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# Analysis of image processing methods in the Internet of Things systems based on wavelet transformations

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**Abstract.** Increasing the compression ratio of images to reduce their transmission time in sensor networks based on microcontrollers helps to increase the overall energy efficiency of the system. The purpose of the study was to investigate the effectiveness of using Haar, Daubechies, and Coiflet wavelet transformations for image compression on 32-bit microcontrollers. An experimental comparison of the efficiency of three types of wavelet transformations for processing images obtained from the built-in camera was performed by the metrics of root-mean-square error, peak signal-to-noise ratio, structural similarity index, and Euclidean distance. Haar, Daubechies, and Coiflet wavelet transform algorithms were implemented on the ESP32 microcontroller. The results showed that at the second level of decomposition, the Haar wavelet provided high image quality (MSE 25.153, PSNR 34.124 DB), but at the fourth level, the quality significantly deteriorated (MSE 73.449, PSNR 29.470 DB). The Daubechies wavelet showed similar results, but at the fourth level, its efficiency also decreased (MSE 78.241, PSNR 28.974 dB). Coiflet wavelet showed the worst results at the fourth level (MSE 89.630), but at the second level its quality was competitive. For the first time, three types of wavelet transformations were compared using an additional metric – Euclidean distance, which made it possible to better estimate artifacts and image distortions. The proposed approach allowed improving the efficiency of image compression and transmission in the Internet of Things systems on microcontrollers, which provides less data transfer time and, accordingly, reduces power consumption, which is critical for autonomous sensor networks

**Keywords:** Haar; Daubechies; Coiflet; Peak Signal-to-Noise Ratio; structural similarity index measure; ESP32 microcontroller

## Introduction

Modern microcontrollers allow providing efficient image processing in the Internet of Things systems and significantly expand their capabilities. One of the tools for reducing the size of images while maintaining their quality is wavelet transform. Among the most common wavelets for image processing on microcontrollers, it is worth highlighting the Daubechies, Haar, and Coiflet wavelets, each of which has specific properties that determine their effectiveness in certain areas of application, which determines their feasibility for processing various types of images and solving a wide range of computational problems.

The study by R. Krishnaswamy and S. NirmalaDevi (2020) demonstrated how an upgraded wavelet transform-based image compression algorithm implemented for a 256x256 pixel medical image reduces the size of the original file. When using the proposed compression method, the parameters of the peak signal-to-noise ratio (PSNR) have values above 42 dB, which is an indicator of good

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image quality. However, the researchers examined images of sizes smaller than the quarterly video graphics array (QVGA) standard.

The study by Rohima & M.B. Akbar (2020) investigated the use of the Coiflet wavelet to compress images with a size of 256x256 pixels. The researchers compared the efficiency of using the Coiflet wavelet and compressed the image to 75% of the original with PSNR values close to 56 dB, which is an indicator of good quality. These indicators were obtained without using a microcontroller, which did not impose any restrictions when using the wavelet transform algorithm.

The efficiency of wavelet transform-based compression algorithms for use on the Raspberry PI 3 Model B microcomputer (Raspberry Pi Foundation, UK) was investigated by M. Patlayenko *et al*. (2021). A method for optimising calculations for image reduction was proposed, and image compression was achieved by 18 times compared to the original. However, Raspberry PI microcomputers have higher performance and belong to a different class of embedded systems.

O. Bychkov *et al*. (2019) created an algorithm that uses a transform wavelet for image processing and performed an analysis of human recognition after the transformation. The researchers performed the conversion using the Python programming language without using a microcontroller, which significantly expanded the resources for image processing.

The author of another study, A. Izmailov (2019), proposed a new approach to the wavelet transform algorithm. The efficiency of applying the transformation was evaluated, and a comparison with existing methods based on the standard root-mean-square error criterion was made. In turn, the use of a single method of mean square error (MSE) for evaluation has a number of limitations. For greater accuracy, several metrics should be used.

