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Analysis of Wavelet-Based Features for Identifying Similarities in Turtle Scute Patterns

Analisis Ciri Berasaskan Wavelet untuk Mengenal Pasti Persamaan dalam Corak Scute Penyu

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ABSTRACT

Turtle scute identification is vital for ecological and conservation research but traditional methods, relying on manual observation and image comparison, are time-consuming and error-prone, especially with varying scales and orientations of scute patterns. This study explores wavelet-based features for analyzing similarities in turtle scute patterns. Utilizing multiple wavelet families, including Coif1, Sym2, Db1, and Haar, a comprehensive analysis of scute patterns was conducted by extracting from two images. Features such as energy, variance, standard deviation, waveform length, and entropy are computed from wavelet decompositions to evaluate their effectiveness in capturing subtle differences and complexities in the patterns. The findings highlight Coif1 as the most effective wavelet family, demonstrating higher Euclidean distances and greater sensitivity to variations in scute patterns. Notably, the study reveals consistent feature values across rotations (0°, 90°, 180°, and 270°), underscoring the reliability of these wavelet families in maintaining pattern recognition accuracy under different orientations. These results contribute valuable insights for advancing turtle identification methods based on their distinctive scute patterns.

Keywords: Image Analysis, Wavelet Families, Feature Extraction, Wavelet-Based Features, Turtle Scute Identification.

ABSTRAK

Pengidentifikasian Scute Penyu adalah penting untuk penyelidikan ekologi dan pemuliharaan, tetapi kaedah tradisional yang bergantung pada pemerhatian manual dan perbandingan imej adalah mengambil masa dan cenderung kepada ralat, terutamanya dengan variasi skala dan orientasi corak scute. Kajian ini meneroka ciri berasaskan wavelet untuk menganalisis persamaan dalam corak scute penyu. Dengan menggunakan beberapa keluarga wavelet, termasuk Coif1, Sym2, Db1, dan Haar, analisis komprehensif corak scute telah dilakukan dengan mengekstrak ciri daripada dua imej. Ciri-ciri seperti tenaga, varians, sisihan piawai, panjang gelombang, dan entropi dikira daripada dekomposisi wavelet untuk menilai keberkesanan mereka dalam menangkap perbezaan dan kerumitan yang halus dalam corak tersebut. Penemuan kajian menunjukkan bahawa Coif1 adalah keluarga wavelet yang paling berkesan, menunjukkan jarak Euclidean yang lebih tinggi dan kepekaan yang lebih besar terhadap variasi dalam corak scute. Kajian ini juga mendedahkan nilai ciri yang konsisten merentasi putaran (0°, 90°, 180°, dan 270°), menekankan kebolehpercayaan keluarga wavelet ini dalam mengekalkan ketepatan pengenalan corak di bawah orientasi yang berbeza. Hasil ini memberikan pandangan berharga untuk memajukan kaedah pengenalan penyu berdasarkan corak scute mereka yang unik.

Kata kunci: Analisis Imej, Keluarga Wavelet, Ekstraksi Ciri, Ciri Berasaskan Wavelet, Pengidentifikasian Scute Penyu.

INTRODUCTION

Turtle scute identification plays a pivotal role in ecological and conservation research, aiding in population monitoring, habitat assessment, and individual tracking (Tanabe et al., 2023). Traditional methods for turtle identification often rely on manual observation and image comparison, which can be time-consuming and prone to errors (Rupilu et al., 2019). These methods frequently face challenges in accurately extracting and analyzing features from turtle facial images, especially due to varying scales, orientations, illumination variations, rotations, image distortion, blur, and variable backgrounds (Zimm et al., 2017; Ascarrunz & Sánchez-Villagra, 2022; Dunbar et al., 2021). The process of turtle scute recognition generally involves two steps: scute detection and localization, where scutes are identified and separated from the background, followed by scute feature extraction and recognition. To enhance the robustness of turtle scute recognition methodologies, researchers are increasingly exploring advanced computational techniques, such as wavelet transforms, known for their effectiveness in extracting features from complex patterns. These techniques offer promising solutions to the challenges posed by variable image conditions, including different scales, orientations, and background complexities. By leveraging insights from signal processing applications like electromyography (EMG), where wavelet transforms have been pivotal in enhancing feature extraction and pattern classification (Kakoty et al., 2015; Phinyomark et al., 2011; Too et al., 2018; Nogales & Benalcázar, 2023), researchers aim to adapt and optimize these methodologies for analyzing and identifying subtle variations in turtle scute patterns. This approach not only seeks to improve the accuracy and efficiency of turtle identification processes but also contributes to the broader application of wavelet-based methods in biodiversity monitoring and conservation efforts.

