Chapter 3

Pattern Analysis for Feature Extraction in Multi-Resolution Images

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Abstract

A pattern is a concept that has proven to be effective in one situation and is likely to be useful in others. A pattern can take many different forms, each with its own set of specializations that are appropriate for that particular pattern. Anything can be considered a pattern. It could be a collection of objects that work together. These patterns are necessary to analyze for better recognition. Pattern analysis is an area of artificial intelligence and computer science focused with using an algorithm to find patterns in data. Patterns refer to any underlying correlations, regularities, or structure in a data stream. A system could foresee making predictions based on new information arriving a similar source if it detects significant patterns in the existing data. In this study pattern analysis based on feature extraction is being discussed and implemented. Features contain all the vital information of any image pattern and hence to gather all the necessary information, feature like edges that are informative in nature is essential to extract and combine for any type of pattern recognition and analysis.

Keywords: feature extractions, pattern, pattern analysis, pattern recognition

1. Introduction

Patterns have been one of the most popular subjects in the object community in recent years [1-3]. They're quickly becoming the hottest trend, generating a lot of interest and the usual buzz. Internal disputes over what belongs in the community are also raging, with various disagreements about exactly what a pattern is? Pattern comes from data and data comes from the word 'datum' that means basic unit of measuring and calculating anything [4-6]. Generally, data is everywhere, whatever we use either to manipulate or to calculate we refer data. Data is any factual information (such as measurements or statistics) that is used to support argument, debate, or calculation. Depending on the data and the patterns, the process of gathering data on a regular basis in order to look for patterns, such as upward trending numbers or connections between two sets of numbers, can occasionally reveal such patterns in a basic tabular presentation of the data. [7-10]. Other times, a chart, such as a time series, line graph, or scatter plot, might aid to visualize the data.

- A pattern, for example, could be an object or an event as shown in Figure 3.1.

The University of California was the first to investigate patterns in engineering in a systematic manner, establishing an architectural pattern language that is considered a paradigm for patterns in a variety of other domains. A pattern can also be defined as a "morphological law that describes how to build an artifact in order to address a problem in a certain setting". Pattern analysis is separated into three categories: classification, regression (or prediction), and clustering, with each attempting to discover patterns in data in a different method [11, 12].

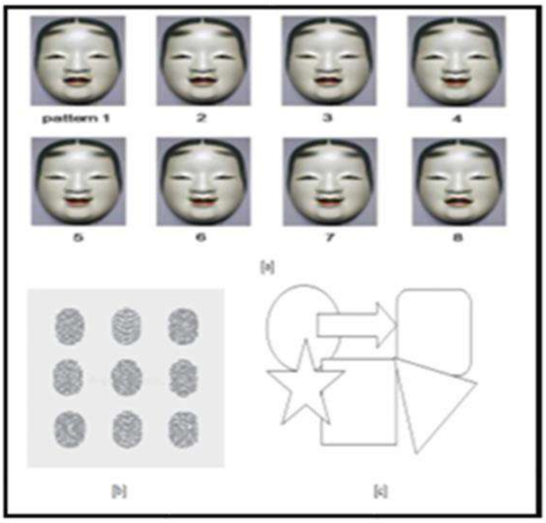


Figure 1. Patterns.

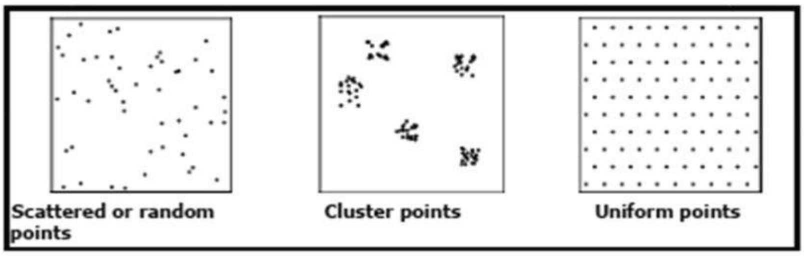


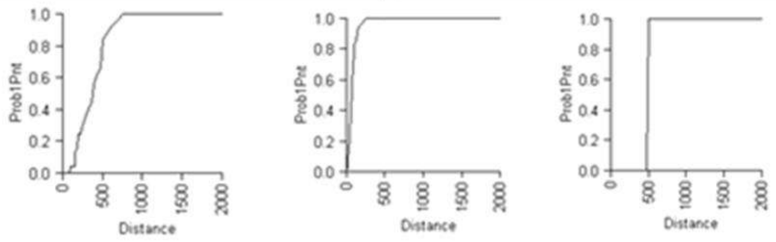
Figure 2. Patterns sample point maps.