R. Odarchenko *et al*. (2021) used a transform wavelet to process audio signals for subsequent filtering and compression. The conclusion of this paper is that this approach is adaptive and increases the efficiency of compression and filtering of speech signals. However, the researchers considered only speech signals, which are less complex structures than images.

V. Barannik *et al*. (2023) proposed a method for segmental video processing using a wavelet transform. It is noted that as a result, groups of values are represented by codes that occupy a smaller volume in bits, which indicates effective compression. The disadvantage should be considered demanding on computing resources, which is essential for use on microcontrollers.

The purpose of this study was to compare wavelet transformations such as Daubechies, Haar, and Coiflet when used as an additional image processing to the JPEG method in microcontroller systems.

## Materials and Methods

**Description of hardware and software for studying the efficiency of wavelet transformations in image compression.** The ESP32-CAM camera development board (2020) (manufacturer Ai-Thinker, China) was used for image and video processing, due to the presence of a camera and additional RAM. This module was equipped with a dual-core Tensilica Xtensa LX6 processor (manufacturer Espressif Systems, China), operating at a frequency of up to 240 MHz, and had built-in Wi-Fi, which allows transfering data over the Internet without the need for additional devices. The microcontroller also had 4 MB of pseudostatic RAM (PSRAM), which was used for image processing, and 4 MB of flash memory for storing software. The 2-megapixel camera provided high-quality images for many tasks, such as object recognition or monitoring. The appearance of the ESP-CAM module with the camera connected is shown in Figure 1.

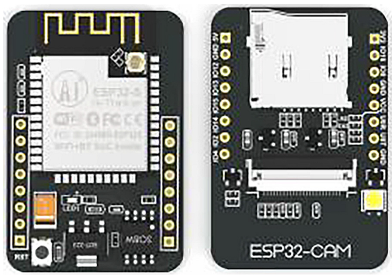


***Figure 1****. Appearance of the ESP32-CAM module with USB interface card*
***Source:*** *ESP32-CAM camera development board (2020)*

The experiment used wavelet transformations of Haar, Daubechies, and Coiflet to process images from the camera. The conversion was performed to reduce the image size after it was compressed to JPG format. To simplify the configuration and testing process, a web page was developed that was stored in the microcontroller's memory, which allowed quickly changing the number of iterations of the wavelet transform and adjusting the quality level of the compressed JPG file. For JPG image processing on the ESP32 platform, the corresponding library by A. Daoui *et al*. (2024) was used.

The experiment process consisted of the following steps:

1. Image preparation: for the experiment, an image from a 320x240 pixel camera was used, which was processed using three wavelet transformations: Daubechies, Haar, and Coiflet.

2. Wavelet transform process: each image was decomposed into several levels using each of the wavelets. The

process used the high and low frequency coefficients for each type of wavelet transform, which are shown in Table 1.

3. Assessment of image quality: for each type of wavelet transform, quality metrics such as MSE, PSNR, structural similarity index measure (SSIM), and Euclidean distance were calculated. This helped to assess changes in the image structure and its perception by the human eye after image compression and restoration.

4. Estimation of the processing time of each image, considering the number of mathematical operations performed by the microcontroller.

5. Assessment of the compression level: for each wavelet transform method, the compression level was calculated, which was represented as the ratio of the volume of the original value to the one processed using the wavelet transform and compressed using JPEG.

6. Estimation of the difference between pixels for three wavelets: Haar, Daubechies, and Coiflet at the 2nd and 4th levels of decomposition on a scale from 0 to 1, where 0 – total pixel similarity for both images, and 1 – total pixel difference for both images. When running the algorithm, the colour value ranged from 0 to 255, where 0 – black and 255 – white.

7. Calculation of the number of arithmetic operations. The following equation was used for finding it:

$$NoAO = (h \cdot w) \cdot l \cdot c, \qquad (1)$$

where $h$ – image height (240 pixels), $w$ – image width (320 pixels), $l$ – decomposition level, $c$ – number of coefficients used for the wavelet transform. During the experiment, the number of coefficients for Haar transform wavelets was 2, for Daubechies – 4, and for Coiflet – 6.

