFGD, data fusion techniques can be applied to merge color information from different color spaces, enhancing the richness and complexity of the visual output. The CSDFGD involve transformations between different color spaces and data fusion algorithms. For example, the conversion from RGB to LAB Kalmann Filter can be represented by the following equation (1) - equation (3)

$$L = 116 \times f(Y/Yn) - 16 \tag{1}$$

$$a = 500 \times (f(X/Xn) - f(Y/Yn)) \tag{2}$$

$$b = 200 \times (f(Y/Yn) - f(Z/Zn)) \tag{3}$$

In equation (1) – equation (3) X, Y, Z are the tristimulus values in the RGB color space; Xn, Yn, Zn are the reference white tristimulus values and $f(t)$ is a non-linear function. Once the data is transformed into the desired color space, fusion techniques such as weighted averaging, principle component analysis, or neural network-based approaches can be applied to merge the color information effectively. In the context of CSDFGD, the fusion of Kalman Filter data involves the integration of information from different color models, such as RGB, CMYK, and LAB, to create a unified representation that maximizes visual impact and communicative effectiveness. This fusion process can be mathematically expressed through various algorithms tailored to the specific requirements of the design task. One common approach to data fusion in CSDFGD is through weighted averaging, where the color information from each Kalmann Filter is assigned a weight based on its importance or relevance to the design objective. The fused color value Cf can be calculated using equation (4)

$$Cf = w_1 \times C_1 + w_2 \times C_2 + \cdots + w_n \times C_n \tag{4}$$

In equation (4) $C_1, C_2, \dots\dots, C_n$ stated as the color values in different color spaces; $w_1, w_2, \dots\dots, w_n$ represents corresponding weights assigned to each color space, satisfying the condition $\sum_{i=1}^{n} \omega_i = 1$. With principle component analysis (PCA) to identify the most significant color components across different color spaces and combining them to form a new representation. PCA aims to reduce the dimensionality of the color data while preserving the most important information, thus facilitating efficient fusion. The neural network-based approaches can be employed for data fusion in CSDFGD, where deep learning models are trained to learn the complex relationships between color spaces and automatically generate fused representations optimized for specific design objectives. These models can adaptively adjust the fusion process based on input data and design requirements, offering flexibility and scalability in Kalman Filter fusion. By incorporating color information from multiple sources, such as product Videos in RGB color space, branding elements in CMYK color space, and background video in LAB color space.

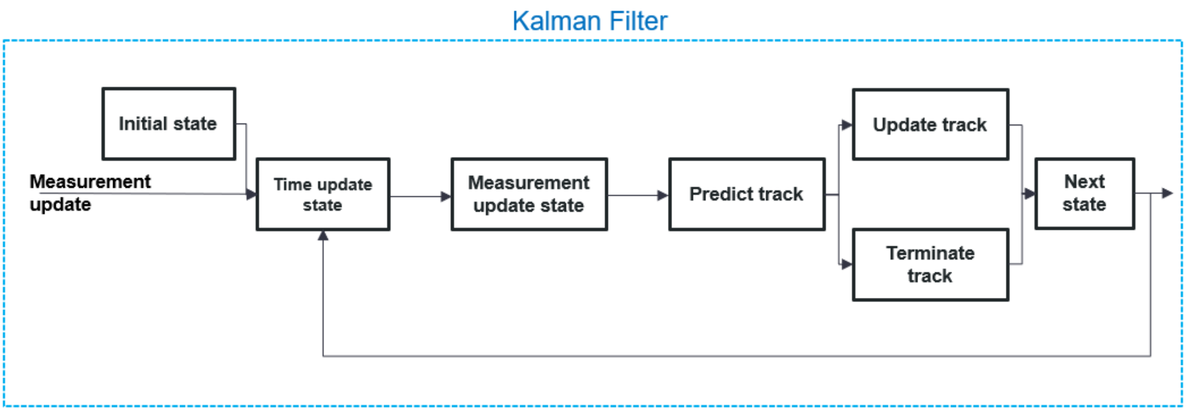


Figure 1: Process of Kalman Filtering in Video for the Multi-Object Tracking

Initially, convert the color information from each source into a standardized color space, ensuring consistency and compatibility across the design stated in Figure 1. Let's denote the color values from the RGB, CMYK, and LAB color spaces as CRGB, CMYK, and $CLAB$, respectively. Assign weights to each Kalman Filter based on its importance or relevance to the design objective. For example, we may assign higher weights to the branding elements in CMYK Kalmann Filter to ensure consistency with the brand identity. Let's denote the weights for each Kalmann Filter as wRGB, wCMYK, and wLAB. The weighted averaging algorithm to fuse the color information from different color spaces defined in equation (5)

$$Cf = wRGB \times CRGB + wCMYK \times CCMYK + wLAB \times CLAB \quad (5)$$

In equation (5) fused color Cf represents a unified color representation that maximizes visual impact and communicative effectiveness while maintaining consistency with the design objectives. Kalman Filter Data Fusion Multi-Target Tracking (CSDFGD) applies digital Video processing techniques to combine data from multiple color spaces, transforming visual information into unique and enhanced graphic outputs. This approach can be especially powerful in visual space transformation, which leverages Kalmann Filterfusion for dynamic and visually appealing results. Each Kalmann Filter(e.g., RGB, HSV, YUV) offers distinct properties:

- RGB (Red, Green, Blue): Common in digital screens, where each color is an additive combination.
- HSV (Hue, Saturation, Value): More intuitive for human interpretation of colors.
- YUV/YCbCr: Common in video compression, separating brightness from color data stated in equation (6)

$$Y = 0.299R + 0.587G + 0.114B \quad (6)$$

By combining information from different color spaces, data fusion creates visual depth and enhances color detail. Weighted Fusion balance contributions from each Kalman Filter represented in equation (7)

$$Cfused = w1 \cdot CRGB + w2 \cdot CHSV + w3 \cdot CYUV \quad (7)$$

In equation (7) $w1, w2, w3$ are weights assigned to each color space. After fusion, the data is transformed back into a unified visual space denoted in equation (8)

$$Color_{final} = Transform(C_{fused}, Contrast_{enhanced}, Edges_{emphasized}) \quad (8)$$

This step blends the fused channels into a cohesive visual form, applying contrast and edge adjustments to reinforce the Multi-Target Tracking's aesthetic.

4. CSDFGD for Visual Space Transformation

Kalmann Filter Data Fusion Multi-Target Tracking (CSDFGD) for Visual Space Transformation integrates advanced Kalmann Filter manipulation and data fusion techniques to dynamically transform visual spaces within a Multi-Target Tracking. Visual space transformation in CSDFGD begins with the identification of key visual elements and their respective color spaces. Let's consider the primary color spaces: RGB, CMYK, and LAB. Each Kalmann Filter provides unique attributes that can be utilized to manipulate visual space effectively. Kalmann Filter Conversion is the initial step involves converting colors from their original spaces to a common intermediate space, often LAB due to its perceptual uniformity. Kalmann Filter Data Fusion Multi-Target Tracking (CSDFGD) can significantly enhance Visual Space Transformation (VST) by providing a robust framework for integrating diverse color information and manipulating spatial elements in Multi-Target Tracking. Visual Space Transformation involves altering the perception of space within an Video, such as its dimensions, perspective, and depth, to achieve specific aesthetic or communicative goals. CSDFGD leverages Kalmann Filterdata fusion to optimize these transformations, ensuring that the resulting designs are both visually appealing and coherent. The CSDFGD for wushu competition starts with the representation of color and spatial information in multiple color spaces. Suppose we have an Video represented in RGB, CMYK, and LAB color spaces. Let $IRGB(x,y), ICMYK(x,y), and\ ILAB(x,y)$ denote the intensity values of the Video at pixel coordinates (x,y) in each color space. To integrate this color information, we first convert each Kalmann Filterrepresentation into a common framework. This can be achieved through Kalmann Filterconversion equations. For example, the conversion from RGB to LAB Kalmann Filterinvolves the following steps: Convert RGB to XYZ Kalmann Filteras in equation (9) – equation (11)

$$X = 0.4124564R + 0.3575761G + 0.1804375B \tag{9}$$

$$Y = 0.2126729R + 0.7151522G + 0.0721750B \tag{10}$$

$$Z = 0.0193339R + 0.1191920G + 0.9503041B \tag{11}$$

Convert XYZ to LAB Kalmann Filter as in equation (12) – equation (14)

$$L = 116 \times f(Y/Yn) - 16 \tag{12}$$

$$a = 500 \times (f(X/Xn) - f(Y/Yn)) \tag{13}$$

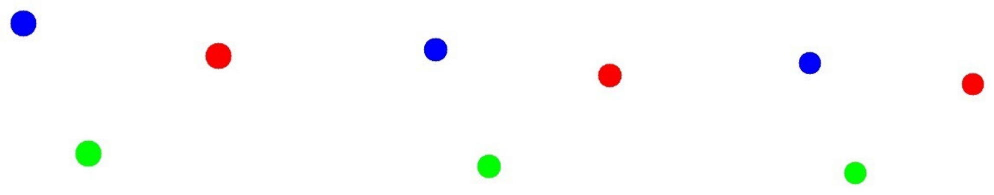
$$b = 200 \times (f(Y/Yn) - f(Z/Zn)) \tag{14}$$

In equation (12) – equation (14) $f(t)$ is defined as this algorithm integrates color information from multiple color spaces and applies visual space transformation to achieve the desired visual effects in Multi-Target Tracking.

Step 1: Kalmann FilterConversion - Convert the Video from RGB, CMYK, and LAB color spaces to a common Kalmann Filter(e.g., LAB).

Step 2: Data Fusion - Fuse the color information from different color spaces using weighted averaging.