The three basic pattern kinds are shown in the examples of three point maps below in Figure 2.

The sample's measured results aren't significant (they were all set to 1). A Pattern analysis operation was utilized to input each point map.

Output Map of above pattern: Pattern analysis produced an output table for each input point map. Graphs of the Distance column against the Prob1Pnt column and the Distance column against the ProbAllPnt column were created from each output table: Graphs of the Distance column versus the Prob1Pnt column first, and then against the Prob All Pnt column second.

Finding at least one point neighbor probability and distance is shown in Figure 3.



For Scattered samples: Distances between points and the likelihood of discovering at least one neighbor.

For clustered sample: Distances between points and the likelihood of discovering at least one neighbor.

For uniform points: Distances between points and the likelihood of discovering at least one neighbor.

Figure 3. Output of pattern sample point map.

Concluded definition of pattern is: A pattern can be a real object, such as a book or a chair, or it can be an abstract concept, such as a speaking or writing style. It's also a trait that a group of objects has in common, such as chairs, rectangles, or blue-colored objects. It's a subset of comparable objects in a bigger collection (a class or a cluster) also used to describe the overall similarity structure in a group of objects as well as a single object that is representative of a group of similar objects.

1.1. Pattern Class

Every pattern has a corresponding class, which represents the pattern that can be found in the real world. The symbolic or numerical property of a real-world object can be used to determine its class [13]. This is also referred to as "attribute." However, the amount of properties assigned to each item may vary whereas the same features may usually be measured for all items in a given situation. A feature vector or a set of characteristics can thus be used to represent an object. A dataset feature attribute that refers to the set of values that a specific feature may have. When adding new objects to a dataset, the feature values for the defined domain can be validated.

1.2. Analysis

Breaking down a notion, proposition, linguistic complication, or truth into its simplest or most fundamental elements is known as analysis. Analysis is rarely employed to address the complete body of knowledge in a field, but rather to address a specific problem. Now, analysis entails focusing on what is already known about the problem we're attempting to address [14]. The whole point of the art is to extract many truths from this investigation that will bring us to the understanding we seek. The genuine process through which the thing in question was discovered methodically and as though a priori is shown in analysis. The scientific process of evaluating something to determine what it is made up of is known as analysis.

1.3. Pattern Analysis

Pattern analysis refers to the process in all of its forms and applications, and is sometimes referred to as Machine Learning, Pattern Recognition, Pattern Matching and Data Mining. The name is often determined by the application domain, the pattern sought, or the algorithm designer's professional experience. Many correspondences and parallels will be made apparent by combining these diverse techniques into a single framework, allowing for a relatively seamless expansion of the number of pattern types and application areas. Early methods were effective for detecting linear relationships, but nonlinear patterns were handled in a less principled manner. Pattern analysis is a broad discipline that examines systems that utilise machine learning to find patterns in data [14]. Many various sorts of patterns are sought, including classification, cluster analysis, regression, Feature extraction, grammatical inference, and parsing are all examples of statistical pattern recognition (also known as syntactical pattern recognition).

Pattern analysis is the sub branch of pattern recognition.

1.3.1. Pattern Recognition

Pattern recognition is the act of identifying input data, such as voice, images, or a stream of text, by recognizing and outlining patterns and their relationships in computer science. Pattern recognition includes processes such as measuring the item to find distinctive traits, extracting features for defining attributes, and comparing the item to existing patterns to determine a match or mismatch [15]. A pattern recognition algorithm is shown in Figure 4.

To tackle the pattern recognition problem, different paradigms are used. The two main paradigms are:

- Statistical Pattern Recognition
- Recognition of Syntactic Patterns

Statistical Pattern Recognition has proven to be more effective and popular, and it has gotten a lot of press in the literature. This is due to the fact that the majority of the practical challenges in this field have to deal with a lot of noise, uncertainty, and statistics. Vectors are used to represent patterns and class labels from a label set in statistical pattern recognition. The abstractions usually deal with point probability density/distributions in multidimensional spaces, trees and graphs, rules, and vectors themselves. It's useful to talk about subspaces/projections and similarity between points in terms of distance measures because of the vector space representation. This concept is related with a number of soft computing techniques. Imprecision, uncertainty, and approximation is not a problem for soft computing systems. Neural networks, fuzzy systems, and evolutionary computation are some of the tools that can be used [16-19].