RELATED WORK

Recently, Kakoty et al. (2015) identify the most effective wavelet transform functions for classifying electromyogram (EMG) signals based on grasp types. The researchers evaluate various wavelet families, including Haar, Daubechies, Coiflets, and Symlets and extract various features from the wavelet coefficients, including energy, variance, and standard deviation. Phinyomark et al. (2011) The reseacher presents a method that uses multi-level wavelet decomposition to extract features from EMG signals, which are then used for pattern classification. The method is evaluated using two criteria: the ratio of Euclidean distance to standard deviation and scatter graphs. Too et al. (2018) proposes a novel method for electromyography (EMG) pattern recognition by combining the discrete wavelet transform (DWT) and spectrogram to extract time-frequency features from EMG signals, which are then used for accurate pattern recognition and classification. Nogales and Benalcázar, (2023) presents a method for classifying hand movements using EMG signals, which involves extracting enhanced features based on wavelength and mean absolute value from the signals using discrete wavelet transform. The wavelet transform can be applied to a periodic angle function derived from the extracted object contour to generate wavelet descriptors that can be compared against stored contour patterns (Abou Nabout, 2013). In the field of bioacoustics, Yudhana et al. (2010) implement wavelet analysis to identify green turtle hearing ability by analysing the auditory brainstem response (ABR) spectrum. Dellinger et al. (2022) implemented wavelet-based techniques for in-water abundance monitoring of juvenile pelagic sea turtles, leveraging the ability of wavelets to capture low-density, widely dispersed species. The ability of wavelets to capture multi-scale features makes them a powerful tool for these applications (Abou Nabout, 2013; Yudhana et al., 2010; Dellinger et al., 2022).

In this study, the effectiveness of various wavelet families was explored in accurately capturing and analyzing turtle scute patterns. While recent research has successfully integrated wavelet transforms with machine learning models for precise pattern recognition in other domains, their application to turtle scute identification remains underdeveloped. This research fills this gap by identifying optimal wavelet families to enhance the robustness of automated scute pattern recognition systems. This research aims to overcome current methodological limitations, offering a more dependable and efficient solution for identifying and comparing turtle scute patterns. Key contributions of this study include evaluating how different wavelet families capture essential features of turtle scutes, quantifying pattern similarities using Euclidean distances based on wavelet-derived features and analyzing scute patterns across various angles to discern unique individual characteristics.

The remainder of this paper is organized as follows. Section 2 outlines the proposed methodology, including the definitions of Wavelet Transform DW and RBFNN. Section 3 conducts a sensitivity analysis concerning neural network control parameters. Section 4 presents a case study, while Section 5 discusses the results and engages in comparative analysis with other prediction models. Finally, Section 6 provides the conclusions of this research.

METHODOLOGY

DATA PREPARATION

The dataset includes images of turtle scute patterns, depicting two sets of images where each set features the same scute pattern at different orientations. Each set comprises four images showing rotations of 0° (original), 90° clockwise, 180° clockwise, and 270° clockwise. Figure 1 illustrates these images demonstrating the variability in turtle scute orientations

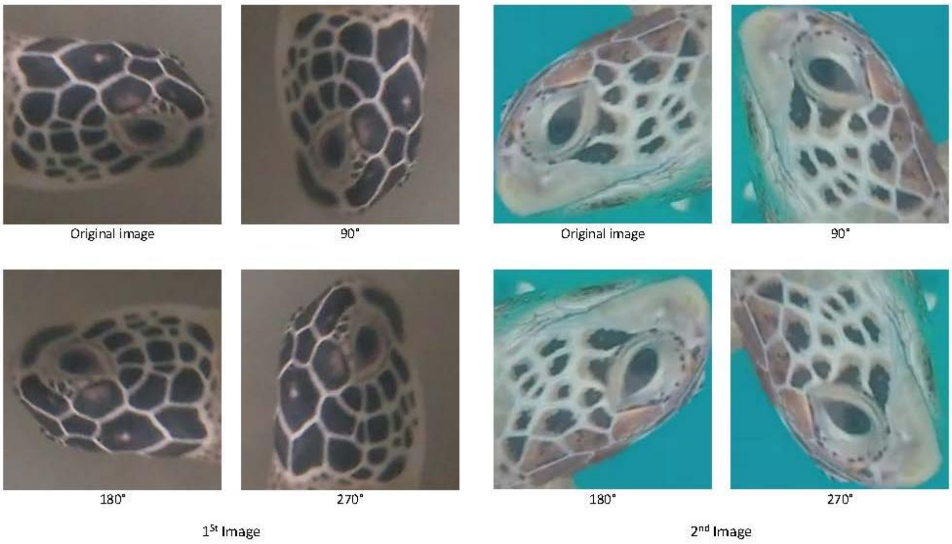

FIGURE 1. The images of a scute turtle in different orientations.