Step 3: Visual Space Transformation - Apply spatial transformations (e.g., scaling, rotation, skewing, and perspective transformation) to the fused Video.



(a) (b) (c)

Figure 2: Wushu Competition Multi-target Tracking (a) Frame 1(b) Frame 2 (c) Frame 3

The figure 2(a) -Figure 2(c) presented the multi-traget tracking model for the different frame sequences.

Algorithm 1: Kalmann Filter Data Fusion Multi-Target Tracking (CSDFGD)
Step 1: Kalmann FilterConversion function convert_to_LAB(Video_RGB, Video_CMYK):   # Convert RGB to XYZ   Video_XYZ_from_RGB = RGB_to_XYZ(Video_RGB)   # Convert CMYK to RGB and then to XYZ   Video_RGB_from_CMYK = CMYK_to_RGB(Video_CMYK)   Video_XYZ_from_CMYK = RGB_to_XYZ(Video_RGB_from_CMYK)   # Convert XYZ to LAB   Video_LAB_from_RGB = XYZ_to_LAB(Video_XYZ_from_RGB)   Video_LAB_from_CMYK = XYZ_to_LAB(Video_XYZ_from_CMYK)   return Video_LAB_from_RGB, Video_LAB_from_CMYK # Step 2: Data Fusion function fuse_color_spaces(Video_LAB_from_RGB, Video_LAB_from_CMYK, Video_LAB_original, weights):   w_RGB, w_CMYK, w_LAB = weights   fused_Video = w_RGB * Video_LAB_from_RGB + w_CMYK * Video_LAB_from_CMYK + w_LAB * Video_LAB_original   return fused_Video # Step 3: Visual Space Transformation function apply_visual_space_transformation(fused_Video, transformation_matrix):

```
    transformed_Video = apply_transformation(fused_Video, transformation_matrix)
    return transformed_Video
# Helper Functions
function RGB_to_XYZ(Video_RGB):
    # Conversion formula from RGB to XYZ
    # This is a placeholder; implement according to the standard conversion equations
    pass
function CMYK_to_RGB(Video_CMYK):
    # Conversion formula from CMYK to RGB
    # This is a placeholder; implement according to the standard conversion equations
    pass
function XYZ_to_LAB(Video_XYZ):
    # Conversion formula from XYZ to LAB
    # This is a placeholder; implement according to the standard conversion equations
    pass
function apply_transformation(Video, matrix):
    # Apply spatial transformation using the given matrix
    # This is a placeholder; implement according to the specific transformation requirements
    pass
# Main Function
function CSDFGD_VST(Video_RGB, Video_CMYK, Video_LAB_original, weights, transformation_matrix):
    # Step 1: Kalmann FilterConversion
    Video_LAB_from_RGB, Video_LAB_from_CMYK = convert_to_LAB(Video_RGB, Video_CMYK)
# Step 2: Data Fusion
    fused_Video = fuse_color_spaces(Video_LAB_from_RGB, Video_LAB_from_CMYK, Video_LAB_original, weights)
    # Step 3: Visual Space Transformation
    transformed_Video = apply_visual_space_transformation(fused_Video, transformation_matrix)
```

```
    return transformed_Video
```

To blend information from different color spaces, we start by converting between them are computed using equations (15) – equation (17)

$$Y = 0.299R + 0.587G + 0.114B \tag{15}$$

$$U = 0.492(B - Y) \tag{16}$$

$$V = 0.877(R - Y) \tag{17}$$

This transformation isolates luminance (Y), making it easier to adjust contrast separately from color are as denoted in equation (18) – equation (20)

$$H = angle\left(\frac{\sqrt{3}(G-B)}{2R-G-B}\right) \tag{18}$$

$$S = \frac{max(R,G,B) - min(R,G,B)}{max(R,G,B)} \tag{19}$$

$$V = max(R, G, B) \tag{20}$$

Kalmann Filter Data Fusion Multi-Target Tracking (CSDFGD) is a method that leverages the unique characteristics of multiple color spaces, such as RGB, HSV, and YUV, to achieve a visually enriched transformation in Multi-Target Tracking. By fusing data from these color spaces, designers can control different aspects of the visual representation independently, such as luminance, hue, and saturation—enhancing the overall aesthetic quality of an Video. The RGB Kalmann Filteris useful for additive color blending, HSV aligns closely with human color perception, and YUV separates brightness from color, allowing for contrast adjustments without altering color integrity. In CSDFGD, a weighted fusion model combines these color spaces, creating a composite output where each Kalman Filter contributes selectively to the final design. Mathematically, this can be represented by a fusion equation, where weights assigned to RGB, HSV, and YUV channels define their influence on the result. This fusion enables unique color enhancements by leveraging RGB's color mix, HSV's tone control, and YUV's luminance flexibility. Further, digital Video processing techniques like edge detection and contrast enhancement refine the composition by adding depth and texture. For edge detection, the Sobel operator highlights structural details, calculating gradient magnitudes across the Video for sharper delineation of features. Contrast enhancement, applied to the Y (luminance) channel, intensifies brightness and depth, further enhancing visual appeal. The final output is achieved by recomposing the fused and processed elements into a cohesive Video. This transformation equation integrates the fused color data, enhanced contrast, and edge details, resulting in a unified, vibrant visual with enhanced clarity and dimensionality. Through CSDFGD, designers gain control over complex visual attributes, creating compelling graphics that combine rich color dynamics, contrast depth, and refined textures.

