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SYMMETRY LINE DETECTION IN IMAGES USING ANGLED-LINE AND MIDDLE-OUTWARD TECHNIQUES

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ОБНАРУЖЕНИЕ СИММЕТРИЧНЫХ ЛИНИЙ В ИЗОБРАЖЕНИЯХ С ПОМОЩЬЮ МЕТОДОВ УГЛОВЫХ ЛИНИЙ И СРЕДИННЫХ ЛИНИЙ

Reflection symmetry is a key geometric feature that plays a vital role in various fields like computer vision, pattern recognition, and medical image analysis. In this research, we present a refined and easy-to-understand approach for detecting symmetry lines. We use two different techniques: a straightforward brute-force angled-line sweep and a clever middle-outward search strategy. These methods leverage reflection transformations, assess the similarity of binary masks, and rely on a solid mathematical foundation.

Keywords: symmetry; reflection; rotation; images; Jaccard coefficient; cosine coefficient; explainable artificial intelligence (XAI).

Зеркальная симметрия — это важная геометрическая характеристика, которая находит применение в самых разных областях, таких как компьютерное зрение, распознавание образов и анализ медицинских изображений. В нашем исследовании мы предлагаем более понятный и усовершенствованный подход к обнаружению линий симметрии. Мы используем две разные техники: простой перебор угловых линий и продуманную стратегию поиска от центра к периферии. Эти методы используют зеркальные преобразования, оценивают сходство бинарных масок и опираются на прочную математическую базу.

Ключевые слова: симметрия; отражение; поворот; изображения; коэффициент Жаккара; косинусное сходство; объяснимый искусственный интеллект.

Introduction

Symmetry is an essential structural principle in natural and artificial objects. In computer vision, reflection symmetry serves as a powerful geometric prior that can simplify tasks such as shape analysis, segmentation, classification, and medical image interpretation [1-4]. It can also be used in object detection [5], [6], and target tracking and analysis [7]. In the realm of medicine, the symmetry of human organs is a crucial attribute that healthcare professionals can employ for diagnosing specific illnesses. For example, the detection of tumour cells in the brain, liver, lung and prostate tissues [8], [9]. While humans can easily identify axes of symmetry, reliable algorithmic detection remains non-trivial due to noise, occlusions, artifacts, and low contrast—particularly in biomedical images.

Traditional algorithms use methods such as rotation functions, boundary skeleton functions, and pairwise comparisons of skeletal primitives. However, these techniques suffer from computational inefficiencies or limited interpretability. In the context of explainable AI (XAI), explicit geometric descriptors, such as symmetry axes, offer transparent and interpretable representations.

This work introduces two mathematically defined symmetry-line search strategies: a brute-force angular sweep and a middle-outward refinement approach. Both methods rely on explicit reflection transforms and mathematically grounded similarity measures. A central goal is to improve interpretability by enabling users to visually inspect how candidate symmetry lines relate to object structure.

1 Mathematical background

1.1 Definition of Reflection Symmetry:

Let an image be represented as a function:

$$I: \Omega \subset \mathbb{R}^2 \to \mathbb{R}, \tag{1}$$

where Ω is the image domain. A line L with unit normal vector $\vec{n} = (cos\theta, sin\theta)$ and offset $d \in \mathbb{R}$ is defined as:

$$L = \{(x, y) \in \ \mathbb{R}^2 : xcos\theta + ysin\theta = d\}. \tag{2}$$

A point (x', y') is the reflection of (x, y) across L if:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} - 2\big((x, y) \,.\vec{n}^T - d\big)\vec{n}. \tag{3}$$

An image is perfectly symmetric with respect to L if:

$$I(x, y) = I(x', y'),\ \forall (x, y) \in \Omega. \tag{4}$$

1.2 Similarity Measures:

Symmetry is quantified by comparing the original image mask A with the reflected mask B.

1.2.1 Jaccard Similarity

Jaccard coefficient has been introduced in [10] and has been extensively used to measure the similarity of sets in different domains. The Jaccard similarity coefficient can be formulated as below:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| + |A \cap B|}\,. \tag{5}$$

This equation satisfies the given inequalities:

$a)$ $0 \leq J \leq 1$;
$b)$ $J = 1,\ if\ A = B$.

The more the image is dissimilar the more the value of J is closed to 0. This value gets closer to 1 the more A is similar to B.