These variations aim to develop and assess algorithms capable of recognizing identical patterns despite changes in orientation. The original image serves as the baseline reference for comparison, facilitating the evaluation of pattern recognition performance across different rotational angles. To increase the size of the training dataset by applying six data augmentation functions namely, color jittering, Gaussian blurring, flipping, rotation, scaling, and adding salt and pepper noise. These functions are designed to introduce random variations in the images, making them more diverse and representative of real-world scenarios. Figure 2 illustrates a data augmentation pipeline for turtle scute images.

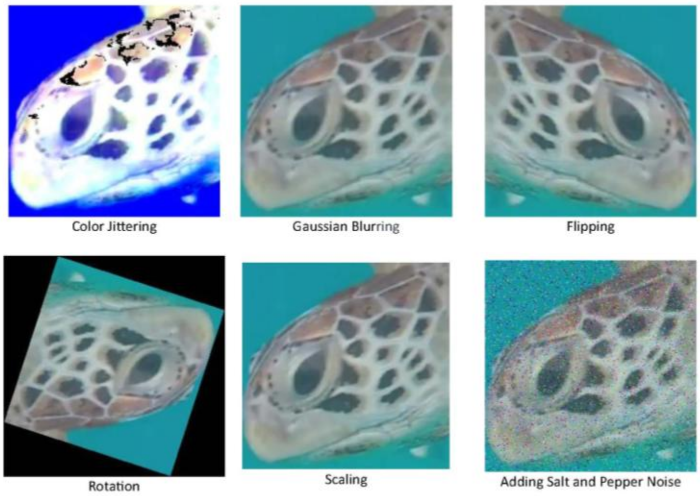

FIGURE 2. A data augmentation pipeline for turtle scute images.

WAVELET FAMILIES

Wavelets are mathematical functions that are useful in analyzing and processing signals and images at different scales. The experiment being conducted by input images are augmented, then wavelet families are applied during the wavelet decomposition step, where the input images are decomposed using each of the four wavelet families. The resulting wavelet coefficients are then used for feature extraction and comparison. Figure 3 illustrates a diagram of framework in this study.

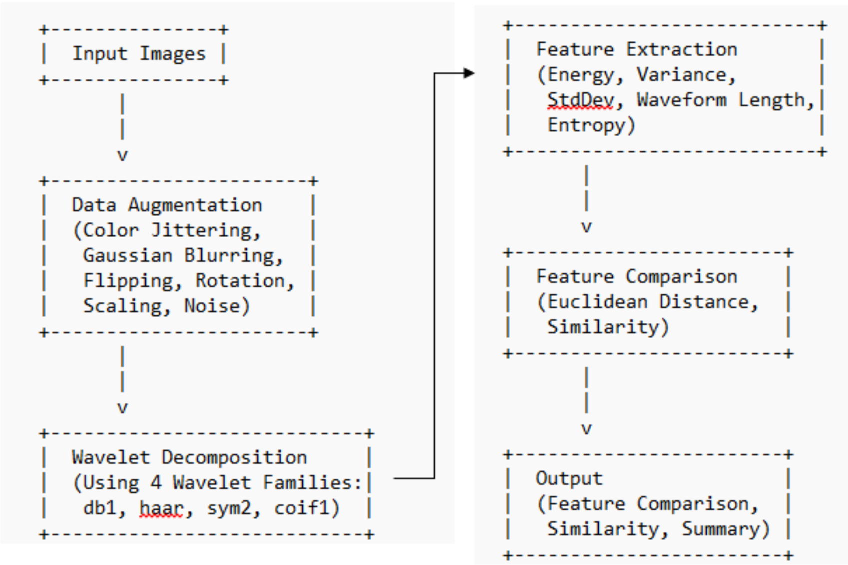

FIGURE 3. A framework of the wavelet families is applied.

