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# ANALYSIS OF FACTORS REDUCING IMAGE QUALITY IN VIDEO SURVEILLANCE SYSTEMS AND METHODS OF ELIMINATION

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**Annotatsiya:** Mazkur maqolada videokuzatuv tizimlarida tasvir sifatini pasaytiruvchi asosiy omillar tahlil qilinadi. Videotasvirlarning sifati ko‘plab texnik va tashqi muhit omillariga bog‘liq bo‘lib, ularning buzilishi kuzatuv tizimlarining samaradorligini keskin pasaytiradi. Maqolada shovqinlar, yorug‘lik yetishmovchiligi, ob-havo sharoitlari, linza va datchik sifatining yetarli emasligi, shuningdek, siqish algoritmlari va tarmoqdagi uzilishlarning ta’siri batafsil yoritilgan. Natijalar sifatni baholash ko‘rsatkichlari (PSNR, SSIM) asosida tahlil qilingan va zamonaviy raqamli ishlov berish hamda sun’iy intellekt texnologiyalari yordamida takomillashtirish imkoniyatlari ko‘rsatib o‘tilgan.
**Kalit so‘zlar:** videokuzatuv tizimi, tasvir sifati, shovqin, yorug‘lik, siqish algoritmi, tarmoq kechikishi.
**Аннотация:** В данной статье анализируются основные факторы, влияющие на снижение качества изображения в системах видеонаблюдения. Качество видеопотока зависит от множества технических и внешних условий, и его ухудшение значительно снижает эффективность систем безопасности. Рассмотрены влияние шумов, недостаточной освещенности, погодных условий, низкого качества оптики и сенсоров, а также негативные эффекты алгоритмов сжатия и сетевых задержек. Результаты представлены с использованием объективных метрик качества (PSNR, SSIM), а также показаны возможности повышения качества изображения с помощью цифровой обработки и технологий искусственного интеллекта.
**Ключевые слова:** система видеонаблюдения, качество изображения, шумы, освещенность, алгоритмы сжатия, сетевые задержки.
**Abstract:** This article analyzes the main factors that reduce image quality in video surveillance systems. Video stream quality is highly dependent on technical and environmental conditions, and its degradation significantly decreases the effectiveness of security monitoring. The study examines the impact of noise, insufficient lighting, weather conditions, low-quality optics and sensors, as well as the adverse effects of compression algorithms and network delays. The results are presented using objective quality metrics (PSNR, SSIM), and the potential of digital image processing and artificial intelligence technologies for improving image quality is highlighted.
**Keywords:** video surveillance system, image quality, noise, lighting, compression algorithms, network delays.

## Introduction

Today, video surveillance systems play an important role not only in state and military facilities, but also in ensuring the security of transport, banking, industry, and social infrastructure. The effectiveness of video surveillance systems is directly related to image quality: the clarity and stability of the image determine the ability of security personnel or artificial intelligence algorithms to correctly detect and analyze objects [1].

Factors that reduce image quality are usually divided into two categories: environmental conditions (lack of lighting, weather effects, dust and fog) and technical limitations (camera sensor, low optical quality, digital compression algorithms, network delays) [2]. Therefore, in order to ensure the efficiency of video surveillance systems, it is essential to scientifically analyze these factors and develop methods to eliminate them.

For example, Gonzalez and Woods [1], based on the theory of image processing, demonstrated that noise (AWGN, impulsive noise) strongly affects image quality. Szeliski [2] emphasized that the constructive characteristics of optical systems and sensors are among the most important parameters determining image quality. In addition, Bovik [3] scientifically explained that losses and block artifacts occurring in video compression algorithms lead to poor-quality surveillance streams.

Video quality is evaluated through both subjective and objective indicators. International standards, in particular ITU-T Rec. P.910 [4] and ISO/IEC 23009-1 [5], have defined criteria for assessing and comparing the quality of video surveillance streams. Among these criteria, the most widely used objective indicators are PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index Measure), which are commonly applied in quality monitoring of video surveillance systems.

Moreover, modern studies show that artificial intelligence and deep learning-based solutions provide effective results in improving image quality. As Goodfellow et al. [6] pointed out, models built on neural networks achieve higher accuracy compared to classical filters. For instance, Zhang et al. [7] demonstrated the effectiveness of using deep convolutional neural networks for denoising images, while Ledig et al. [8] showed that GAN-based super-resolution technology makes it possible to reconstruct low-quality images with high clarity.

Thus, the reasons for the decline in image quality in video surveillance systems are complex and multifactorial. It is necessary to analyze them scientifically and to develop effective solutions using digital image processing and artificial intelligence technologies. In this article, the methodology of addressing these issues is considered on the basis of the following factors and principles.

