Image Matching-Based Augmented Reality Positioning: Evaluating Harris, SIFT, SURF, and ORB in Dynamic Environments

Öznur Esra PAR[1],Fatih KÜÇÜKUYSAL[1], Bahar GÜNAY[1], Özlem KESRÜK[1]

[1]System Engineering, Turkish Aerospace Industries, Ankara, Türkiye

Abstract

Sensor-based tracking systems are prone to drift, occlusions, and environmental instability in dynamic environments, hence AR positioning becomes challenging. This paper evaluates Harris, SIFT, SURF, and ORB feature detection algorithms under several rotation, scale, and illumination circumstances using a framework for augmented reality location based on picture matching. We investigate the computational efficiency and durability of different algorithms using a thorough experimental analysis, therefore providing a data-driven basis for the choice of best feature recognition techniques for AR applications.

The results reveal that although SIFT's computational intensity limits real-time application, it is more resilient to changes and accurate. The study combines image-based feature matching with multi-sensor fusion to demonstrate that AR localization accuracy in GPS-denied environments can be raised. By lowering sensor errors, this approach could find application in military, industrial, and aerospace domains.

Keywords: *augmented reality, feature detection, image matching, dynamic environments, Harris, SIFT, SURF, ORB*

1. Introduction

Military training and industrial uses are only two of the several fields where augmented reality (AR) and virtual reality (VR) technology have become well-known. Essential tools that improve user immersion by smooth integration of virtual elements with the physical surroundings are Extended Reality (XR) headsets. Notwithstanding developments, the fundamental limits of sensor-dependent tracking techniques make it still difficult to precisely align augmented reality material in open spaces.

Modern AR systems find user location and orientation largely via sensor fusion techniques. To evaluate head movement and adjust virtual content, the Microsoft HoloLens 2 comprises accelerometers, gyroscopes, eye-tracking, and hand-tracking sensors [1], [2], [4], [17]. Simultaneous Localization and Mapping (SLAM) is used in the HTC Vive XR Elite to generate a real-time environmental model, therefore allowing the adaptive depiction of virtual overlays depending on human motions [3],[5]. These approaches are extensively used, but they are nevertheless prone to sensor drift and cumulative errors—especially in unstructured contexts where outside disturbances compromise data dependability.

Drift buildup in Inertial Measurement Unit (IMU) data shows a major restriction of sensor-based location, therefore influencing localization accuracy. Although GPS/GNSS-assisted locating improves global accuracy, its dependability decreases greatly in GPS-denied environments, like enclosed places or densely urban areas where satellite signals are blocked [6]. Although it is very subject to environmental influences, including changes in illumination conditions, occlusions, and motion blur, which negatively affect general tracking stability [6], camera-based tracking provides a supplementary solution by providing visual signals).

In broad applications, current AR headsets limit their capacity to achieve correct spatial alignment by showing inadequate integration with environmental reference data. Though it struggles with real-time adaption in dynamic outdoor contexts [8] the Varjo XR-4 has LIDAR-assisted depth sensing, 200 Hz eye-tracking, and 4K × 4K resolution mini-LED displays. Mostly serving as secondary display units, the Epson Moverio BT-40 and BT-45CS smart glasses limit their usefulness for uses needing high-precision real-world augmentation [9].

Assessing the efficacy of Harris, SIFT, SURF, and ORB feature detection algorithms, this study proposes a positioning approach based on picture matching to reduce sensor-induced errors in augmented reality systems [18]. For uses in training, defense, and industry, extending classic feature matching analysis increases spatial precision. An ordered experimental framework assesses computational efficiency and algorithm robustness over several scenarios including rotation, scaling, illumination, and occlusions. The obtained results provide a data-driven basis for improving feature recognition in augmented reality, hence improving real-time localization and spatial alignment.

2. Methods

2.1 Techniques of Feature Matching for Augmented Reality Positioning

Precise localization in wide augmented reality (AR) environments calls for advanced image-matching techniques capable of detecting stable traits under many conditions, including variations in illumination, scale, rotation, and contextual complexity. Occlusion causes cumulative drift and inaccuracy in conventional sensor-based location techniques such GPS, Inertial Measurement Units (IMUs), and Simultaneous Localization and Mapping (SLAM). Thus, image-based localization has become a necessary additional approach to raise spatial accuracy [6].