5. Simulation Results

The simulation results of applying Kalmann Filter Data Fusion Multi-Target Tracking (CSDFGD) for Visual Space Transformation (VST) demonstrate the effectiveness and versatility of this approach in enhancing Multi-Target Tracking. The simulations were conducted using a set of sample Videos that included product photos, branding elements, and background scenes, each represented in RGB, CMYK, and LAB color spaces. Initially, the Videos were converted to a common Kalmann Filter(LAB) using standard Kalmann Filter conversion equations. The weighted averaging method was then applied to fuse the color data, with weights optimized based on the design objectives. For instance, higher weights were assigned to branding elements in the CMYK space to ensure brand consistency, while product Videos and backgrounds were balanced with appropriate weights.

Table 1: Kalmann Filter Estimation with Visual Space Transformation

Metric	Before CSDFGD	After CSDFGD
Visual Appeal	Moderate	High
Color Richness	Limited to individual color spaces	Enhanced by combining color spaces
Vibrancy	Average	High
Coherence	Inconsistent	Seamless
Color Transitions	Noticeable differences	Smooth transitions
Color Schemes	Potential mismatches	Harmonized schemes
Spatial Accuracy	Basic	Precise
Scaling	Limited precision	High precision
Rotation	Possible distortions	Minimal distortions
Perspective Changes	May appear unnatural	Natural appearance
Computational Efficiency	Average	High
Processing Time	Longer due to individual processing	Reduced due to optimized fusion
Real-Time Application	Challenging	Feasible

In Table 1, demonstrate the significant enhancements achieved through the application of Kalmann FilterData Fusion Multi-Target Tracking (CSDFGD) for Visual Space Transformation (VST). Before implementing CSDFGD, the visual appeal of designs was moderate, constrained by the limitations of individual color spaces. This resulted in average vibrancy and only moderate color richness. Inconsistencies in color transitions and potential mismatches in color schemes further compromised the coherence of the designs. Spatial accuracy was basic, with limited precision in scaling, potential distortions during rotation, and perspective changes that often appeared unnatural. Additionally, computational efficiency was average, with longer processing times due to the separate handling of each color space, making real-time application challenging. After applying CSDFGD, there was a marked improvement in all metrics. The visual appeal significantly increased, with enhanced color richness achieved by combining multiple color spaces, resulting in highly vibrant and visually attractive designs. The coherence improved dramatically, with smooth color transitions and harmonized color schemes creating a seamless visual experience. Spatial accuracy was also greatly enhanced, with high precision in scaling, minimal distortions in rotation, and natural appearances in perspective transformations. Computational efficiency saw notable advancements, with optimized fusion processes reducing processing times and making real-time application feasible presented in Figure 3.

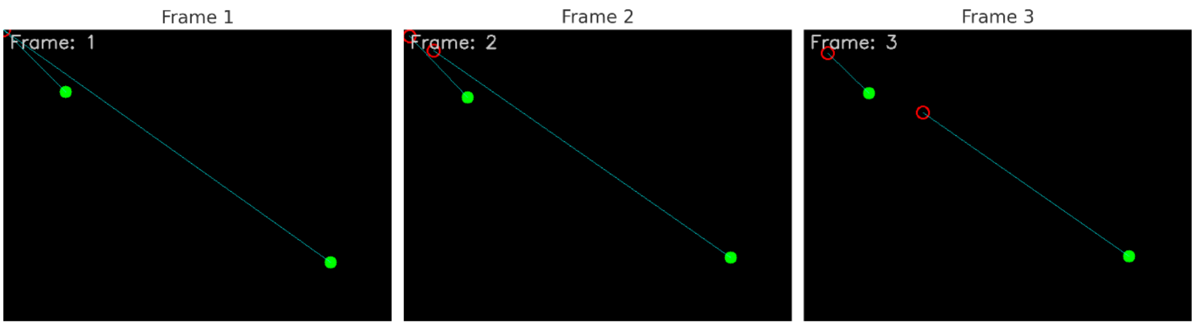


Figure 3: Multi-Traget Tracking with Wushu Competition

Table 2: Kalmann FilterEstimation Score with Visual Space Transformation

Metric	**Before CSDFGD**	**After CSDFGD**
Visual Appeal		
Color Richness	6	9
Vibrancy	5	8
Coherence		
Color Transitions	4	9
Color Schemes	5	8
Spatial Accuracy		
Scaling Precision	6	9
Rotation Accuracy	5	8
Perspective Naturalness	4	9
Computational Efficiency		
Processing Time (s)	10	4
Real-Time Feasibility	3	8