The most crucial step in this method is selecting an appropriate wavelet family, including the mother wavelet function, for signal characterization. Additionally, it is essential to determine the optimal wavelets and the appropriate number of decomposition levels (Poulose Jacob et al., 2013). Four prominent wavelet families, each with unique properties, are 'db1' (Daubechies wavelet of order 1), 'haar' (Haar wavelet), 'sym2' (Symlets wavelet of order 2), and 'coif1' (Coiflets wavelet of order 1). The mother wavelet $\psi(t)$ is the prototype wavelet from which all other wavelets in the family are derived. The scaled and translated versions of the mother wavelet are given by:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

where a denotes the scale parameter (dilation), b represents the translation parameter and t is the time or spatial variable.

Haar Wavelets (haar)

The Haar sequence, proposed in 1909 by Alfréd Haar, introduced an orthonormal system for the space of square-integrable functions on the unit interval [0, 1]. As the simplest wavelet, the Haar wavelet has distinct characteristics. One notable technical disadvantage is its lack of continuity, rendering it non-differentiable. However, this property can be advantageous for analyzing signals with sudden transitions, such as discrete signals used in monitoring tool failures in machinery. The Haar wavelet's mother wavelet function, $\psi(t)$, can be described as follows:

$$\psi(t) = \begin{cases} 1 & if\ 0 \le t < \frac{1}{2} \\ -1 & if\ \frac{1}{2} \le t < 1 \\ 0 & otherwise \end{cases} \quad (2)$$

Its scaling function $\emptyset(t)$ can be described as:

$$\emptyset(t) = \begin{cases} 1 & 0 \le t \le 1 \\ 0 & otherwise. \end{cases} \quad (3)$$

Daubechies Wavelets (db1)

The 'db1' wavelet, or Daubechies wavelet of order 1, is characterized by its compact support and orthogonality. It is also known as the simplest member of the Daubechies wavelet family. Daubechies wavelets are defined by a filter with a finite number of coefficients, making them suitable for applications requiring high computational efficiency and accuracy (Lee & Yamamoto, 1994). The 'db1' wavelet is particularly effective in capturing abrupt changes in signals, making it ideal for edge detection and signal compressions (Salem et al., 2009). The Daubechies wavelet, often denoted as $\psi^{(1)}(t)$ is the simplest member of the Daubechies wavelet family. It is defined by a specific set of filter coefficients. The formula for the scaling function $\phi(t)$ associated with the Daubechies wavelet can be used to derive the wavelet function $\psi(t)$. Symlets are a modification of Daubechies wavelets designed to be nearly symmetric.

Symlet Wavelets (sym2)

The 'sym2' wavelet, or Symlets wavelet of order 2, is a modification of the Daubechies wavelet designed to be nearly symmetric. Symlets maintain many of the desirable properties of Daubechies wavelets, such as orthogonality and compact support, but with improved symmetry. This makes Symlets particularly suitable for applications where phase information is important, such as signal reconstruction and image processing. The 'sym2' wavelet has a more balanced approach to capturing both smooth trends and oscillatory components in signals, providing flexibility in handling various types of signal features.

Coiflets Wavelets (coif1)

The 'coif1' wavelet, or Coiflets wavelet of order 1, is designed to have a higher number of vanishing moments compared to Daubechies wavelets. Vanishing moments allow the wavelet to represent polynomial trends accurately, making Coiflets particularly effective for applications requiring precise localization of both high-frequency and low-frequency components. The 'coif1' wavelet is characterized by its ability to capture oscillatory behavior while maintaining good time-frequency localization. This makes it suitable for tasks such as signal denoising, feature extraction, and transient signal analysis. Coiflets are wavelets with both the mother wavelet $\psi(t)$ and its scaling function $\phi(t)$ having vanishing moments. The 'coif1' wavelet is a member of the Coiflets family, typically denoted as $\psi^{(1)}(t)$ as with other families, it's defined by filter coefficients.

FEATURE EXTRACTION

Feature extraction is a crucial step in the preprocessing of data, especially in the context of dimensionality reduction. This process simplifies data processing by identifying and extracting the most significant features, thereby reducing the datasets overall volume while preserving its essential characteristics (Latif et al., 2019). The approximation coefficients represent a low-resolution version of the original image, capturing its most significant features and retaining the overall structure. The horizontal detail coefficients emphasize the horizontal edges and fine details, making horizontal patterns more prominent. Similarly, the vertical detail coefficients highlight vertical edges and details, while the diagonal detail coefficients capture the variations along diagonal directions, emphasizing diagonal patterns and textures (Tian, 2013). Figure 4 shows the wavelet decomposition for a turtle's scute pattern using db1, haar, sym2, and coif1. These features are combined into a feature vector for each image, which serves as the input for further analysis. This approach effectively reduces the data volume while preserving crucial information, facilitating efficient processing and analysis (Pina et al., 2016).