1.2.2 Cosine Similarit

Representing masks as binary vectors $\vec{a}, \vec{b} \in \mathbb{R}^n$, the cosine similarity index can be expressed as [11]:

$$cos(\vec{a}, \vec{b}) = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|}. \quad (6)$$

If the images are binary:

$$\vec{a} \cdot \vec{b} = |A \cap B|. \quad (7)$$

To stabilize detection and take advantage of both method:

$$S(\theta, d) = \alpha J(A, B) + (1 - \alpha) \cos(a, b), \quad (8)$$

with $\alpha \in [0,1]$. In this work, α was taken as 0.5.

Both the Jaccard and Cosine similarity indexes have been used in literature extensively for similarity measures in data for varied applications [12-15].

2 Data

For this study, two datasets were used. A synthetic dataset composed of 2-D shapes: rectangles, circles, semi-circles, ovals, triangles, parallelograms and hexagons. Each image was an RGB image of 200×200 [16] in dimension. Each image was a 2-D shape rotated at random angles from the origin. This served as our first dataset. The Kaggle platform is where our second dataset was collected [17]. It is composed of brain MRI FLAIR images with segmentation masks. Both tumour and non-tumour magnetic resonance (MRI) slices are included in the second dataset. The dataset consisted of 700 images depicting 2D shapes (10 images for each shape), along with 100 MRI images.

3 Methods

3.1 Brute-Force Angled-line Method

A candidate line with equation:

$$xcos\theta - ysin\theta = d \quad (9)$$

is used to find the potential line of symmetry. The search space of candidate lines is:

$$\theta \epsilon [0, \pi), \ d \epsilon [-D_{max}, D_{max}], \quad (10)$$

where D_{max} is the longest diagonal of the image, W is the width of the image and H the height of the image.

$$D_{max} = \sqrt{W^2 + H^2} \quad (11)$$

For each candidate line:

a) convert image to binary;
b) reflect pixels above the candidate line;
c) compute Jaccard and cosine similarity;
d) select the line maximizing the combined score $S(\theta, d)$.

Algorithmic Complexity.

Let:

$N_\theta = \pi / \Delta\theta$; total number of operations per θ,
$N_d = 2D_{max} / \Delta d$; total number of operations per d,
$C =$ number of pixels in the object mask.

using well known Big O notation analysis [18], the computational complexity of the algorithm is about:

$$T_{brute} = O(N_\theta, N_d, C). \quad (12)$$

Almost all angles and pixels are touched using this approach, this explains the long computation time observed experimentally.

3.2 Middle-Outward Method

In this approach, we first define a region of interest (ROI) in our image. This region is the minimal space needed to contain our object (2-D figure or MRI of the brain) within a square box. Furthermore, given that the boundary of the image has been reduced to that very closed to the region of interest, the axis of symmetry should be very closed to the centre of mass of the figure. Therefore, we begin the search of this axis of symmetry from this middle point.

Centre of Mass

Let A be the mask. Then:

$$x_c = \frac{1}{|A|}\sum\nolimits_{(x,y)\epsilon A} x,\ y_c = \frac{1}{|A|}\sum\nolimits_{(x,y)\epsilon A} y. \tag{13}$$

The search is centred at (x_c, y_c), reducing the parameter d to:

$$d' = d - (x_c cos\theta - y_c sin\theta). \tag{14}$$

Given that the object is centred at the middle of the image, the object extends only half of its width or height in each direction. Thus:

$$x'\epsilon\left[-\frac{W_{obj}}{2},\ \frac{W_{obj}}{2}\right],\ y'\epsilon\left[-\frac{H_{obj}}{2}, \frac{H_{obj}}{2}\right]. \tag{15}$$

The maximum possible distance from the centre to a line is:

$$D'_{max} = \frac{1}{2}\sqrt{W^2{}_{obj} + H^2{}_{obj}}\ , \tag{16}$$

this is half the size of the original diagonal. So:

$$d' \in [-D'_{max}, D'_{max}]. \tag{17}$$

Comparing the maximum diagonals and given that the object is smaller than the image:

$$D'_{max} \ll D_{max}. \tag{18}$$

Algorithm complexity is influenced by pixel count in image, distance-sampling range and angle range. For both methods, the angle range remains constant. However, in the second method, both the pixel count and the distance-sampling range are considerably reduced linearly, which leads to a significant decrease in algorithm complexity.