1.4. Problem Definition

Pattern analysis' main purpose is to assess whether an object belongs to a given group. Attempting to identify the attributes of an unlabeled object can be used to address the difficulty of assigning it to a group and evaluating the group, assuming that items in one group have a greater degree of similarity than items in other groups. Because the optimum features for discriminating between groups and the mapping of attributes to groups can both be identified with certainty, if all prospective items and the categories to which they might be placed are known, the identification problem is simple. The properties and mapping to use must be inferred from known group membership in example objects when understanding of the identification problem is inadequate or incomplete. The functionality of an automated pattern analysis system can be separated into two main jobs, both of which aim to classify objects based on their features: the description task uses feature extraction techniques to generate attributes for an object, and the classification task uses a classifier to assign a group label to the object based on those attributes. The pattern recognition system combines the description and classification functions to determine the most appropriate label for each unlabeled object it investigates.

Automated pattern recognition systems are effective for handling a wide range of real-world issues because of the universality of the description and classification architecture, as well as the flexibility provided by the training phase. Data sets comprising qualities that were automatically collected and are reflective of the physical or behavioral objects to be identified are normally the objects under investigation in real-world pattern recognition systems.

1.5. Pattern Analysis Algorithm

Input: A finite amount of source data to be analyzed.
Output: Positive pattern data set or no pattern detectable.

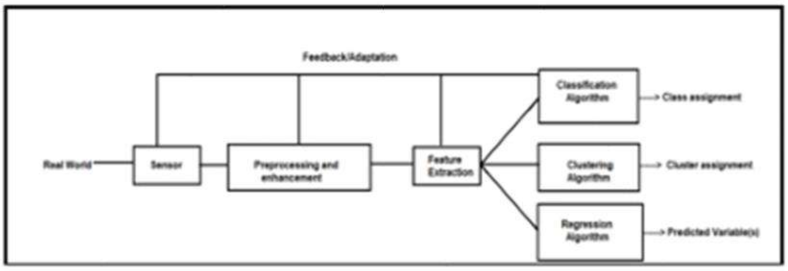


Figure 4. Pattern recognition algorithm.

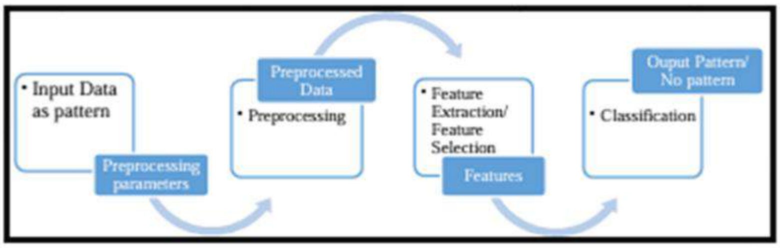


Figure 5. Pattern analysis algorithm.

A pattern analysis algorithm is shown in Figure 5. The main goal of pattern analysis is to determine whether or not an object belongs to a specific group. Assuming that things from one group have more in common with those from other groupings, The problem of assigning an unlabeled object to a group can be solved by first finding the qualities of the object in the form of a pattern, and then deciding which group those attributes are most reflective of (i.e., the recognition). The identification problem is straightforward if knowledge about the universe of all conceivable objects and the groups to which they can be allocated is known, because the features that best discriminate across groups and the mapping from attributes to groups can both be identified with certainty.

Identifying patterns in a limited collection of data poses a variety of unique problems. We'll look at three important characteristics that a pattern analysis algorithm must have in order to be considered effective.

(i) Computational Efficiency: Pattern analysis algorithms must be able to handle very huge datasets because we're seeking for practical solutions to real-world situations. As a result, an algorithm's performance must scale over large datasets, not just on tiny toy examples. Efficient algorithms have resource requirements that scale polynomially with the amount of input, according to the study of computational complexity or scalability of algorithms. This means that the method's necessary number of steps and memory may be described as a polynomial function of the dataset size as well as other key aspects like the number of features, desired precision, and so on. Many pattern analysis algorithms fail to meet this seemingly innocuous requirement, and in certain cases, there is no guarantee that a solution will be identified at all.

(ii) Robustness: The fact that data is frequently contaminated by noise in real-world applications is the second issue that a successful pattern analysis algorithm must overcome. By noise, we imply that measurement errors or even miscoding, such as human error, might impact the values of features for individual data items. This is related to the previously discussed concept of approximation patterns, because even if the underlying relationship is perfect, it will inevitably become approximate and statistical if noise is introduced.