Energy

The energy of a wavelet coefficient set is a measure of the magnitude of the coefficients. It is calculated as the sum of the squared coefficients.

$$Energy = \sum_i c_i^2 \tag{4}$$

where c_i are the wavelet coefficients. The energy feature captures the overall energy content of the signal, which can be useful for detecting transients, bursts, or other high-energy events.

Variance

Variance measures the dispersion of the wavelet coefficients around their mean.

$$Variance = \frac{1}{N}\sum_i (c_i - \mu)^2 \tag{5}$$

where μ is the mean of the wavelet coefficients, and N is the total number of coefficients. The variance feature can provide information about the regularity or irregularity of the signal. Signals with higher variance tend to be more irregular or contain more abrupt changes.

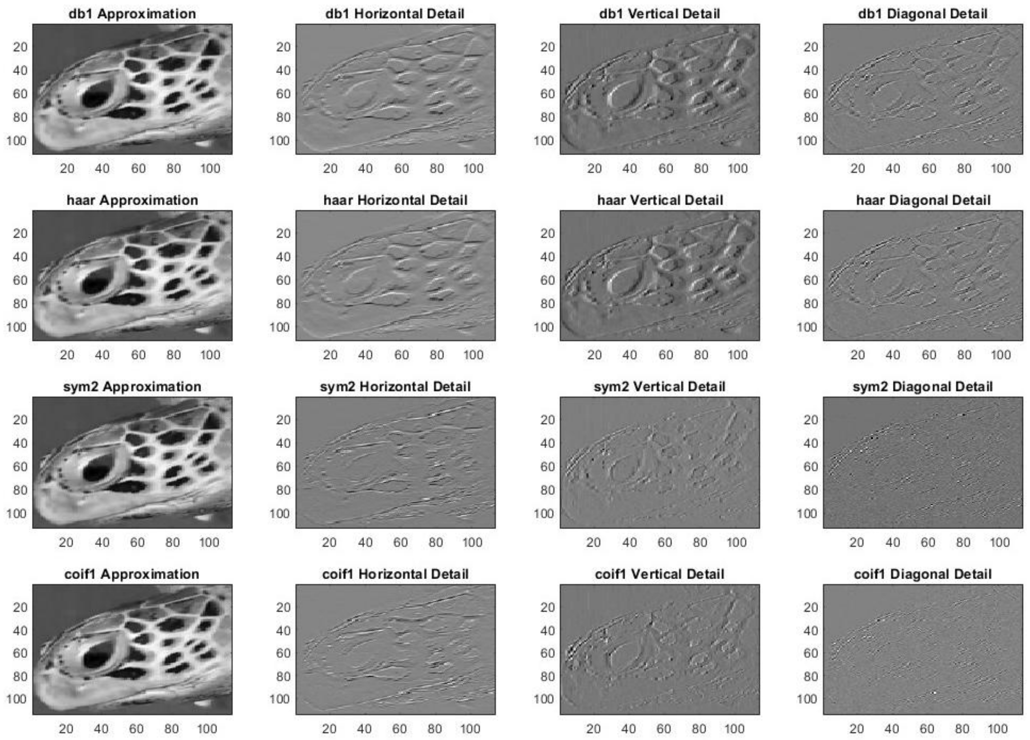

FIGURE 4. The wavelet decomposition for a turtle's scute pattern using db1, haar, sym2, and coif1.

Standard Deviation

The standard deviation is the square root of the variance and represents the average deviation of the wavelet coefficients from their mean value.

$$Std\ Dev = \sqrt{Variance} \tag{6}$$

The standard deviation feature is closely related to the variance and can also be used to quantify the regularity or irregularity of the signal.

Waveform length

Waveform length is a measure of the cumulative sum of the absolute differences between successive wavelet coefficients. It is related to the signal's smoothness.

$$Waveform\ Length = \sum_i |c_{i+1} - c_i| \quad (7)$$

The waveform length feature captures the degree of fluctuations or irregularities in the signal. Signals with higher waveform length tend to be more complex or irregular. The entropy of the wavelet coefficients is a measure of their information content or uncertainty.

Entropy

$$Entropy = \sum_i p_i \, log(p_i) \quad (8)$$

where p_i is the probability (normalized magnitude) of the wavelet coefficient c_i. The entropy feature provides information about the randomness or predictability of the signal. Signals with higher entropy tend to be more random or unpredictable, while signals with lower entropy are more regular or predictable.