Let ρ be the ratio of ROI size to whole image:

$$T_{mid} \approx \rho^2 T_{brute}. \tag{19}$$

Results

The proposed methods were applied on both datasets and the results are presented in the following tables (see table 1 and table 2). There were very slight angular and spatial errors recorded in the symmetry lines found. MRI slices showed slightly higher error due to the fact that the brain anatomy is not perfectly symmetric. Testing of the algorithm was carried out on a laptop with characteristic: Intel® Core™ i5-8300H CPU @ 2.30Ghz.

The tables presented below illustrate that the symmetry lines of geometric shapes are clearly identifiable. In contrast, MRI images exhibit greater complexity, resulting in the identification of symmetry lines that are less precise.

The accuracy of the symmetry lines identified is notably higher for classical geometric shapes when juxtaposed with those observed in MRI images.

Furthermore, the Jaccard coefficient values appear to provide a more effective representation of the complexity inherent in both MRI images and geometric shapes.

Table 1– Symmetry line results for geometric shapes

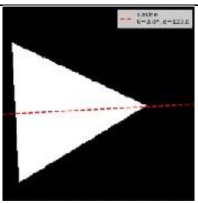
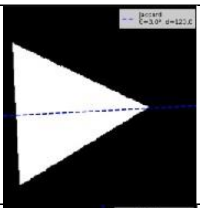
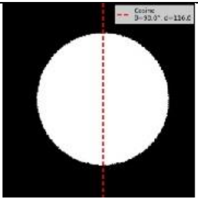
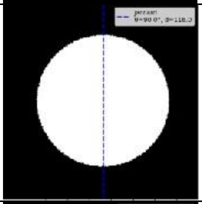
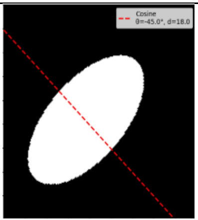
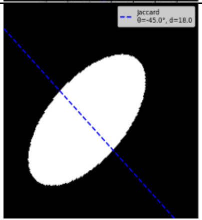
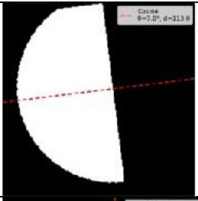
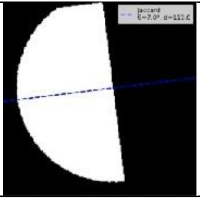
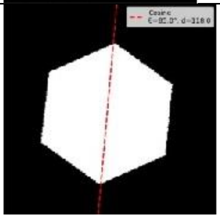
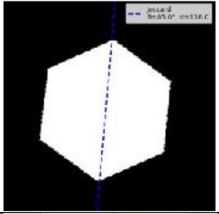
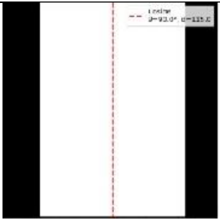
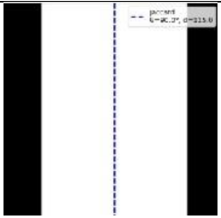
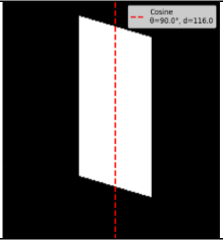
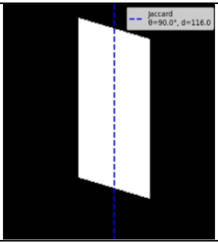
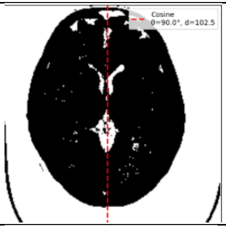
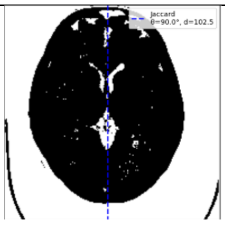
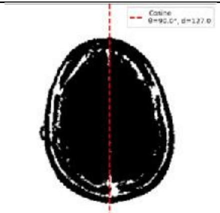
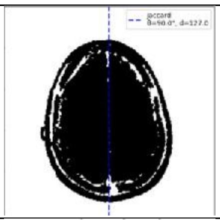
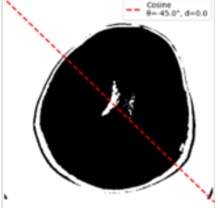
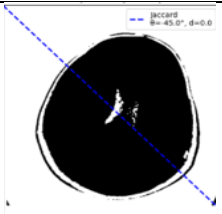
Category	Cosine line	Jaccard line	Cosine value	Jaccard value
Triangle			0.988	0.977
Circle			0.996	0.991
Oval			1	0.999
Semi-circle			0.957	0.917
Hexagon			0.976	0.953
Rectangle			1	1
Parallelogram			0.933	0.874