## Results and Discussion

As a result of the experiment, images corresponding to different types of wavelet transformations at the 2nd and 4th levels of decomposition were obtained, which can be analysed and visible artefacts can be detected. Figure 2 shows the original 320x240 image obtained using the built-in camera of the ESP32-CAM module. Further, the image from the camera was processed using Haar, Daubechies, and Coiflet wavelet transformations of the 2nd level of decomposition. The conversion result is saved in JPEG format and shown in Figure 3. The original image was also processed by wavelet transformation of the 4th level of decomposition and saved in JPEG format. The saved images are shown in Figure 4.

***Figure 2**. Original image obtained from the ESP32-CAM module camera*

***Source:** obtained by the authors using the ESP32-CAM module*

a b c

***Figure 3**. Image after 2nd-degree wavelet transform*

***Note:** (a) – Haar, (b) – Daubechies, (c) – Coiflet*

***Source:** obtained by the authors by processing the image algorithm with the ESP32-CAM module*

a b c

***Figure 4**. Image after 4th-degree wavelet transform*

***Note:** (a) – Haar, (b) – Daubechies, (c) – Coiflet*

***Source:** obtained by the authors by processing the image algorithm with a ESP32-CAM module*

**Analysis of experimental results.** Table 1 shows the results of experiments for each of the wavelet transformations used, the level of decomposition, the value of image quality in the form of MSE, PSNR, SSIM coefficients, the time for which the transformation algorithm was performed, the level of image compression compared to the original, and the number of arithmetic operations performed by the microcontroller during the execution of the wavelet transformation algorithm. The decomposition level is presented – this is the number of iterations or steps during which a signal (such as an image) is broken down into low-frequency and high-frequency components during a wavelet transform.

***Table 1****. Comparison of JPEG conversion results and JPEG + wavelet conversion results*

| DWT (Discrete Wavelet Transform) | Decomposition level | MSE | PSNR, dB | SSIM | Conversion time, ms | Compression level, times | Number of arithmetic operations, $(h * w) * l * c$ |
|---|---|---|---|---|---|---|---|
| Haar | 2 | 25.153 | 34.124 | 0.965 | 40 | 5.03 | 166,400 |
| | 4 | 73.449 | 29.470 | 0.921 | 84 | 11.11 | 332,800 |
| Daubeshies4 | 2 | 25.274 | 34.103 | 0.965 | 96 | 5.31 | 665,600 |
| | 4 | 78.241 | 28.974 | 0.894 | 178 | 11.27 | 1,331,200 |
| Coiflets1 | 2 | 25.144 | 34.126 | 0.965 | 105 | 5.21 | 998,400 |
| | 4 | 89.630 | 29.103 | 0.901 | 212 | 10.52 | 1,996,800 |

***Source:*** *developed by the authors based on the study by M. Mazin & Yu.O. Onykiienko (2023)*

Using the Haar wavelet transform for the image demonstrated high image quality at 2nd level with satisfactory MSE values (25.153) and high PSNR values (34.124) and SSIM values (0.965). However, at the 4th level, the quality significantly decreased (MSE – 73.840, PSNR – 29.470 dB), which indicates image deterioration with increasing decomposition levels. This may be due to the fact that the Haar wavelet has the simplest structure, which cannot preserve image details at high levels of decomposition. The processing time at the 2nd level (40 ms) is the lowest among all wavelets, which makes this wavelet efficient for fast processing, but at the 4th level the time increases to 84 ms. The compression ratio (11.22) at the 4th level shows a good compression ratio.

The Daubechies wavelet transform provided slightly worse MSE and PSNR values compared to the Haar transform at the 2nd level, but showed almost the same quality with a high SSIM (0.965). At the 4th level of decomposition, the quality significantly deteriorated (MSE – 78.241, PSNR – 28.974 dB), although the image still remains at an acceptable quality. The processing time was longer (96 MS at the 2nd level and 178 ms at the 4th level) due to the more complex wavelet structure expressed by more arithmetic operations. In particular, the number of operations for this wavelet is approximately 4 times the number of operations required to calculate the Haar wavelet. The Daubechies wavelet transform provided a better compression ratio (11.27) at the 4th level, which shows its ability to effectively reduce image size.