SIMILARITY USING EUCLIDEAN DISTANCE

The formula for calculating the Euclidean distance between two feature vectors can be derived. Each image is represented by a feature vector. For simplicity, let's denote the feature vectors as f_1 and f_2 for the first and second images. Each feature vector consists of features Energy [E], Variance [V], Standard Deviation (StdDev) [S], Waveform Length [W], and Entropy [H]. The Euclidean distance d between two vectors f_1 and f_2 is calculated as the square root of the sum of the squared differences between corresponding components of the vectors. Given two feature vectors:

$$f_1 = [f_{11}, f_{12}, f_{13}, f_{14}, f_{15}] \quad (9)$$

$$f_2 = [f_{21}, f_{22}, f_{23}, f_{24}, f_{25}] \quad (10)$$

The Euclidean distance d between these vectors is calculated as:

$$d= \sqrt{(f_{11} - f_{21})^2 + (f_{12} - f_{22})^2 + (f_{13} - f_{23})^2 + (f_{14} - f_{24})^2 + (f_{15} - f_{25})^2} \quad (11)$$

If each feature vector consists of n features, the Euclidean distance d is calculated as:

$$d= \sqrt{\sum_{i=1}^{n} (f_{1i} - f_{2i})^2} \quad (12)$$

This study computes the Euclidean distance for each wavelet family, first calculate the features vectors.

$$f_1 = [E_1, V_1, S_1, W_1, H_1] \quad (13)$$

$$f_2 = [E_2, V_2, S_2, W_2, H_2] \quad (14)$$

Then, Euclidean distance formula is given by:

$$d= \sqrt{(E_1 - E_2)^2 + (V_1 - V_2)^2 + (S_1 - S_2)^2 + (W_1 - W_2)^2 + (H_1 - H_2)^2} \quad (15)$$

This formula is applied iteratively for each wavelet family (db1, haar, sym2, coif1).

RESULTS AND DISCUSSION

THE EFFECTIVENESS OF DIFFERENT WAVELET FAMILIES

The features for two images of turtle scute patterns have been extracted using four different wavelet families: db1, haar, sym2, and coif1. To evaluate the effectiveness of these wavelet families in capturing key features of turtle scute patterns, various metrics such as energy, entropy, and waveform length were analyzed. The results indicate that the coif1 wavelet captures the highest energy and exhibits the lowest entropy values, suggesting it retains the most information and provides the most structured representation of the scute patterns. Both sym2 and coif1 show higher values in terms of variability and complexity, indicating their superior capability in capturing detailed image features. Higher waveform length values for coif1 and sym2 wavelets further highlight their ability to provide a more detailed and intricate representation of the scute patterns. The calculated extracted features for the images are presented in Tables 1 and Table 2.

TABLE 1. Extracted features for image 1

	Energy	Variance	StdDev	WaveformLength	Entropy
db1	9.5421e+08	2950.8	54.321	1.5959e+05	-2.7503e+07
haar	9.5421e+08	2950.8	54.321	1.5959e+05	-2.7503e+07
sym2	9.6809e+08	2969.7	54.495	1.6557e+05	-2.7936e+07
coif1	9.8327e+08	2947.3	54.289	1.6609e+05	-2.8401e+07

TABLE 2. Extracted features for image 2

	Energy	Variance	StdDev	WaveformLength	Entropy
db1	5.0077e+08	3216.6	56.715	1.8217e+05	-1.8375e+07
haar	5.0077e+08	3216.6	56.715	1.8217e+05	-1.8375e+07
sym2	5.1296e+08	3276.1	57.237	1.9e+05	-1.8764e+07
coif1	5.239e+08	3261.8	57.112	1.9125e+05	-1.9144e+07

Overall, coif1 appears to be the most effective wavelet family for capturing the key features of turtle scute patterns, followed closely by sym2. Both these wavelet families excel in retaining energy, capturing variability, and providing detailed and structured representations of the patterns. db1 and haar, while useful, tend to offer smoother and less detailed representations, making them less effective for capturing the intricate details of the scute patterns compared to coif1 and sym2. Figure 5 shows the The comparison of features based the wavelet decomposition between 2 images.