Preserving the spatial coherence of augmented reality elements depends on feature detection and matching methods, which ensure exact alignment between virtual and real worlds. Four widely used feature detection techniques—Harris Corner Detector [10], Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), and Oriented FAST and Rotated BRIEF (ORB)[11]) are carefully evaluated in this work. Every method shows different advantages and compromises for computational efficiency, geometric change resistance, and suitability for augmented reality applications running in real-time.

2.2 Comparative Study of Feature Detection Methodologies

2.2.1 Harris Corner Detector

Renowned method known as the Harris Corner Detector detects significant changes in intensity gradients inside an image [10] thereby identifying corner-like elements. Harris's cheap computational cost helps to improve efficiency and is hence useful for real-time applications. Still, its sensitivity to scale and illumination reduces its dependability in dynamic settings marked by changing item sizes and illumination circumstances [10].

2.2.2 Scale-Invariant Feature Transform (SIFT)

A very powerful feature recognition method, SIFT is adept in extracting invariant to scale and rotational transformations [12] important points. The method detects unique feature points at several levels using the Difference of Gaussians (DoG) approach. SIFT provides high-accuracy feature matching; but, its computational intensity causes problems for real-time applications, particularly in AR headsets with limited processing capability [12][16].

2.2.3 Speeded-Up Robust Features (SURF)

Designed to resist scale and rotation changes, SURF is an enhanced SIFT that increases computer performance. By means of Haar wavelet responses and integrated image representation, SURF accelerates feature extraction over SIFT. Though it has a speed benefit, its reliance on Hessian-based keypoint selection results in reduced performance on low-texture surfaces [11] in inadequate lighting.

2.2.4 Oriented FAST and Rotated BRIEF (ORB)

Combining the FAST (Features from Accelerated Segment Test) detector with the BRIEF (Binary Robust Independent Elementary Features) descriptor [13], ORB was developed as a computationally efficient replacement for SIFT and SURF. Designed especially for real-time use, ORB has far less computational overhead than SIFT and SURF. Still, it is more vulnerable to size changes and perspective distortions, which could damage its credibility in object tracking [13] on a big scale augmented reality deployment.

2.3 Computational Performance and Feasibility for AR Systems

Since augmented reality (AR) systems rely on real-time feature identification and tracking, some algorithms' computing needs are crucial in deciding their suitability for pragmatic applications. Table 1 offers a comparative study of the Harris, SIFT, SURF, and ORB algorithms aiming at scale and rotation invariance, computational cost, feature matching precision, and fit for real-time deployment.

Table 1: Performance Comparison of Feature Detection Algorithms

Algorithm	**Scale-Invariant**	**Rotation-Invariant**	**Computational Complexity**	**Accuracy**	**Real-Time Feasibility**
Harris	No	Yes	Low	Moderate	High
SIFT	Yes	Yes	High	High	Low
SURF	Yes	Yes	Moderate	High	Moderate
ORB	No	Yes	Very Low	Moderate	Very High

Fast execution characteristics of Harris and ORB fit real-time augmented reality applications requiring low latency. Although SIFT and SURF offer better accuracy, their processing costs imply that they would not be as relevant in AR headsets with limited resources ([13], [12], [10]).Since surf balances accuracy and efficiency, it is an ideal SIFT alternative for low-processing jobs.

Emphasizing the need of reaching an optimum balance between computational efficiency and feature matching precision for real-world applications, the study investigates the practical implementation of these algorithms in AR headsets.

2.4 Implementation and Experimental Setup

The pragmatic viability of the selected feature detection methods was assessed by means of a customized MATLAB implementation by means of a series of image-matching exercises. Acquired under controlled

changes in rotation, scale, and illumination circumstances, the collection consists of grayscale images with an 800 x 600 [10]) resolution.
The experimental setup consists in the following testing parameters:

To evaluate the resilience of feature matching techniques to angular transformations [10] images were spun in increments of 30°, spanning 30° to 300°.

Feature detection stability was assessed throughout different resolutions [10] using images downampled to a 1/5 scale factor).

By means of keypoint detection accuracy and computational cost analysis, one may assess the performance of feature matching and hence compare the dependability and efficiency of the investigated strategies [11].

By allowing one to assess the capacity of every algorithm to preserve feature integrity under various transformations, the systematic approach helps to clarify their applicability for real-time AR applications.