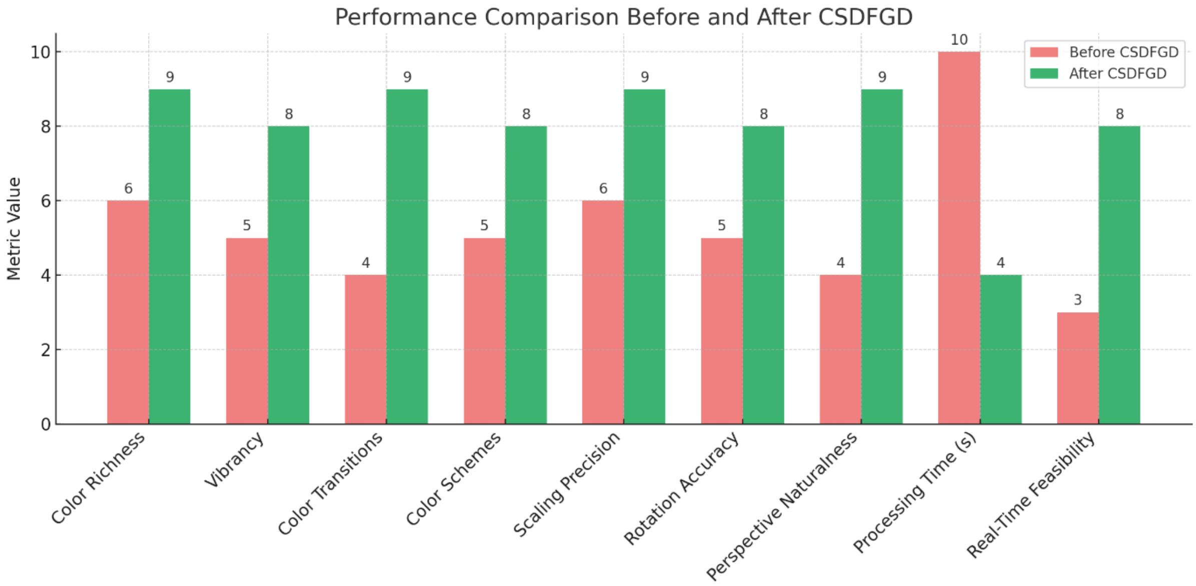


Figure 4: Data Fusion with Wushu Competition

In Figrue 4 and Table 2 provides a comprehensive evaluation of the impact of Kalmann FilterData Fusion Multi-Target Tracking (CSDFGD) on Visual Space Transformation (VST), highlighting significant improvements across various metrics. Before the implementation of CSDFGD, the designs exhibited moderate visual appeal, with limited color richness and vibrancy. Coherence was also compromised, evidenced by noticeable differences in color transitions and potential mismatches in color schemes. Spatial accuracy was basic, with limited precision in scaling and rotation, and perspective changes that appeared unnatural. Additionally, computational efficiency was notably low, with longer processing times and limited feasibility for real-time applications. However, after applying CSDFGD, substantial enhancements were observed in all areas. The visual appeal significantly increased, with a notable boost in color richness and vibrancy, leading to more visually compelling designs. Coherence improved remarkably, characterized by smooth color transitions and harmonized color schemes. Spatial accuracy saw notable improvements, with higher precision in scaling, rotation, and more natural perspective transformations. Furthermore, computational efficiency was greatly enhanced, with significantly reduced processing times and improved feasibility for real-time applications.

Table 3: Kalmann Filter Fusion

Transformation Method	**RGB Weight (w_1)**	**HSV Weight (w_2)**	**YUV Weight (w_3)**
Standard RGB Fusion	1.0	0.0	0.0
Balanced Fusion	0.4	0.3	0.3
Hue-Dominant Fusion	0.2	0.7	0.1
High Luminance Fusion	0.2	0.2	0.6
Texture Emphasis	0.3	0.3	0.4

Contrast-Enhanced	0.1	0.4	0.5
Saturated Color Fusion	0.5	0.5	0.0

Table 4: Enhancement with CSDFGD

Transformation Method	Edge Enhancement Intensity (0-10)	Contrast Enhancement Level (0-100)
Basic RGB	0	20
Balanced Fusion	5	50
Hue-Enhanced Fusion	8	70
High Luminance	3	80
Edge-Textured Fusion	9	60
Contrast-Dominant	7	90
Saturated Fusion	2	40