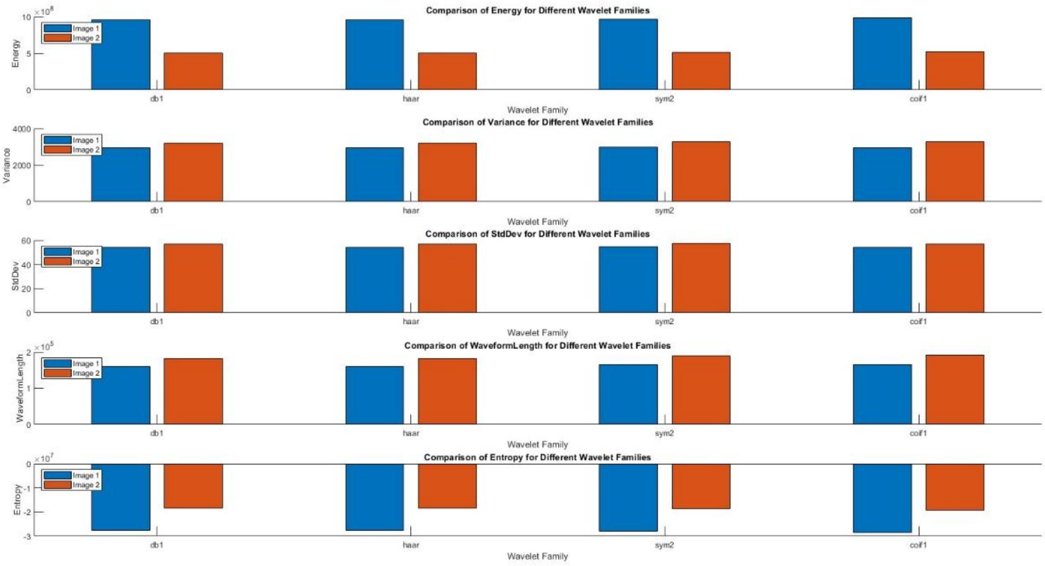

FIGURE 5. The comparison of features based the wavelet decomposition between 2 images.

QUANTIFY THE SIMILARITY BETWEEN TURTLE SCUTE PATTERNS

Table 3 reveals that coif1 is the most effective wavelet family for capturing and distinguishing detailed differences in turtle scute patterns. It consistently shows higher Euclidean distances, indicating a greater sensitivity to variations and complexities within the images. Sym2 also performs well, capturing more nuanced differences compared to db1 and haar. Therefore, for applications requiring detailed pattern recognition and differentiation, coif1 and sym2 are recommended due to their superior capability in highlighting subtle differences in turtle scute patterns. The Euclidean distances between Image 1 and Image 2 are presented in Table 3

TABLE 3. The Euclidean distances between the features of Image 1 and Image 2 using different wavelet families

	Energy	Variance	StdDev	WaveformLength	Entropy
db1	4.5343e+08	265.83	2.3941	22578	9.1284e+06
haar	4.5343e+08	265.83	2.3941	22578	9.1284e+06
sym2	4.5513e+08	306.4	2.7423	24427	9.1718e+06
coif1	4.5937e+08	314.5	2.8231	25162	9.2572e+06

IDENTIFYING TURTLE SCUTE PATTERNS UNDER DIFFERENT ROTATIONS

Identifying unique scute patterns of individual turtles across different angles reveals that coif1 is the most effective wavelet family, demonstrating consistent feature extraction and sensitivity to subtle differences in scute patterns. Figure 6 illustrates the comparison of features for the same image under different orientations.