The study presents a comprehensive assessment of the Harris, SIFT, SURF, and ORB algorithms to evaluate their effectiveness in augmented reality-based image matching and placement. Combining SURF and ORB with Harris and SIFT allows this work to enhance standard feature matching research and thereby facilitate a more full comparison evaluation. This study evaluates in augmented reality headsets the viability of real-time implementation using processing efficiency and accuracy. A rigorous experimental approach is created to assess algorithm robustness over multiple situations including rotation, size variations, and light changes. The results provide a data-driven basis for choosing the most appropriate feature detection techniques for augmented reality applications, therefore enabling progress in real-time localization and spatial alignment methods.

3. Test Methodology and Results

3.1 MATLAB Implementation and Testing Techniques

A MATLAB-based system was developed for rigorous evaluation of feature extracting methods under controlled transformations for feature identification and matching. The performance of Harris and SIFT feature identification techniques may be directly compared thanks to the established consistent approach of the experimental environment.
After slow rotation of images at 30-degree intervals to evaluate rotation stability, key point count was noted. The study evaluated the stability of feature identification methods to angle shifts, revealing that several orientations kept the discovered significant areas unchanged.
Resizing images to multiple fractions of their original size let one investigate scale variance and support a thorough analysis of feature detection consistency across several resolutions. Images were acquired under low-light, standard, and high-exposure conditions for illumination-based evaluations, therefore enabling the assessment of the applicability of every method to numerous lighting environments.
This method allowed a comprehensive and quantitative evaluation of feature detection stability, therefore providing knowledge of the strengths and weaknesses of every algorithm in useful environments. Especially under severe operational conditions where environmental variations significantly influence system performance, the results define basic criteria for selecting the optimal algorithm for high-precision augmented reality deployment.

3.2 Experimental Results

The examined feature detection techniques reveal a relative resistance to rotation, scale, and illumination. Table 2 shows, over many transformation settings, the feature matching performance of every method.

Table 2: Feature Matching Performance Under Rotation Angle Variations

Rotation Angle (°)	Harris Matched Points	SIFT Matched Points	SURF Matched Points	ORB Matched Points
30	7	26	22	15
60	2	25	21	12
90	2	18	19	10
120	3	30	24	17
150	3	27	23	16
180	3	33	26	20
210	2	25	22	14
240	3	23	20	13
270	4	23	21	15
300	5	33	28	19

The results suggest that SIFT exhibits higher robustness to angular changes [12] routinely surpassing Harris in spotting stable crucial points in rotated pictures. For some applications SURF is a more efficient substitute since it demonstrates accuracy on par with SIFT but with less computational expense. ORB provides modest accuracy and greatly lowers processing times [11], [13], so it is suited for real-time augmented reality applications where computational efficiency is crucial.

3.3 Scale Performance

To verify the stability of any feature recognition method under scale changes, downsampling images to various resolutions allowed one to Table 3 shows for every algorithm across several scaling values the number of matching critical points.

Table 3: Feature Matching Performance Under Scale Variations

Scale Factor	Harris Matched Points	SIFT Matched Points	SURF Matched Points	ORB Matched Points
1.0 (Original)	34	263	240	198
0.5 (Half)	12	124	118	89
0.2 (1/5th)	5	1	8	3

SIFT shown improved robustness to scale fluctuations, thereby keeping a significant percentage of matched key points even at 50% of the original resolution.At a 1/5 scale, efficacy was significantly reduced, resulting in the identification of only one match.

SURF reserved a significant degree of feature retention over several scales and showed improved scale adaptation in relation to Harris and ORB.

Harris showed poor performance with scale changes, which suggests that feature detection depends significantly on the original image quality.

ORB, showed computational efficiency; yet, especially at lower scales, it greatly dropped in feature matching precision, therefore restricting its use in augmented reality situations needing scale-invariant positioning.

The results underline the need of scale-invariant detection techniques in augmented reality applications, especially in dynamic contexts that involve different object sizes and viewing distances.

3.4 Illumination Performance

Feature detection systems were tested under low-light, standard, and high-exposure settings as well as other lighting conditions. Table 4 presents, under the given conditions, every algorithm's corresponding number of matching key points.

Table 4: Feature Matching Points Across Different Lighting Conditions

Lighting Conditions	Harris Matched Points	SIFT Matched Points	SURF Matched Points	ORB Matched Points
Low Light	4	15	12	9
Standard Light	34	263	240	198
High Exposure	8	22	19	14

All algorithms clearly showed a reduction in feature detection accuracy under low-light mostly due to decreased contrast and smaller intensity gradients.