(iii) Statistical Stability: The third criterion is arguably the most important and the patterns identified by the algorithm are true patterns from the data source, not merely an unintentional relationship that occurred in the small training sample. This feature may be thought of as the output's statistical robustness, in that it should detect a similar pattern if the algorithm is run again on a new sample from the same source. As a result, the algorithm's output should be unaffected by the dataset in question, only by the data's underlying source.

Efficient algorithms have resource requirements that scale polynomially with the amount of input, according to the study of computational complexity or scalability of algorithms. The difference is that statistical stability assesses a pattern function's capacity to reliably process unseen examples, whereas robustness examines the effect of sampling on the pattern function itself.

When the results show that the identification challenge is weak or incomplete, the attributes and mappings to utilise must be inferred from known group membership in sample objects. The functionality of an automated pattern recognition system can be separated into two basic jobs, given the purpose of classifying objects based on their features. The description task uses feature extraction techniques to generate attributes for an item, while the classification task uses a classifier to assign the object a group label based on those attributes. The pattern analysis system analyses each unlabeled object and determines the best appropriate label based on the outcomes of the description and classification tasks. Pattern analysis is used by the researcher to discover and find systematic regularity in a much larger data set. These methods frequently employ computer modeling and simulation techniques, as well as data mining, image processing, and network analysis.

Various pattern analysis techniques are shown in Figure 6.

1.6. Feature Extraction

Feature extraction is a very important step in pattern analysis to extract features that are good for analysis and classification [20, 21]. Good features (as shown in Figure 7) are those possessing following key points:

- Feature values are comparable across objects of the same class.
- Various types of objects have different values.

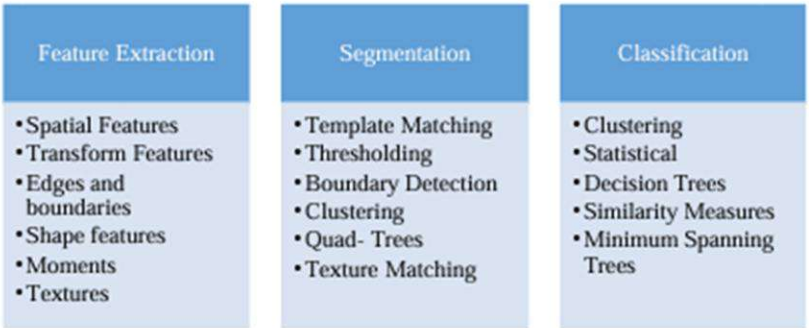


Figure 6. Pattern analysis techniques.

Figure 7. Good and bad features.

Features are categorized as:

(i) Spatial Features: The grey levels, joint probability distribution, geographical distribution, and other spatial characteristics of an item can be used to characterise it.

(ii) Transform Features: Transform features give frequency domain information of the data, are also a vital element of analysis. Zonal-filtering of the picture in the chosen transform space can be used to extract these characteristics.

(iii) Edge and Boundaries:
- Edge detection lowers the quantity of data in an image and filters out irrelevant information while maintaining the image's key structural features.
- Edges are the lines that separate various textures.
- Edges are also described as picture intensity discontinuities from one pixel to the next.
- The image's borders are always the most essential qualities that indicate a higher frequency.

- Edge identification in noisy pictures is challenging because both the noise and the edges include high-frequency information, making it difficult for image segmentation, data reduction, and good matching, such as image reconstruction and so on.

2. Literature Review

Fowler M et.al. [22] Introduced analysis patterns with the help of some real world example that he had gone through in the book. Examples were illustrated as UML diagrams and java interface declaration. The author identifies the need for a book that goes beyond the tools and techniques of a standard methodology book in the object-oriented community with the help of this book. In Analysis Patterns: Object-Oriented Analysis and Design, Martin Fowler focuses on the models themselves, the end product of object-oriented analysis and design. Models of Reusable Objects. He shares his extensive object modeling knowledge as well as his good eye for detecting recurring issues and turning them into reusable models with you. Analysis Patterns is a collection of patterns that have arisen in a variety of fields, such as trade, measurement, accounting, and organisational interactions. Recognizing that conceptual patterns cannot exist in isolation, the author includes a set of "support patterns" that explain how to convert conceptual models into software that can then be integrated into a large-scale information systems architecture. Each pattern includes a rationale for its creation, rules for when and when not to use it, and implementation recommendations. The examples in this book serve as a recipe book for usable models and insights into the skill of reuse, both of which can help you better your analysis.