The Coiflet conversion provided better MSE and PSNR results for the 2nd level of decomposition, but at the 4th level, the quality of the restored image becomes less than that of Haar, but better than that of Daubechies. At the 4th level, the MSE is 89.630, indicating a significant loss of image quality, and the PSNR is better than Daubechies, but worse than Haar. However, at the 2nd level, the SSIM remained high (0.901), which indicates the preservation of structural image information. The processing time was the longest (212 ms at the 4th level), which is conditioned by the large number of coiflet wavelet coefficients (the number of arithmetic operations is 1.5 times greater than Daubechies, which was the largest value among all the studied wavelets). Although the compression ratio at the 4th level was also high (10.52), it should be noted that compression using the Coiflet wavelet had the lowest rate among all the wavelets under study.

H. Ding *et al*. (2021) demonstrated that a two-level real-time image transformation wavelet is compressed by 4 times compared to the original, which correlates with the results of an experiment where 5-fold compression is demonstrated. It is confirmed that the method is suitable for compressing large amounts of waveform data that are continuously recorded by the dynamic monitoring device of the power system in real time. However, the disadvantage of this operation is that the algorithm is not adaptable to the limited resources of the microcontroller.

The obtained PSNR values for the 2nd level of decomposition are almost identical (34.1 dB). In the study by A. Genta & D.K. Lobiyal (2018), PSNR values vary between (29-32 dB) depending on the image type. In the study of P. Mohindru *et al.* (2022), PSNR values differ and add up for the Haar (38 dB) and Daubechies (39.2 dB) transformations, respectively, due to differences in the sizes and types of images used. At the 2nd level of decomposition, artefacts are almost invisible for all wavelet transformations. There was a certain blocking of artefacts, the same for all transformations.

At the 4th level of decomposition, artefacts became more visible and manifested differently for each of the wavelet transformations. Regular dark dots were clearly visible for Haar transform. M. Mazin & Yu.O. Onykiienko (2023) suggested that the appearance of artefacts is associated with the accumulation of errors during the calculation of the Haar transform. Such artefacts are caused by a small number of coefficients and their simple values.

This transformation is effective for fast processing, but processing loses a certain amount of information at each level of decomposition, which leads to the accumulation of errors. At the 4th level of the Daubechies wavelet transform, artefacts also appear, but they have a different appearance and are not as noticeable. This indicates the ability of the Daubechies wavelet transform to preserve both high-frequency and low-frequency image components. As confirmation, S. Gunanandhini *et al*. (2022) as a result of research, found that the Daubechies transformation provides higher video quality than the Haar transformation. The study by I. Yamnenko & V. Levchenko (2019), which used the Daubechies, Haar, and orthogonal basis wavelet transform, concluded that the use of the wavelet transform significantly improves the compression efficiency of video data, while maintaining high image quality and reducing the number of artefacts. Notably, the researchers performed video processing without using microcontrollers.

Artefacts at the 4th level of decomposition in the Coiflet wavelet transform are significantly more noticeable than when using the Daubechies wavelet transform. The reproduced image had the same quality as the image reproduced by Haar, although the artefacts were somewhat less pronounced. Despite the fact that the Coiflet wavelet had the largest number of coefficients used, which led to a large number of arithmetic operations (998,400 for 2 levels of decomposition, 1,996,800 for 4 levels of decomposition).

In the study by A. Thakker *et al*. (2022), PSNR values for the 2nd level decomposition of Haar transform varied from 32.8 to 35.4 dB, depending on the selected image. H.M. Al-Dabbas & F.M. Ghazi (2018) showed the PSNR values for the 4th level of decomposition of the Haar and Daubechies transformations, which vary depending on the image from 22.2 to 35.9 dB. Thus, the type of images used significantly affects the PSNR level for the 4th level of decomposition than for the 2nd level of the Haar and Daubechies wavelet transformations.