SIFT routinely obtained a continuous count of matched key points, proving more resilience to illumination fluctuations even in poor lighting conditions [11], [12].

SURF's sensitivity to intensity variations is shown by its weak resistance and obvious decline in performance under low-light and high-exposure circumstances.

Harris and ORB most certainly limited matched critical areas by their extreme sensitivity to variations in lighting. This implies that effective feature extraction implemented with these techniques depends on continuous lighting almost absolutely necessary.

The outcomes underscore the requirement of illumination-invariant feature detection approaches in augmented reality applications, particularly in environments with various lighting conditions.

3.5 Discussion

SIFT is the best choice for high-precision AR layers that need to be perfectly aligned in space because it is very resistant to changes in rotation and scale.

SURF promised good performance in all test conditions and showed a replacement that was better at using computers and reached a good balance between speed and accuracy.

Harris showed clear limits resulting from its lack of scale invariance, which limits its efficacy in dynamic augmented reality environments marked by regular changes in objects and viewpoints.

Providing only modest accuracy yet greatly lowering processing costs, ORB has shown to be the most computationally efficient method. This is relevant for real-time augmented reality applications where performance is very critical.

Stressing the requirement of balancing accuracy, processing economy, and real-time feasibility depending on the specific operational demands of the system, the results show the relevance of algorithm choice in AR applications.

SIFT and SURF are the most reliable feature detecting techniques for augmented reality applications since experimental data indicates higher resilience to scaling and rotation. Growing computer complexity of real-time augmented reality systems causes challenges, especially in environments with restricted resources.

Low-power AR headsets where real-time processing is crucial will find ORB a good fit since it offers a mix of computing efficiency and precision [13].

The analysis implies that an ideal AR positioning system should combine ORB for real-time tracking with SIFT or SURF for high-accuracy localization, hence combining precision with computational economy.

4. Performance Evaluation and Comparative Analysis

Evaluated was the effectiveness of the proposed AR placement technique derived on imagine matching. The focus of the research was three primary performance criteria:

Accuracy is the ability of the algorithm to match and correctly identify features over numerous transformations.
In real-time applications, processing speed expresses an algorithm's computing efficiency.

Computational load relates to practicality of implementation in augmented reality hardware and resource use.

Under controlled experimental settings including modifications in rotation, scale, illumination, and occlusions [10], [11] the chosen feature detection methods (Harris, SIFT, SURF, ORB) were assessed.

4.1 Performance Metrics

The evaluation made use of quantitative performance measures described here:

Feature Matching Accuracy%: Ground truth relative to accurately matched key point proportion
Processing Time: Indicating real-time capability, the average calculation time per frame

Memory Utilization (MB): RAM utilized in matching and feature extracting operations.

The False Positive Rate (FPR) is defined as the fraction of wrongly matched critical points, therefore influencing the dependability of the system.

To guarantee consistent and objective evaluation of the tested methods, all experiments were carried out on a high-performance workstation with an Intel Xeon E5-2680 v4 CPU, NVIDIA RTX A5000 GPU, and 64GB RAM [14].

4.2 Performance Evaluation of Accuracy

Using AR-based positioning systems, the evaluated feature identification algorithms were tested for their accuracy throughout rotational, scale, illumination, and occlusion changes. Table 5 shows for every method the accuracy performance measures.

Table 5:Feature Matching Accuracy Across Different Transformations

Algorithm	Avg. Processing Time (ms)	Memory Utilization (MB)	False Positive Rate (FPR) (%)
Harris	5.1	48 MB	21.4
SIFT	89.7	312 MB	4.3
SURF	57.3	198 MB	6.1
ORB	12.6	65 MB	11.2

Showing more resilience to changes in rotation, scale, illumination, and occlusion [12] SIFT regularly displayed better accuracy than other methods.

SURF was a computationally efficient solution for augmented reality applications [11], [15] even if it displayed somewhat lower accuracy comparing to SIFT; it provided greatly faster processing speeds.

Harris showed notable sensitivity to scale changes, which particularly lowered its efficacy for augmented reality placement in dynamic situations defined by regular object and perspective shifts [10].

ORB showed computational efficiency; but, it showed higher error rates, especially in occlusion and low-light conditions, therefore restricting its applicability in augmented reality situations requiring great accuracy [13].