Table 2 – Symmetry line results for MRI

Category	Cosine line	Jaccard line	Cosine value	Jaccard value
MRI image			0.943	0.892
MRI image			0.944	0.894
MRI image			0.926	0.863

The algorithms employed yielded outstanding results in identifying the lines of symmetry across all images within the dataset. In Table 3 below, one can observe the average processing time for each method categorized by image type. Our middle-outward approach was approximately twice as fast as the brute-force angled line method. The processing time is particularly critical when dealing with complex images such as MRI scans. The output from a standard MRI examination is a video, which consists of a sequence of images displayed at a specific speed. The task of identifying lines of symmetry in the images contained within a video correlates with the complexity of those images. Symmetry in the brain is an essential factor utilized by medical professionals for tumour detection. For a decision support system designed to assist physicians in this task in real-time, maintaining a low average processing time is vital.

Table 3 Processing time

Category	Brute-force angled line (average time in minutes)	Middle-outward (average time in minutes)
Parallelogram	3.59	1.42
Circle	4.85	1.25
Semi-circle	5.16	1.97
Triangle	4.86	1.34
Oval	3.36	1.26
Hexagon	4.67	1.22
Rectangle	5.72	2.37
MRI images	27.57	9.85

Discussion

Both algorithms produce high symmetry scores across synthetic and MRI datasets. The brute-force approach is mathematically complete but computationally expensive. The middle-outward approach improves computational efficiency while maintaining accuracy.

An average reduction of 66% for the 2-D shapes and 63% for MRI images, in processing time was observed with the middle-outward technique. However, due to the non-perfect symmetric nature of the brain, the best symmetry line differed from the ground-truth. Importantly, the explicit mathematical formulation of the reflection transforms and similarity measures contributes to interpretability—supporting explainable artificial intelligence (XAI) principles [19].

Conclusion

This study proposes two mathematically grounded, explainable approaches for symmetry line detection. The methods deliver high accuracy across diverse shapes and medical images. Although computationally expensive, the angled-line brute-force method is robust, while the middle-outward approach provides a practical compromise. Symmetry lines were successfully found for all images in the dataset. The essence of this work was to find a threshold value for MRI similarity measure. Based on the results obtained, a threshold of 0.87 for the similarity measure could be proposed. Beneath this value, the symmetry line is less accurate.

Future work includes continuous optimization of parameter space and employing differentiable symmetry operators.

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RESUME

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Symmetry Line Detection In Images Using Angled-Line And Middle-Outward Techniques

Reflection symmetry is a fundamental geometric property that supports object analysis in computer vision, pattern recognition, and medical image interpretation. Accurately identifying symmetry axes enables improved shape understanding, structural analysis, and anomaly detection. Some methods based on contours, rotation functions, or skeleton primitives are also used to estimate symmetry, but some lack interpretability or struggle with noise and imaging artifacts, particularly in medical data. In the context of explainable artificial intelligence (XAI), explicit geometric symmetry descriptors offer transparent and reliable insights. This study proposes two mathematically grounded techniques for detecting symmetry lines in 2D images: (1) a brute-force angled-line sweep and (2) a middle-outward optimized approach. Both methods are based on reflection operations and similarity metrics of binary masks. The objective is to improve symmetry estimation accuracy, computational efficiency, and explainability across synthetic shapes and MRI brain scans.

Two datasets were evaluated. The first consisted of 2D synthetic geometric shapes (circles, rectangles, squares, ovals, triangles, semicircles, and hexagons), each embedded in a 200×200 image and randomly rotated. The second dataset comprised brain MRI FLAIR slices from the Kaggle dataset, including both healthy and tumor images. Candidate symmetry lines were parameterized using the angled formulation of a line. Symmetry was quantified by two similarity measures: the Jaccard index and cosine similarity. Two strategies were implemented. The brute-force method exhaustively evaluated the full parameter space, ensuring maximal accuracy at high computational cost. The middle-outward method determined the region of interest and center of mass, constraining the scan around the object and reducing the search space by a factor proportional to the ROI size.