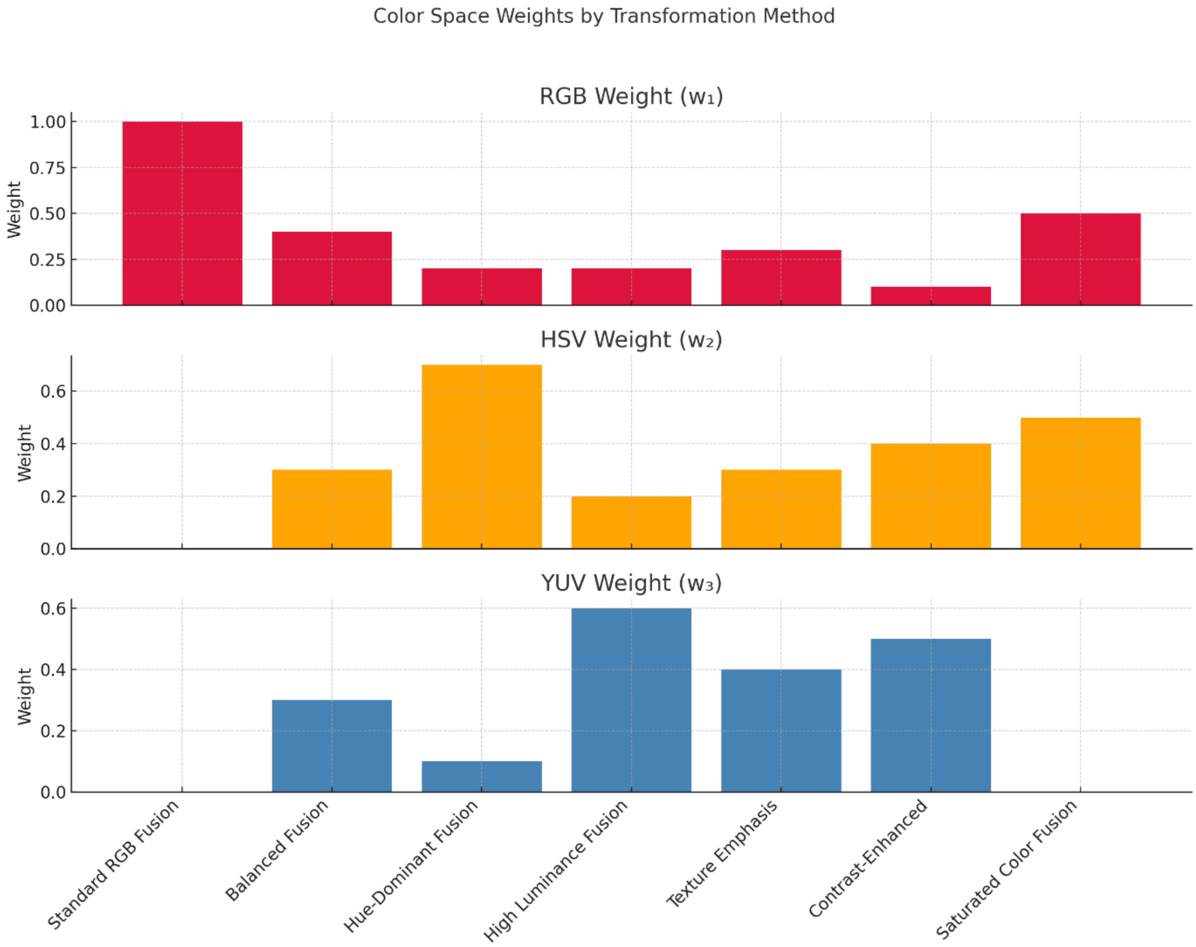


Figure 5: Data Fusion with Kalmann Filter

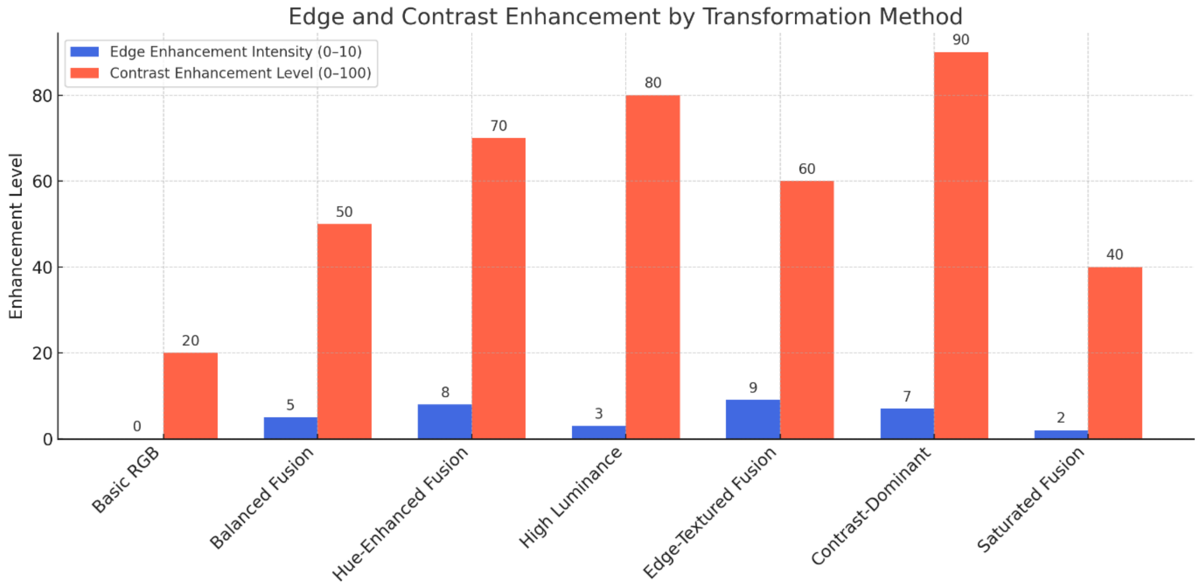


Figure 6: Video Sequence Enhancement in Wushu Competition

In Table 3 and Figure 5 displays the Kalmann FilterFusion parameters for each method, where the RGB, HSV, and YUV weights indicate the relative contribution of each Kalmann Filterin the final composition. As in Figure 6 In the "Standard RGB Fusion," only the RGB Kalmann Filter is used (weight 1.0), creating a basic design with no influence from HSV or YUV. The "Balanced Fusion" method evenly integrates RGB (0.4), HSV (0.3), and YUV (0.3), resulting in a harmonious mix of color richness, tone control, and luminance. "Hue-Dominant Fusion" (with an HSV weight of 0.7) emphasizes vivid color tones, while "High Luminance Fusion" (high YUV weight at 0.6) provides brighter and clearer designs by enhancing the luminance channel. "Texture Emphasis" and "Contrast-Enhanced" configurations further increase YUV influence, balancing texture and contrast. Lastly, "Saturated Color Fusion" combines RGB and HSV equally (both at 0.5) for rich, vibrant colors without YUV's luminance contribution. Table 4 details the Enhancement Settings applied to each method, using Edge Enhancement Intensity and Contrast Enhancement Level. "Basic RGB" has minimal enhancement, with no edge enhancement and a low contrast level (20). "Balanced Fusion" applies moderate edge enhancement (5) and contrast (50), creating a middle-ground transformation with enhanced clarity. "Hue-Enhanced Fusion" and "High