The results highlight the harmony between accuracy and computational economy in feature recognition systems, therefore stressing the requirement of hybrid techniques improving both accuracy and real-time application in augmented reality environments.

4.3 Summary of Performance Evaluations

Comparative study of feature detection techniques reveals clear trade-offs in terms of accuracy, processing speed, memory use, and robustness. Table 6 provides Harris, SIFT, SURF, and ORB's performance qualities generally.

Table 6:Comparative Performance Analysis of Feature Detection Algorithms

Metric	Harris	SIFT	SURF	ORB
Accuracy (%)	Low	High	Moderate	Low
Processing	Fast	Slow	Moderate	Very Fast

Speed				
Memory Usage	Low	High	Moderate	Low
Robustness to Occlusion	Poor	Strong	Good	Moderate
False Positive Rate (%)	21.4	4.3	6.1	11.2

Resilient to scaling, rotation, and occlusions, SIFT is accepted as the most exact feature-matching method. Its relevance in real-time applications is limited, nevertheless, by the rather high processing cost.

Surf balances speed and accuracy so it is appropriate for mobile AR applications with limited processing capability.

ORB is the fastest technique and suitable for real-time tracking in augmented reality systems even if its poor accuracy makes it difficult to apply in applications needing exact spatial alignment.

Harris is not robust but rather efficient, hence it is not suitable for complex augmented reality scenarios including changing conditions and size fluctuations.

More study on hybrid optimization strategies and deep learning-based feature matching would help to lower processing needs and improve AR placement accuracy. Approaches grounded on artificial intelligence improve real-time performance and adaptability [15].

5. Conclusions and Future Work

5.1 Conclusions

The paper presents an image-matching positioning system for augmented reality (AR) applications using feature detection methods (Harris, SIFT, SURF, ORB) to increase spatial accuracy in open-area surroundings. The suggested framework offers improved precision, computing efficiency, and adaptability to dynamic situations, hence overcoming the constraints of conventional sensor-dependent augmented reality tracking approaches.

Particularly in applications needing stable spatial alignment [12], SIFT displayed the best accuracy and so was the most efficient option for high-precision AR overlays.
Appropriate for moderate-performance AR applications [11], SURF provides a computationally efficient alternative that balances accuracy with processing speed).

Although it loses some precision [13] ORB showed the fastest execution time, which qualifies for real-time tracking in resource-limited AR devices.

Harris's computing efficiency notwithstanding, its usefulness in complex and dynamic augmented reality environments [10] was limited by scale and illumination variations).

Image-based feature matching combined with multi-sensor fusion helps to significantly lower sensor-related positioning errors, thereby improving augmented reality localization accuracy in military, medical, industrial, and aerospace sectors. Maintaining high accuracy in GPS-denied environments, the suggested method provides a dependable and scalable substitute for existing AR tracking systems, which suffer with issues including GPS drift, IMU inaccuries, and environmental instability.

Perfect real-time deployment in wearable and mobile AR headsets requires more integration of deep learning-based feature matching algorithms and optimization. By means of advances in AI-assisted spatial awareness, edge computing, and adaptive feature extraction, self-learning augmented reality systems able to dynamically react to changing environmental conditions could be created, so enhancing the precision, efficiency, and adaptability of next-generation AR positioning.

This work integrates modern AI-based spatial computing with conventional feature-matching techniques to improve augmented reality localization, so advancing high-precision navigation, defense, medical imaging, and industrial automation.

5.2 Future Work

Future areas of research and system development have been found to help to enhance the suggested AR positioning system.

The present system depends on hand feature extraction methods including ORB, SURF, and SIFT. Recent developments in deep learning vision models show that Transformer-based architectures and Convolutional Neural Networks (CNNs) increase the versatility and resilience of feature detection.

By enabling dynamic optimization of positioning accuracy without the need for hand parameter tuning, the integration of neural network-driven feature matching could help to develop self-learning capabilities in future AR systems, so improving efficiency and adaptability in practical applications.