Across all geometric shapes, cosine and Jaccard similarity values ranged from 0.874 to 1.0. Highly symmetric shapes such as circles, and rectangles achieved perfect or near-perfect scores. More complex shapes (triangles, semicircles) produced slightly lower but still strong symmetry values. Hexagons and ovals consistently showed high accuracy with both metrics. For MRI images, the method achieved a mean cosine similarity of 0.833 and a mean Jaccard similarity of 0.937 despite natural anatomical asymmetries and imaging artifacts. The middle-outward algorithm substantially reduced computation time by 1.5-2.5 times while preserving accuracy, confirming the benefit of restricting the search around the object's centre.

This work introduces two interpretable and mathematically explicit approaches for symmetry-line detection applicable to synthetic shapes and medical images based on known mathematic formulations. Both approaches consistently identified accurate symmetry axes, with the brute-force method guaranteeing exhaustive evaluation and the middle-outward method offering a significantly more efficient alternative. The results demonstrate the potential of using symmetries within XAI approaches for medical diagnostics and decision support tasks.

РЕЗЮМЕ

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Обнаружение симметричных линий в изображениях с помощью методов угловых линий и срединных линий

Симметрия является важным геометрическим свойством, широко используемым в задачах компьютерного зрения, распознавания образов и анализа медицинских изображений. Определение оси симметрии способствует более точному описанию формы объекта, анализу его структурных особенностей и выявлению аномалий. Однако существующие подходы нередко чувствительны к шуму, артефактам и низкой контрастности изображений, что особенно характерно для медицинских данных. В контексте объяснимого искусственного интеллекта (XAI) явные дескрипторы геометрической симметрии предоставляют прозрачные и надёжные инструменты. В работе предлагаются два математически обоснованных и интерпретируемых метода поиска линии симметрии: (1) брутфорсное угловое сканирование и (2) стратегию поиска от центра к периферии. Оба метода основаны на операциях отражения и метриках сходства бинарных масок. Цель — повысить точность оценки симметрии, вычислительную эффективность и объяснимость синтетических форм и МРТ-сканирования мозга.

Для исследования использовались два набора данных. Первый включал синтетические двумерные фигуры (круги, прямоугольники, квадраты, овалы, треугольники, полукруги, параллелограммы, шестиугольники), представленные в виде RGB-изображений размером 200×200 пикселей с произвольным поворотом. Второй набор состоял из FLAIR-срезов МРТ головного мозга (здоровые и опухолевые) с Kaggle. Линии-кандидаты задавались параметрическим уравнением прямой. Для оценки симметрии использовались коэффициент Жаккара и косинусное сходство. Метод углового перебора вычислял значения метрик для всех допустимых пар параметров линии. Срединный метод определял центр масс объекта и ограничивал поиск в пределах ROI, что позволяло существенно сократить вычислительные затраты.

Для синтетических фигур коэффициенты Жаккара и косинусного сходства находились в диапазоне от 0,874 до 1,0, что подтверждает высокую точность определения линии симметрии. Наиболее симметричные фигуры (круги, прямоугольники) давали почти идеальные результаты. Более сложные фигуры (треугольники, полукруги) демонстрировали несколько более низкие значения метрик, но сохраняли хорошее качество обнаружения. В случае МРТ-изображений средние значения косинусного сходства составили 0,833, а коэффициента Жаккара — 0,937. Срединный метод обеспечил сокращение времени обработки в 1,5–2,5 раза по сравнению с полным угловым перебором при сохранении сопоставимой точности.

Предложенные методы обеспечивают интерпретируемое и устойчивое определение линий симметрии для синтетических и медицинских изображений. Метод полного перебора обеспечивает максимальную точность, но требует значительных вычислительных ресурсов. Срединный подход является более эффективным и практически применимым, особенно при анализе медицинских данных. Результаты демонстрируют потенциал использования симметрии в рамках подходов объяснимого искусственного интеллекта для задач медицинской диагностики и поддержки принятия решений.

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