Ding et al. [23] covers frontier methods in this area and discusses feature extraction in general, covering linear and nonlinear feature extraction, before concluding with a discussion of feature extraction's development trend in his article. More trials will be required to validate some ideas, while the theories of some approaches will need to be refined. Because most of the systems we encounter in practice are nonlinear, time-varying systems, high-dimensional nonlinear pattern feature extraction and selection is currently a popular subject of research. The organic integration of different types of theories, such as adding information theory, neural networks, and other theories to feature extraction, is considered frontier research from the standpoint of method theory; the current Manifold Learning and Independent Component Detection methods; the current Manifold Learning and Independent Component Detection methods; and the current Manifold Learning and Independent Component Detection methods; and the current Manifold Learning and Independent Component Detection methods; and the current Manifold Learning and Independent Component Detection methods; and the current Manifold Learning and Independent Component Detection methods; and the current Manifold Learning and Independent Component Detect.

Olszewski et al. [24] discussed about the limitations of the implementation of spatial feature recognition system to any new domain as it takes thorough knowledge of domain to make the implementation successful. After discussing about the limitation author also suggest some solutions to overcome this limitation such as author told about the need of developing a domain-independent approach to structural pattern recognition that can extract morphological characteristics and perform classification without the use of domain knowledge. Secondly, A natural solution is a hybrid system that uses a statistical classification technique to accomplish structural feature-based discrimination. The effectiveness of the structure detectors to create features helpful for structural pattern recognition is assessed by comparing classification accuracy achieved using the structure detectors to commonly utilised statistical feature extractors by the author. Also the author evaluates the uses data from two real-world datasets with vastly diverse properties and well-established ground truth. The classification accuracies obtained using the structure detectors' features were consistently as good as or better than those obtained using the statistical feature extractors' features, demonstrating that the suite of structure detectors effectively performs generalised feature extraction for structural pattern recognition in a variety of situations.

In [25]. the physical mechanisms underlying subaqueous bed load movement and ripple development are explained by the author. In this study, the researchers used a direct numerical simulation of horizontal channel flow over a thick substrate of mobile sediment particles. The DNS-DEM method yielded results that were totally consistent with the reference experiment's data. Once the Shields number is exceeded, the simulations show a cubic fluctuation in particle flow rate (normalised by the square of the Galileo number times viscosity). The creation of patterns was next investigated using a variety of medium- to large-scale simulations in both the laminar and turbulent regimes. To accurately model the phenomenon, large computational domains with up to O (109) grid nodes were used, with up to O(106) freely moving spherical particles representing the mobile sediment bed. The simulations' results are quite close to the experimental data in terms of pattern wavelength, amplitude, asymmetric shape, and propagation velocity. In order to specify the cutoff length for pattern formation, the computational box size was carefully tuned to get the smallest box dimension that accommodates an unstable pattern wavelength. In order to characterise the structure of the driving turbulent flow and its association with the bed forms, a comprehensive dune-conditioned statistical analysis of the flow field and particle motion was carried out, which took into account the spatial and temporal variability of the sediment bed.

In [26], there have been shown several significant advancements in the underlying algorithms and methodologies, resulting in a substantial machine learning is seeing a surge in practical applications. Bayesian methods, for example, have evolved into a full framework for expressing and using probabilistic techniques, while graphical models have evolved into a comprehensive framework for expressing and using probabilistic techniques. Approximation inference methods like variational Bayes and expectation propagation have substantially improved Bayesian techniques' practical usefulness, while new kernel-based models have had a considerable impact on both algorithms and applications. This textbook includes these latest advancements while providing a thorough overview of pattern recognition and machine learning ideas. Advanced undergraduates and first-year PhD students, as well as researchers and practitioners, are all targets. There is no requirement that you have any prior experience with pattern recognition or machine learning. Prior experience with probabilities, as well as a working knowledge of multivariate calculus and basic linear algebra, is necessary (though this is not required because the book contains a self-contained introduction to basic probability theory).

Alexander et al. [27] termed a pattern language by the authors, that is developed from timeless concepts known as patterns. "All 253 patterns together form a language," Page xxxv of the introduction is where they write. Patterns describe a problem before proposing a remedy. The authors hope that by doing so, regular people, not only experts, will be able to collaborate with their neighbours to enhance a town or neighborhood, design a home for themselves, or collaborate with coworkers to create an office, workshop, or public building like a school. It has 253 patterns, including Community of 7000 (Pattern 12), which is treated over several pages; on page 71, it asserts, "Individuals have no effective voice in any community of more than 5,000–10,000 people." It is written in the form of a set of problems with detailed solutions.