Based on the experimental results, it should be noted that the MSE, PSNR, and SSIM coefficients do not always adequately reflect the quality of images obtained after wavelet transformation by the three methods under study. In particular, high MSE values may indicate a significant difference from the original image, while high PSNR and SSIM values indicate preservation of relatively high quality. This discrepancy was observed, for example, when using the Coiflet wavelet transform, where MSE indicates a loss of accuracy, but PSNR and SSIM showed acceptable visual image quality. These coefficients also showed the difference between the converted image and the original, but they do consider the influence of artefacts on the processed images that affect the final perception of the image by the user. N.M. Varma & A. Choudhary (2019) compared several metrics for evaluating images for similarity and identifying image artefacts. As a result of the comparison, the Euclidean distance method was the best method.

A. Schlamm & D. Messinger (2011) demonstrated that presenting images as Euclidean distances for further analysis can detect differences between distant points, localise this region, and detect anomalies. Based on this data, as well as the study by A. Sarkar & K.K. Halder (2021), several important conclusions were drawn. In this paper, the researchers showed that Euclidean distance shows a greater correlation with actual visual artefacts in the images. This is because it takes into consideration differences in each colour channel and highlights changes between pixels. This approach is especially important for processed images, which often contain complex artefacts. In this regard, it is proposed to use the maximum Euclidean distance between the pixel colours of two images of the same dimension. This method provides accurate distance calculation and efficient estimation of image artefacts.

$$dmax\left(\sqrt{(R'_{ij}-R_{ij})^2+(G'_{ij}-G_{ij})^2+(B'_{ij}-B_{ij})^2}\right)_{max}, \quad (2)$$

where $i$ and $j$ – pixel position in width and length, $R_{ij}$, $G_{ij}$, $B_{ij}$ – red, green, and blue colour values for the original image, $R`_{ij}$, $G`_{ij}$, $B`_{ij}$ – red, green, and blue colour values for the restored image.

Table 2 shows the relative difference between pixels for three wavelets: Haar, Daubechies, and Coiflet at the 2nd and 4th levels of decomposition. The relative difference is estimated from 0 to 1, where 0 indicates the total similarity of pixels, and 1 indicates the maximum difference between them.

***Table 2.*** *Comparison of Euclidean distance results for different wavelet transformations*

| Method | Decomposition level | Relative difference |
|---|---|---|
| Haar | 2 | 0.041 |
| | 4 | 0.537 |
| Daubechies | 2 | 0.029 |
| | 4 | 0.147 |
| Coiflet | 2 | 0.034 |
| | 4 | 0.355 |

***Source:*** *developed by the authors based on the study by M. Mazin & Yu.O. Onykiienko (2023)*

As can be seen from Table 2 for the Haar wavelet transform, the relative difference increases from 0.041 at the 2nd level to 0.537 at the 4th level. For the Daubechies conversion, this indicator is lower: 0.029 at the 2nd level and 0.147 at the 4th level. The Coiflet transform shows a relative difference of 0.034 at the 2nd level and 0.355 at the 4th level.

Thus, as the level of decomposition increases, the differences between pixels increase: the Haar wavelet transform shows the greatest differences, while the Daubechies wavelet transform shows the smallest. Moreover, as indicated by S. Zoican *et al*. (2019), the combination of a two-way filter and Wavelet transform implemented on Blackfin dual-core microcontrollers (Analog Devices, USA) can be effectively applied to remove real-time noise in medium-sized video clips.

## Conclusions

The results of using the Haar wavelet transform demonstrated the fastest processing at the $2^{nd}$ level of decomposition (40 ms), which makes it suitable for fast image transformations on devices with limited computing resources, such as microcontrollers. However, at the $4^{th}$ level, image quality significantly decreased, which was reflected in the high MSE value (73.449) and the deterioration of SSIM (0.921). The maximum Euclidean distance between pixels, which was 0.537 for the $4^{th}$ level of decomposition, indicates the presence of significant image artifacts, reflecting significant differences between the original and restored image at this level of transformation.