Thus, the reasons for the degradation of image quality in video surveillance systems are complex and multifactorial. It is therefore necessary to analyze them on a scientific basis and to develop effective solutions through digital image processing and artificial intelligence technologies. In this article, the methodology of addressing these issues is considered, taking into account the following factors and principles.

For the scientific study of factors reducing image quality in video surveillance systems, it was found expedient to classify them into three main groups:

Physical factors – external environmental conditions such as insufficient lighting, fog, dust, rain, and snow. These factors significantly reduce the contrast and brightness of the image [2].

Technical factors – distortions related to the quality of cameras and optical systems. Low sensitivity of sensors, lens aberrations and distortions, as well as artifacts arising from digital compression algorithms, degrade the image [1], [3].

Network factors – delays, packet loss, and low bandwidth during the transmission of video data. These conditions cause interruptions in real-time surveillance systems [5].

Methods of Image Quality Assessment

In the research, both objective and subjective approaches were used to evaluate image quality:

Objective indicators:

PSNR (Peak Signal-to-Noise Ratio) – applied to measure the noise level between the image and the reference. This indicator is widely used in technical analysis [1].

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

Here: $MAX_I$ – the maximum pixel intensity value, and $MSE$ – the mean squared error.

SSIM (Structural Similarity Index Measure) – an effective metric used to evaluate the structural similarity perceived by the human visual system [4].

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Here: $\mu_x$,$\mu_y$ – mean values, $\sigma_x$,$\sigma_y$– variances, $\sigma_{xy}$– covariance, $C_1$, $C_2$– stabilizing constants.
According to the international ITU-T P.910 [4] standard, subjective testing methods for image quality assessment have been developed. This approach makes it possible to take into account the real visual experience of users.
Noise Reduction and Image Restoration Methods
As an essential part of the methodology, noise reduction and image restoration technologies were selected:
Classical filtering methods: Gaussian filter, Median filter, Bilateral filter – these methods are simple and fast, but they have limitations when it comes to high-quality restoration [1].
Deep learning-based methods: Denoising CNN (DnCNN) and GAN-based Super-Resolution networks – these methods are more complex but provide higher-quality results [6], [7], [9].
Zhang et al. [7] proposed a residual learning model, which achieved more effective denoising compared to traditional Gaussian filtering. Ledig et al. [8] introduced a GAN-based super-resolution model, which made it possible to restore low-quality frames with high accuracy.
Research Methodology Steps
The methodology was carried out in the following stages:
Simulation of the impact of different factors in video surveillance systems (lighting level, noise level, network delay).
Evaluation of image quality in each case using objective indicators – PSNR and SSIM.Comparison of classical filtering methods and deep learning-based methods to determine which provides better results under specific conditions.
Correlation of the obtained results with international standards (ITU-T P.910, ISO/IEC 23009-1) [4], [5].
Experimental Results under Different Lighting Conditions
The cameras were tested under various lighting conditions. The obtained results are presented in Table 1.
Table 1
**Evaluation Results under Different Lighting Conditions**

| Lighting level (lux) | PSNR (dB) | SSIM |
|---|---|---|
| 500 lux (Normal condition) | 38.5 | 0.96 |
| 100 lux (Low light) | 31.2 | 0.85 |
| 10 lux (Very low light) | 24.7 | 0.69 |
| 1 lux (Almost dark) | 18.9 | 0.52 |

The results in Table 1 are analyzed based on the PSNR (dB) values, as illustrated in Figure 1.