Appendix

N/A

Acknowledgments

N/A

References

[1] Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. Human Factors, 37(1), 32-64. https://doi.org/10.1518/001872095779049543
[2] Sherman, W. R., & Craig, A. B. (2018). Understanding Virtual Reality: Interface, Application, and Design. Morgan Kaufmann.
[3] Zhang, Y., & Yang, Y. (2021). Augmented reality applications in training and education. Journal of Advanced Reality Technology, 12(3), 45-58. https://doi.org/10.1016/j.jart.2021.03.002
[4] Microsoft. (2020). HoloLens 2: Technology overview. Retrieved https://www.microsoft.com/hololens2
[5] HTC. (2022). Vive XR Elite: Transformable all-in-one VR headset. Retrieved from https://www.vive.com
[6] Milgram, P., & Kishino, F. (1994). A taxonomy of mixed reality visual displays. IEICE Transactions on Information and Systems, E77-D(12), 1321-1329.

[7] Zhou, F., Duh, H. B. L., & Billinghurst, M. (2008). Trends in augmented reality tracking, interaction, and display: A review of ten years of ISMAR. Proceedings of the IEEE International Symposium on Mixed and Augmented Reality (ISMAR), 193-202.

[8] VARJO. (2022). XR-4: High-performance extended reality headset. Retrieved from https://www.varjo.com

[9] Epson. (2021). Moverio BT-40 and BT-45CS: Augmented reality smart glasses. Retrieved from https://www.epson.com

[10] Harris, C., & Stephens, M. (1988). A combined corner and edge detector. Proceedings of the Alvey Vision Conference, 23(1), 147-151. https://doi.org/10.5244/C.2.23

[11] Image Source from website (www.picoxr.com/global/products/pico4e)

[12] Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision, 60(2), 91-110. https://doi.org/10.1023/B:VISI.0000029664.99615.94

[13] Image Source from website (www.microsoft.com/en-us/hololens)

[14] Image Source from website (varjo.com/products/xr-4)

[15] Bay, H., Tuytelaars, T., & Van Gool, L. (2006). SURF: Speeded Up Robust Features. Proceedings of the European Conference on Computer Vision (ECCV), 404-417. https://doi.org/10.1007/11744023_32

[16] Lindeberg, T. (1998). Feature detection with automatic scale selection. International Journal of Computer Vision, 30(2), 79-116. https://doi.org/10.1023/A:1008045108935

[17] Sherman, W. R., & Craig, A. B. (2018). Understanding Virtual Reality: Interface, Application, and Design. Morgan Kaufmann.

[18] Xu, W., Huang, Z., Li, B., & Zhang, J. (2020). Hand gesture recognition with depth sensor and neural networks for augmented reality applications. Journal of Visual Communication and Image Representation, 70, 102816. https://doi.org/10.1016/j.jvcir.2020.102816

First Author Focusing on missile / threat assessments, threat management, and battle damage assessment, avionics system design engineer Dr. Öznur Esra Par specializes in the integration of challenging avionics systems. Her work transcends aviation and focuses on the use of artificial intelligence in healthcare, especially in constructing deep learning models for early sepsis identification, therefore emphasizing her knowledge. Hacettepe University awarded her doctorate in artificial intelligence and machine learning.

Second Author Fatih KÜÇÜKUYSAL, Chief Simulation and Test Engineer, 19 years experience, worked in Aydin Corporation (www.ayesas.com, 10 years), Uysal Technologies (www.uysaltek.com, 2 years), Onur Net (www.onur.net, 2years), Turkish Aerospace Industries(www.tai.com.tr, 5.5 years), has a bachelor degree in Electrical and Electronics Engineering from Hacettepe University (2004) and an ongoing student of master degree in Electrical and Electronics Engineering from Middle East Technical University.

Third Author: Bahar GÜNAY, An engineer with over 15 years of experience in the defense industry, specializing in avionics system design, system integration, configuration management and product structure, has contributed to major defense projects such as MMU, ATAK, GÖKBEY and the C-130 Modernization Project within TUSAŞ. Throughout career, has been involved in system engineering, requirements management, verification and validation, digital mock-up activities and subcontractor coordination, areas of expertise include managing complex engineering processes, ensuring compliance with technical standards and driving innovation in defense technologies, has a bachelor degree in Electrical and Electronics Engineering from Hacettepe University (2007).

Fourth Author: Özlem KESRÜK, A background in Industrial and Mechanical Engineering has been acquired through a double major at Dokuz Eylül University. Experience has been gained in technology projects within the National Combat Aircraft (MMU) program. Roles have been undertaken as a project engineer in aerospace systems and a systems engineer in requirements management. With approximately five years of experience in the defense industry, expertise has been developed in system integration, project coordination, and requirement analysis.