As a result of the experiment, the use of the Daubechies wavelet transform at $2^{nd}$ level showed high image quality with PSNR (34.103 dB) and SSIM (0.965) values, which practically does not differ from the Haar results. However, it took longer to process due to the more complex structure (96 ms at $2^{nd}$ level). At the $4^{th}$ level, the quality deteriorated (MSE 78.241), but the compression ratio remained high (11.27), which shows its effectiveness in data compression. The maximum Euclidean distance at the $4^{th}$ level of decomposition, which was 0.147, indicates the least pronounced image artefacts compared to other transformations.

Using the Coiflet wavelet transform provided high quality at $2^{nd}$ level (MSE 25.144, PSNR 34.126 dB), but at the $4^{th}$ level, the MSE value (89.630) indicates a significant loss of image quality, although it is still better than that of Daubechies. The Coiflet wavelet transform required the most processing time (212 ms at the $4^{th}$ level), since it has the most complex structure and the largest number of arithmetic operations. The maximum Euclidean distance for the $4^{th}$ level (0.355) indicated moderate artefacts, but less pronounced than that of Haar.

Thus, considering the visual evaluation, it can be argued that the Daubechies wavelet transform provided the most acceptable image quality without additional processing. Haar wavelet is suitable for fast image processing, but its use at high levels of decomposition can lead to a significant loss of quality in the form of dark dots and requires additional post-processing. It follows that a promising area for continuing this research is to eliminate image noise using the ESP32 microcontroller, which is a more powerful version of the microcontroller used. In the future, it is necessary to focus on investigating the occurrence of artefacts during an increase in the number of iterations of the wavelet transform and developing effective methods for their elimination.

## Acknowledgements

None.

## Conflict of Interest

None.

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# Аналіз методів обробки зображень в системах інтернету речей на основі вейвлет перетворень

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**Анотація.** Збільшення ступеня стиснення зображень для скорочення часу їх передачі в сенсорних мережах на базі мікроконтролерів сприяє підвищенню загальної енергоефективності системи. Метою дослідження було вивчення ефективності застосування вейвлет перетворень Хаара, Добеші та Коіфлета для стиснення зображень на 32-бітних мікроконтролерах. Виконано експериментальне порівняння ефективності трьох типів вейвлет-перетворень для обробки зображень, отриманих з вбудованої камери, за метриками середньоквадратичної похибки, пікового відношення сигнал/шум, індексу структурної схожості та евклідової відстані. Реалізовано алгоритми вейвлет-перетворень Хаара, Добеші та Коіфлета на мікроконтролері ESP32. Отримані результати показали, що на другому рівні декомпозиції вейвлет Хаара забезпечив високу якість зображення (MSE 25.153, PSNR 34.124 дБ), але на четвертому рівні якість значно погіршується (MSE 73.449, PSNR 29.470 дБ). Вейвлет Добеші продемонстрував подібні результати, але на четвертому рівні його ефективність також знижується (MSE 78.241, PSNR 28.974 дБ). Вейвлет Коіфлет показав найгірші результати на четвертому рівні (MSE 89.630), проте на другому рівні його якість є конкурентною. Вперше було виконано порівняння трьох типів вейвлет-перетворень із застосуванням додаткової метрики – евклідової відстані, що дозволило краще оцінити артефакти та спотворення зображень. Запропонований підхід дозволив покращити ефективність стиснення та передачі зображень у системах Інтернету речей на мікроконтролерах, що забезпечує менший час передачі даних і, відповідно зменшення енергоспоживання, що є критично важливим для сенсорних мереж з автономним живленням

**Ключові слова:** Хаар; Добеші; Коіфлет; Peak Signal-to-Noise Ratio; structural similarity index measure; мікроконтролер ESP32