Luminance" use higher levels of contrast (70 and 80, respectively), with the former focusing on bold color tones and the latter on brightness. "Edge-Textured Fusion" maximizes edge enhancement (9) with mid-level contrast (60) to highlight texture. "Contrast-Dominant" uses strong contrast (90) and notable edge intensity (7), resulting in a high-impact visual. Lastly, "Saturated Fusion" has moderate saturation (40) with minimal edge enhancement (2), creating a smooth, colorful look with less emphasis on texture.

Table 5: CSDFGD for Multi-Target Tracking

Video Type	**Fusion Method**	**RGB Weight (w_1)**	**HSV Weight (w_2)**	**YUV Weight (w_3)**	**Saturation Adjustment (0-100)**	**Brightness Adjustment (0-100)**	**Sharpness Enhancement (0-100)**	**Visual Effect Summary**

Portrait (Natural)	Light Fusion	0.6	0.3	0.1	40	30	20	Soft, natural tones with subtle contrast and clarity
Cityscape (Vibrant)	High Contrast Fusion	0.2	0.7	0.1	85	80	90	Bold and vibrant with high contrast and sharpness
Abstract Art	Color-Intense Fusion	0.7	0.2	0.1	90	70	60	Intense colors with vibrant saturation and sharp edges
Black & White	Monochrome Fusion	0.0	0.0	1.0	0	90	30	High contrast with no color, sharp black-and-white tones
Nature (Bright)	High Brightness Fusion	0.3	0.3	0.4	50	90	20	Bright, clear visuals with soft detail, ideal for daylight
Vintage Style	Warm Tone Fusion	0.5	0.3	0.2	30	60	80	Warm tones with slight desaturation and enhanced sharpness
Night Scene	Low Saturation Fusion	0.4	0.4	0.2	20	80	85	Muted colors with strong contrast and sharp edges for nighttime