Verginadis et al. [28] focused on collaborative work patterns as a way to collect best practices concerning recurring collaboration difficulties and solutions among scattered groups. The authors give a comparison of relevant academic and commercial activities in the area of patterns that might be used to improve collaboration. Also author presented the findings of a survey on collaboration-related pattern techniques, models, and languages. Existing projects have two broad categories of work that we've identified. The first dimension contrasts between ways that seek to detect/mine patterns in order to discover deviations from recognised best practices and suggest corrective steps, mostly to the designer/facilitator, and approaches that seek to actively assist participants. The second dimension differs between approaches that rely on manual engagement and those that can give participants with automatic support. We believe that, given the increasing complexity of collaborative working environments (e.g., Virtual Breading Environments, Virtual Organizations, and so on), the focus should be shifted to automatically assisting participants and developing new tools that can proactively recommend corrective actions in ongoing collaborations. The study stated that incorporating ontologies and taxonomies into collaboration patterns provides a technological foundation for recording and reasoning about defined patterns of collaborative activity.

3. Implementation

(i) *Data set:* Data variables include individual data variables, description variables with references, and dataset arrays comprising the data set and its description, when applicable, are all included in data sets.

(ii) *Sample Images*: Some sample images are shown in Figure 8.

(iii) Edge detection:

A curve in an image that follows a path of rapid change in image intensity is known as an edge. Edges are regularly used to link the limits of elements in a scene. Edge detection is a technique for detecting the edges of an image.

The edge function can be used to locate edges. Using one of these two criteria, This function searches the picture for spots where the intensity fluctuates rapidly:

Figure 8. Sample images.

(a) Places where the intensity's first derivative is greater than a certain threshold

(b) Places where the intensity's second derivative crosses the zero line

Each of these definitions is implemented by one of the derivative estimators provided by edge. For several of these estimators, we can specify whether the algorithm should be sensitive to horizontal edges, vertical edges, or both. Edge produces a binary image with 1s where edges are found and 0s everywhere else.

The Canny approach from Edge is the most powerful edge detection method on the market. In contrast to prior edge detection methods, the Canny approach employs two thresholds to discriminate between strong and weak edges, and weak edges are only included in the output if they are connected to strong edges. As a result, this method is less susceptible to noise and is better at recognising actual weak edges than the others.

(iv) Edge Detectors

- Sobel
- Prewitt
- Laplacian
- Canny
- Robert

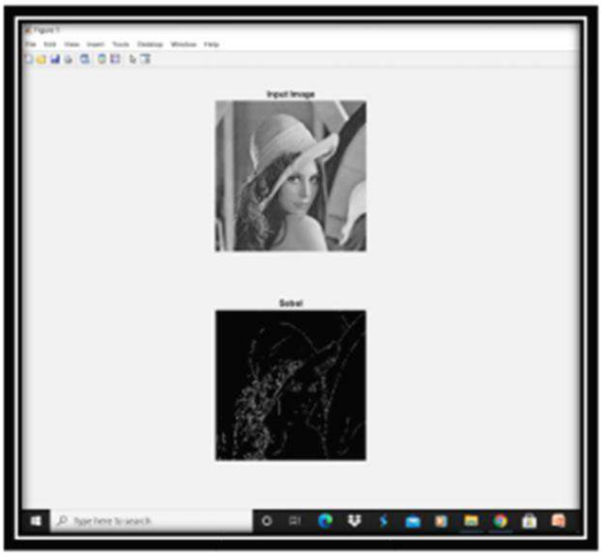


Figure 9. Sobel edge detection.

3.1. Sobel Edge Detector

Edges along the horizontal and vertical axes are detected using this technique (as shown in Figure 9). In both the horizontal and vertical directions, the picture is convolved using a tiny, integer valued filter (3 kernel). As a result, this detector needs less computing.

3.2. Prewitt Edge Detector

It is very much same (as shown in Figure 10) as Sobel edge detector. It detects horizontal and vertical axis and its orientations

3.3. Laplacian Edge Detector

The Laplacian gradient (shown in Figure 11) operator finds the regions where the rapid intensity changes. This is a mix of Gaussian filtering and Laplacian gradient operator. As a result, it's ideal for detecting edges.

Figure 10. Prewitt edge detection.

3.4. Canny Edge Detector

The ingenious edge detector (Figure 12) can recognise a broad variety of actual edges in pictures. The detector removes the undesired noise pixels using a technique called because noisy pixels produce misleading edges, smoothing edges in a picture is necessary. In this edge detection, the signal to noise ratio is higher than in previous methods, alternative approaches. This is why this detector is often utilised in edge detection applications processing of images.