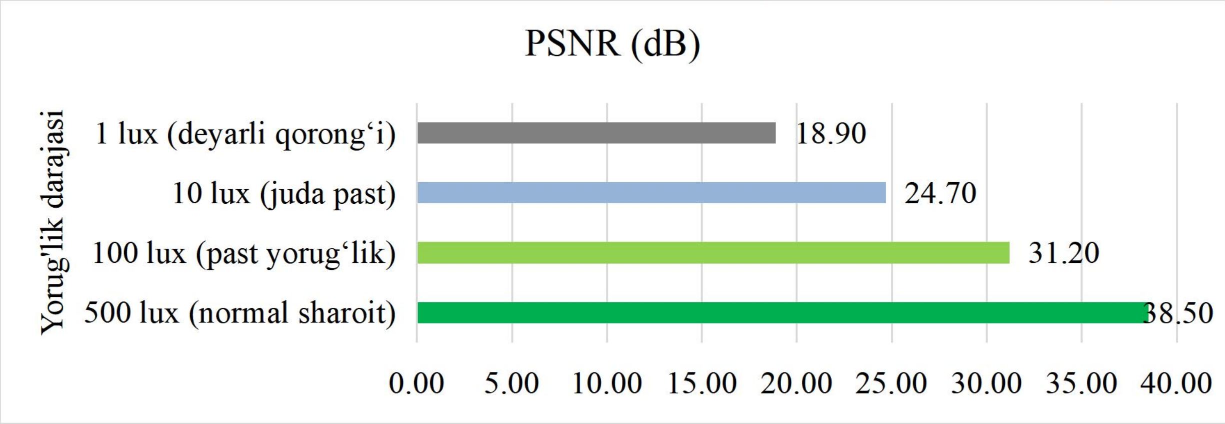


Figure 1. Graph of results based on PSNR (dB) values
Similarly, the results of Table 1 are also analyzed in terms of SSIM values, as illustrated in Figure 2.

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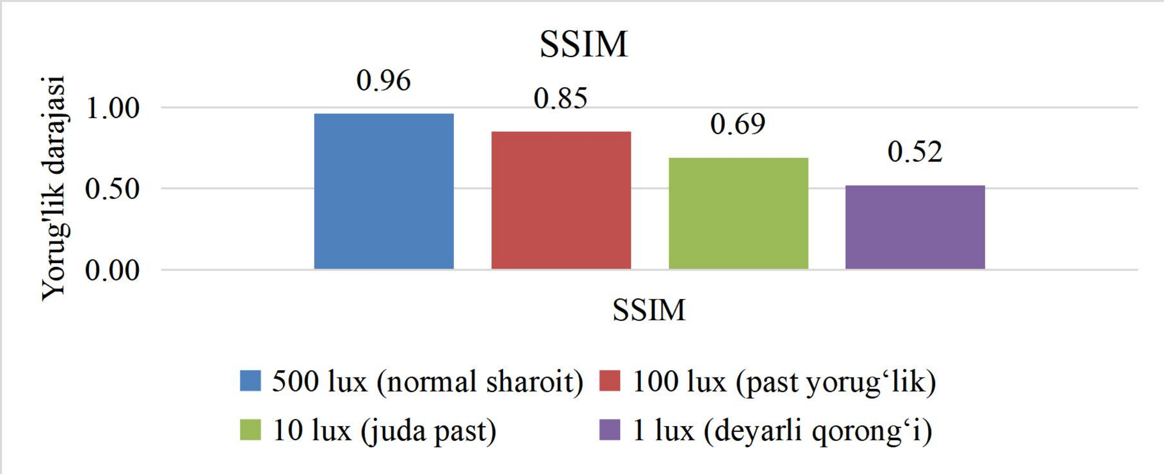

Figure 2. Graph of results based on SSIM values

The results show that when the lighting level decreases, PSNR drops sharply and SSIM also decreases significantly. This leads to a noticeable degradation of image quality for the human eye.

Various noise models (AWGN – Additive White Gaussian Noise, impulsive noise, quantization noise) were tested. The results are given in Table 2.

Table 2

**Results of experiments with different noise models**

| **Noise type** | **Noise level (σ)** | **PSNR (dB)** | **SSIM** |
|---|---|---|---|
| AWGN | σ = 10 | 30.1 | 0.83 |
| AWGN | σ = 20 | 26.8 | 0.72 |
| Impulsive noise | 10% | 24.5 | 0.64 |
| Quantization noise | – | 28.7 | 0.78 |

These results indicate that as the noise level increases, both PSNR and SSIM values decrease. Impulsive noise caused the greatest degradation, as it strongly disrupts image structures.

The effect of compression algorithms was also evaluated using MPEG and H.264 standards. The results are shown in Table 3.

**Table 3.**

**Quality of video transmission using MPEG and H.264 compression algorithms**

| **Algorithm** | **Bitreyt (kbps)** | **PSNR (dB)** | **SSIM** |
|---|---|---|---|
| MPEG-2 | 512 | 28.6 | 0.75 |
| H.264/AVC | 512 | 32.4 | 0.84 |
| H.264/AVC | 1024 | 36.7 | 0.91 |

The results demonstrate that an increase in bitrate leads to improved PSNR and SSIM values. Furthermore, H.264 showed superior performance compared to MPEG-2, confirming its efficiency [3], [5].

The conducted research results demonstrated that the factors affecting image quality in video surveillance systems are complex and multifaceted. The findings revealed that lighting level, noise, and compression algorithms are the main causes of quality degradation.