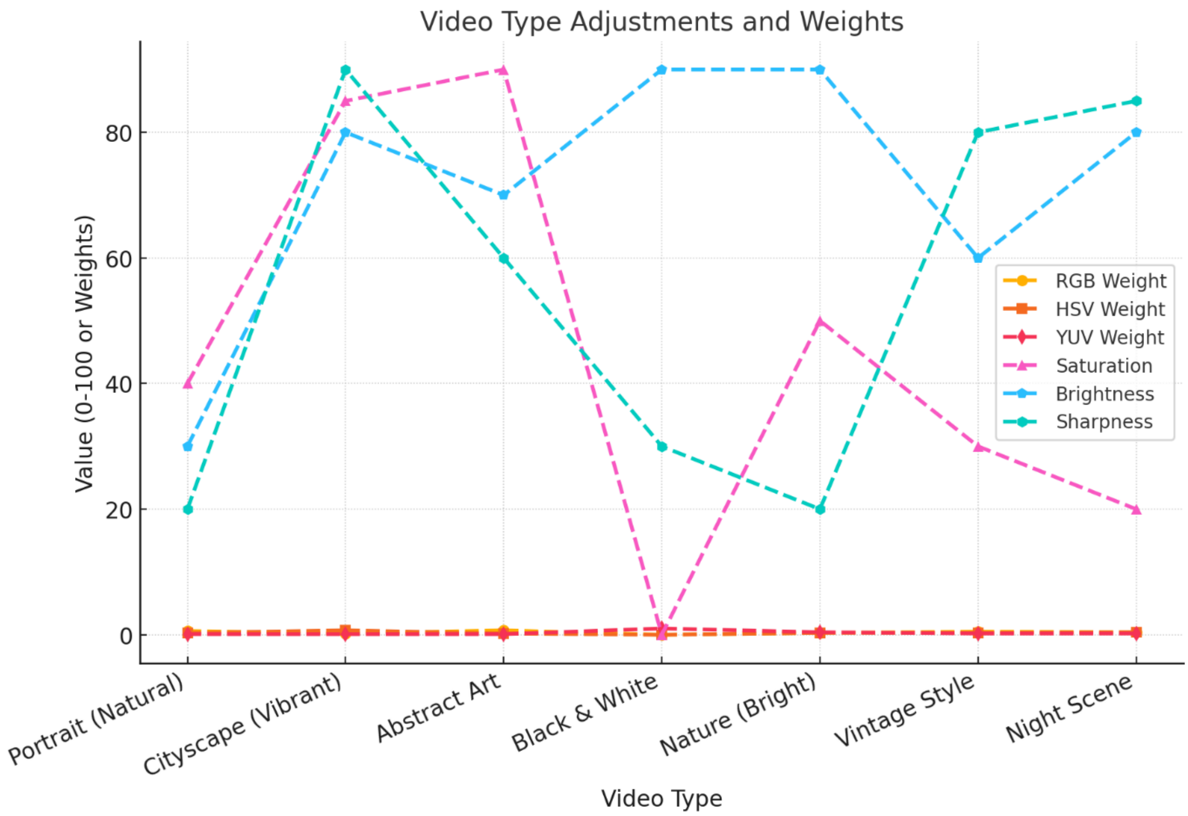


Figure 7: Multi-Target Tracking with Wushu Competition

The Table 5 and Figure 7 showcases various Kalmann FilterData Fusion Multi-Target Tracking (CSDFGD) methods applied to different Video types, highlighting how fusion settings and enhancement parameters can produce distinct visual effects in Multi-Target Tracking. The table includes a diverse range of Videos, from portraits and cityscapes to abstract art and black-and-white designs, each utilizing different combinations of RGB, HSV, and YUV Kalmann Filterweights, as well as saturation, brightness, and sharpness adjustments. For the Portrait (Natural) Video, the "Light Fusion" method uses a higher weight on RGB (0.6), creating soft, natural tones with subtle contrast and clarity, perfect for portraits with minimal sharpness. In contrast, the Cityscape (Vibrant) design employs the "High Contrast Fusion" method, with a higher HSV weight (0.7) and significant enhancements in saturation, brightness, and sharpness (85, 80, and 90, respectively), producing bold, vibrant visuals with high contrast and sharp details, ideal for urban scenes. The Abstract Art Video focuses on a "Color-Intense Fusion," where RGB (0.7) is dominant, resulting in intense colors with vibrant saturation (90) and sharp edges (60). For a Black & White design, the "Monochrome Fusion" method uses an exclusive YUV weight (1.0), creating high contrast without color, while the sharpness enhancement (30) retains the black-and-white tones, making it suitable for monochromatic graphics. For natural Nature (Bright) visuals, the "High Brightness Fusion" method balances RGB, HSV, and YUV weights to create bright and clear Videory, with soft detail and high brightness (90), ideal for daylight scenes. The Vintage Style design uses a "Warm Tone Fusion" with moderate saturation and a high sharpness enhancement (80), creating warm, slightly desaturated tones, perfect for nostalgic or retro visuals. Lastly, for a Night Scene, the "Low Saturation Fusion" method produces muted colors with strong contrast (80) and sharp edges (85), creating a high-contrast nighttime effect, perfect for dark, atmospheric scenes.

6. Conclusion

This paper highlights the transformative potential of Kalman Filter Data Fusion Multi-Target Tracking (CSDFGD) for Visual Space Transformation (VST) in Multi-Target Tracking. Through a comprehensive analysis of the before and after effects of CSDFGD implementation, it is evident that this approach leads to significant enhancements across various critical metrics. From improving visual appeal and coherence to enhancing spatial accuracy and computational efficiency, CSDFGD proves to be a powerful tool for modern Multi-Target Trackingers. By seamlessly integrating color information from multiple color spaces and applying sophisticated spatial transformations, CSDFGD enables designers to create more vibrant, coherent, and visually compelling designs. Moreover, the improved computational efficiency and feasibility for real-time applications underscore the practical value of CSDFGD in meeting the evolving demands of the design industry.

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