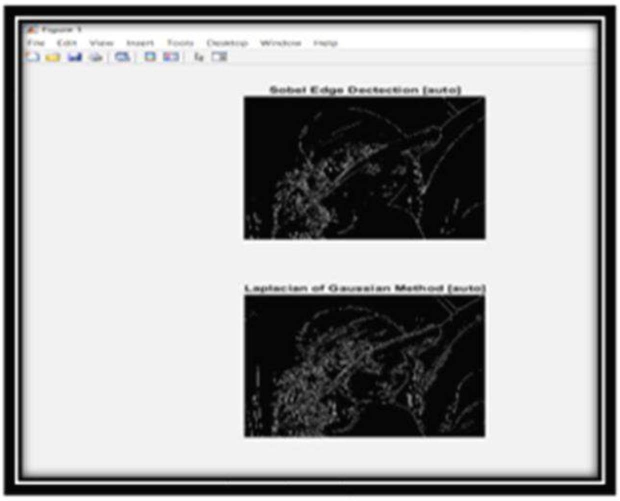


Figure 11. Laplacian edge detection.

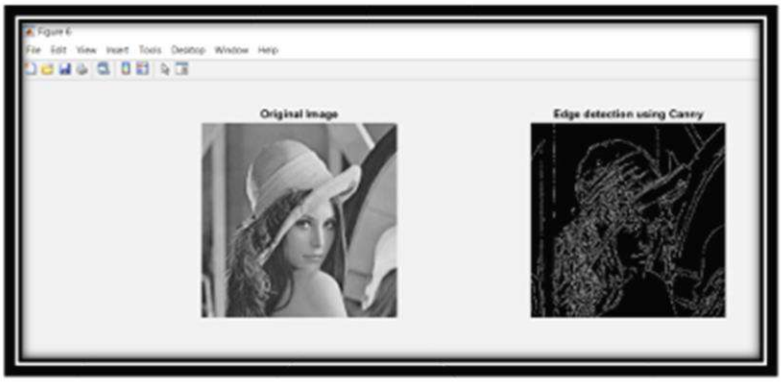


Figure 12. Canny edge detection.

The following is a description of how to locate edges in pictures:

To decrease the influence of noise, the picture is first smoothed using an appropriate filter, such as a mean filter or a Gaussian filter.

After that, each point's local gradient and edge direction are computed. This location has the greatest strength in the gradient's direction.

Ridges appear in the gradient magnitude image as a result of these edge points.

- The edge detector follows the tops of these ridges and sets all pixels that are not on the top of the ridge to zero. As a result, the output is a narrow line.
- Upper threshold (T2) and lower threshold (T1) are used to threshold these ridge pixels (T1).
- Ridge pixels with values larger than the upper threshold (T2) are categorised as strong edge pixels, whereas ridge pixels with values between the lower threshold (T1) and the upper threshold (T2) are classed as weak edge pixels. Finally, by integrating the weak pixels that are related to the strong pixels, the image's edges are joined.

Table 1 shows the comparison between the different Edge detection techniques.

Table 1. Comparison among different edge detection techniques

Edge Detector	Method	Advantage	Limitation
Sobel	Gradient Based	• Simple and easy to calculate • Edges and their orientation are detected.	• Less reliable • Sensitive to noise • Edge detection is unreliable.
Prewitt	Gradient Based	• Simple and straightforward computation • Edges and their orientation are detected..	• Less reliable • Sensitive to noise • Edge detection is unreliable
Laplacian	Gradient Based	• Characteristics are constant in every direction • It is possible to test a large area surrounding a pixel. • Detecting edges and their orientation is straightforward.	• Magnitude of edges is inversely proportional to the noise • The grey level intensity function varies and malfunctions at corners and curves.
Canny	Gradient Based	• More Accurate • Improved signal to noise ratio • More sensitive to noisy pixels	• False Zero crossing • Slow and complex
Robert	Gradient Based	• Simple and straightforward computation • Edges and their orientation are detected..	• Less reliable • Sensitive to noise • Edge detection is unreliable

- It is the process of selecting appropriate features for an object's feature representation.
- This could relate to unprocessed data such as photos or time signals.
- There are numerous approaches for extracting features from images or any other pattern recognition system.

The goal of feature extraction and image analysis is to extract relevant information that may be used to solve problems in applications.

Overall Results of Edge detection in various images are shown in Figures 13, 14 and 15.