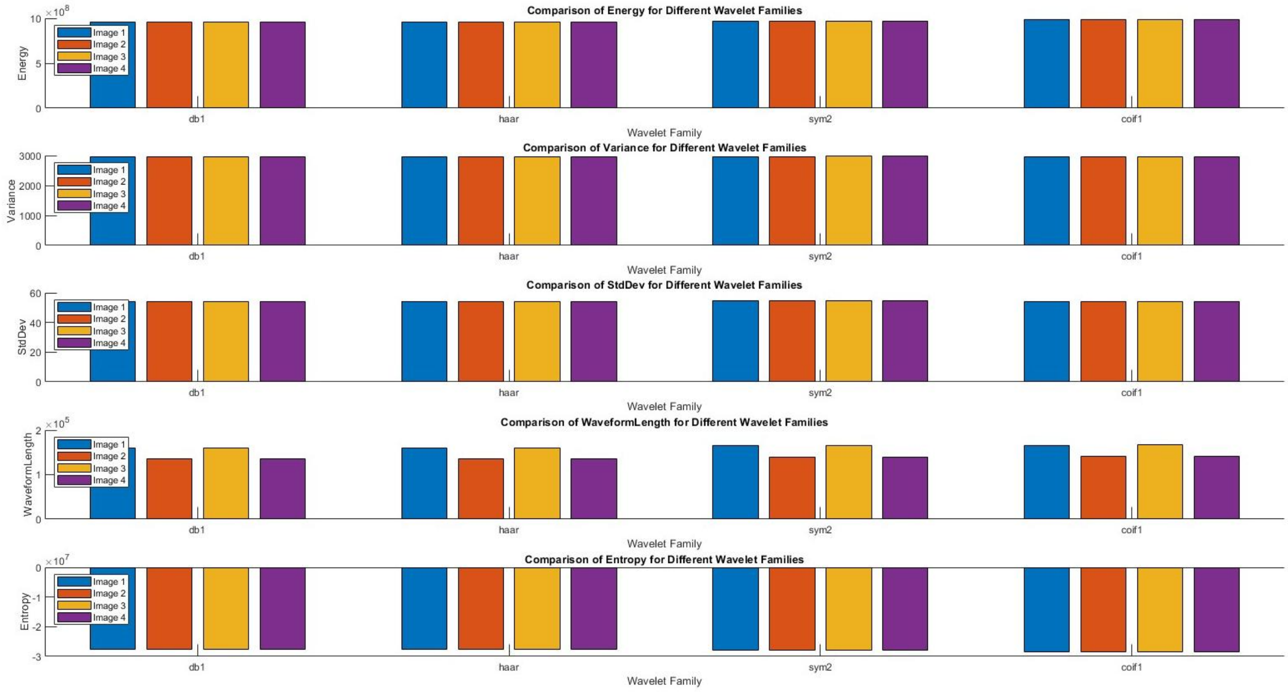

FIGURE 6. The comparison of features for same image but different orientation

Sym2 also performs well, capturing detailed variations across rotations. Db1 and haar show identical results in terms of energy, variance, standard deviation, and entropy across rotations, indicating stability. However, the waveform length varies more significantly for these two wavelet families, suggesting they might be less reliable for capturing rotational invariance in scute patterns. Coif1 exhibits the highest energy values and the most stable entropy, indicating its capability to capture detailed structural information consistently across rotations. Its waveform length and standard deviation also show stability, making it highly effective for recognizing unique scute patterns despite rotational changes.

The energy values are consistent across all orientations, indicating that the total signal strength remains unchanged regardless of the rotation angle. Variance values are also identical across all orientations, further supporting the stability of these features. The standard deviation values remain constant across rotations, confirming the reliability of this feature in identifying unique scute patterns irrespective of orientation. Similarly, waveform length values do not vary with rotation, indicating robustness in capturing the structural details of the scute patterns. Entropy values are stable across all orientations, reflecting that the complexity or randomness of the scute patterns is preserved regardless of rotation. This stability makes entropy a useful feature for distinguishing unique scute patterns. Table 4 presents the Euclidean distances for the same scute turtle under different orientations, highlighting the effectiveness of these features in capturing and distinguishing scute patterns across rotations.

TABLE 4. The Euclidean distances same scute turtle but different orientation.

Image orientations	Energy	Variance	StdDev	WaveformLength	Entropy
Original	2.7956e+05	0.23998	0.0022077	25056	4915.6
90 degrees	2.7956e+05	0.23998	0.0022077	25056	4915.6
180 degrees	2.7956e+05	0.23998	0.0022077	25056	4915.6
270 degrees	2.7956e+05	0.23998	0.0022077	25056	4915.6

CONCLUSIONS

These findings suggest that wavelet-derived features are highly effective in identifying unique scute patterns of individual turtles, regardless of the angle of rotation. The invariance of these features to rotational changes ensures that the scute patterns can be reliably recognized from different perspectives, making them suitable for applications in turtle identification. The objective is to identify unique scute patterns of individual turtles at different angles using Euclidean distance based on wavelet-derived features. Similarly, sym2 performs well, capturing more nuanced differences compared to db1 and haar. Therefore, for applications requiring detailed pattern recognition and differentiation, coif1 and sym2 are recommended due to their superior capability in highlighting subtle differences in turtle scute patterns. Furthermore, for identifying unique scute patterns of individual turtles across different angles, coif1 is again the most effective wavelet family, demonstrating consistent feature extraction and sensitivity to subtle differences in scute patterns. For future work, applying these features in a larger dataset with more varied scute patterns and orientations would further validate their effectiveness and robustness in real-world scenarios.

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