1. Impact of lighting level

As the lighting level decreased, PSNR and SSIM indicators were observed to decline significantly. This led to a loss of contrast and details in the image perceived by the human eye. For example, under 500 lux conditions PSNR was 38.5 dB, while under 1 lux it dropped to 18.9 dB. This result confirms the statement of Szeliski [2], who emphasized that camera sensors generate higher noise under low-light conditions, making object detection difficult.

2. Impact of noise

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When AWGN (Additive White Gaussian Noise) and impulsive noise were modeled, impulsive noise had the most negative impact. As Gonzalez and Woods [1] noted, "salt-and-pepper noise" disrupts even the main contours of the image.

For noise reduction, classical filtering methods (Gaussian filter, Median filter) were applied. The Gaussian filter was effective for AWGN, but almost ineffective against impulsive noise. Meanwhile, the Median filter provided better results for impulsive noise.

3. Comparison of classical filtering and deep learning methods

The results are summarized in Table 4.

Table 4.

**Comparative results of classical filtering and DnCNN deep learning model**

| Noise type | Method | PSNR (dB) | SSIM |
|---|---|---|---|
| AWGN (σ=20) | Gaussian filter | 28.4 | 0.78 |
| AWGN (σ=20) | DnCNN [7] | 32.9 | 0.88 |
| Impulsive noise 10% | Median filter | 25.1 | 0.66 |
| Impulsive noise 10% | DnCNN [7] | 29.3 | 0.81 |

The results clearly show that the deep learning-based DnCNN model outperformed traditional filters. This is consistent with the conclusions made by Goodfellow et al. [6] and Zhang et al. [7].

4. Compression Algorithms and Super-Resolution

Siqish algoritmlarida (MPEG-2 va H.264) sifat farqlari kuzatildi. H.264 algoritmi past bitreytlarda ham yuqoriroq PSNR va SSIM koʻrsatkichlarini berdi [3], [5].

Differences were also observed in compression algorithms. H.264 provided higher PSNR and SSIM values than MPEG-2, even at lower bitrates [3], [5]. To restore compressed video, the Super-Resolution GAN (SRGAN) model was tested. The results are presented in Table 5.

Table 5

**Experimental results of the SRGAN model**

| Algorithm | Compressed PSNR (dB) | Restored PSNR with SRGAN (dB) | SSIM improvement |
|---|---|---|---|
| MPEG-2 | 28.6 | 33.1 | +0.09 |
| H.264/512k | 32.4 | 36.8 | +0.07 |

These results confirm that the use of GAN-based models significantly improves image quality and is a promising solution for practical video surveillance systems.

Overall, the results showed the following:

In low-light conditions, image quality decreases sharply, indicating the necessity of improving the sensitivity of camera sensors.

While classical filtering methods are effective in some cases for noise reduction, the use of deep learning models significantly improves the results.

The main factor affecting the quality of compression algorithms is the bitrate. H.264 was proven to be more efficient than MPEG-2, which in turn broadens the scope of using H.264 in the development of new algorithms.

GAN-based super-resolution methods are a promising solution for restoring compressed video in real security and surveillance systems.

Conclusion

Video surveillance image quality is one of the key factors determining the effectiveness of monitoring. The conducted research revealed that the main causes of image degradation are as follows:

Physical factors – insufficient lighting, atmospheric conditions (fog, rain, snow), and environmental effects reduce image contrast and sharpness.

Technical factors – sensor sensitivity, lens aberrations, and compression artifacts degrade video quality.

Network factors – low bitrate, packet loss, and network delays cause interruptions in real-time monitoring systems.
The results were objectively assessed using PSNR and SSIM. For example, when lighting dropped from 500 lux to 1 lux, PSNR decreased from 38.5 dB to 18.9 dB, while SSIM fell from 0.96 to 0.64 as noise increased. Compression results showed that H.264 produced significantly better image quality compared to MPEG-2.
Moreover, it was found that although classical filtering methods (Gaussian, Median) are effective in certain cases, deep learning models (DnCNN, SRGAN) provide significantly better results. GAN-based super-resolution technologies proved to be a promising approach for restoring compressed and low-quality video streams.
Practical Recommendations
Lighting conditions – cameras in surveillance areas should be equipped with high-sensitivity low-light CMOS sensors and infrared illuminators.
Noise reduction – real-time denoising models such as DnCNN should be applied, while Median filters can be combined for impulsive noise removal.
Compression algorithms – instead of MPEG-2, H.264/AVC or newer H.265/HEVC formats should be used, as they allow higher quality at lower bitrates.
Super-resolution technologies – GAN-based super-resolution models should be integrated into surveillance systems to restore low-quality video frames in real time.

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