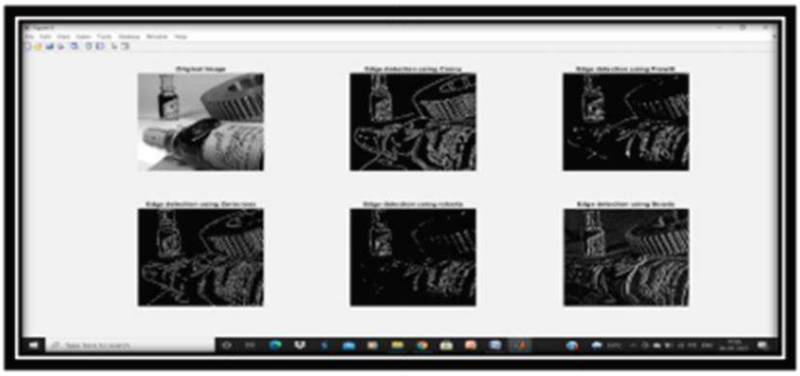


Figure 13. Edge detection for image 1.

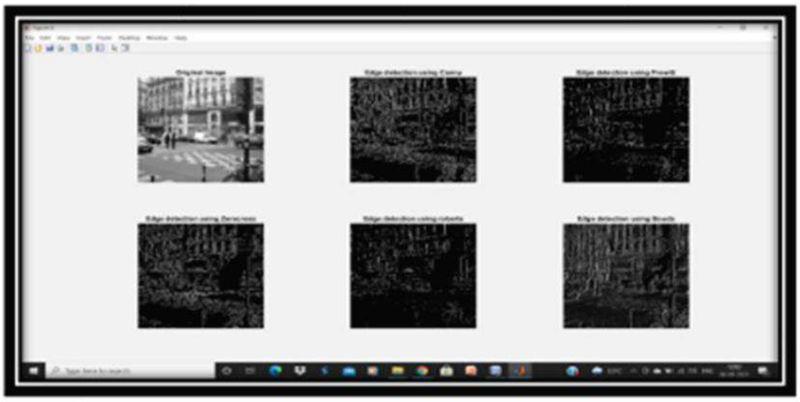


Figure 14. Edge detection for image 2.

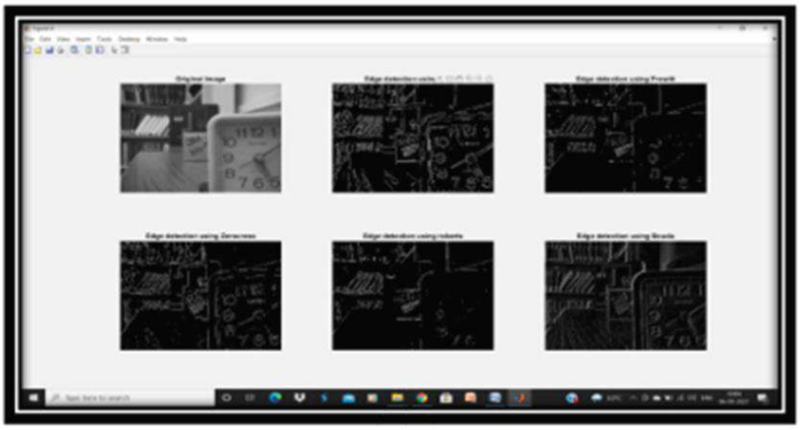


Figure 15. Edge detection for image 3.

Here, in the image, edges of image are being identified by 5 different edge detectors namely Canny, Prewitt, Zerocross, Roberts and Bousta. It is shown that edges from canny edge detector provide better output.

Conclusion

Pattern analysis turned out to be a very important step for feature extraction. If we want to extract features like edge of any image then first we have to analysis it thoroughly for the better implementation and better understanding. Pattern analysis frequently necessitates a pre-processing stage for extracting or selecting features to aid classification, prediction, or clustering or a better representation of the data the explanation for this is simple [29-32]. The raw data must be complex and tough to work with. Without extracting or selecting appropriate features to process beforehand. In order to develop an effective classifier, feature extraction identifies a set of the most useful qualities for categorization. Preprocessing, feature extraction, and classification are the three essential components of pattern analysis. Following the acquisition of the dataset, it is preprocessed to make it appropriate for following sub-processes. Feature extraction is the next phase, which entails transforming the dataset into a series of feature vectors that are designed to represent the original data. These qualities are used in the classification process to divide the data points into different sorts of problems.

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