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SHAPE SYMMETRY-BASED SEMANTIC IMAGE RETRIEVAL USING HIDDEN MARKOV MODEL

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ABSTRACT

In this paper, we propose a novel framework to retrieve semantic images based on shape skeletonizing, ontology base and Hidden Markov Model. First, the region of interest is localized using an adaptive Gaussian model to model the background subtraction. Second, symmetry features for an object is extracted and then quantized using k-means procedure for learning or retrieving processes by Hidden Markov Model. Query Engine, Matching Module and Ontology Manger are to retrieve the semantic image using SPARQL language on input text or image query. The left-right Hidden Markov Model topology using Viterbi algorithm for retrieving and Baum-welch for learning is investigated. The outcome of our proposed framework is empirically tested against the mammals Benchmark. The experiments on the semantic image retrieval yields an efficient result to intricate event by input text or image query than previously notified.

Keywords: *Image retrieval, Query Engine, SPARQL, Hidden Markov Model.*

1. INTRODUCTION

To search, browse and retrieve images from an entire digital image dataset, the image retrieval technique is used. Previously, most researchers focused on low-level apparition with single feature and no retrieval accuracy although the image contains various visual features. In the current decade, collaborative techniques give the idea to deal with the large gap between high-level and low-level perceptions [1, 2, 3, 4]. Texture, shape and color shape are mostly employed as a low-level feature, in which the shape features can be extracted either using boundary-based or region-based technique [5]. The boundary-based procedure is relied on the outer boundary whereas the region-based procedure depends on a high-level feature to retrieve patterns by scanning whole region. The gap between high-level and low-level semantics features are compacted using the mean of prompt feature variations and selection [6]. The semantic image retrieval is one the endowed investigation field in which many researchers consider address methods either to analyze images [7, 8, 9, 10] or to retrieve images [11, 12, 13, 14]. It is being noted that the semantic gap could be reduced using more effective feature for the scene. This represents a difficulty to Content-Based Image Retrieval (CBIR) research [15, 16]. To alleviate this problem, various techniques of machine learning are used. In [17], the authors analyzed image contents in real-time system by extracting the features of color and shape. Their systems used C-Means clustering technique to extract and segment images boundary. Additionally, Fast Fourier Transform is employed to the corresponding region to provide the array features. Then a similarity matching algorithm based on that array is functional to measure the similarity of queried image for retrieving.

The authors in [18], proposed a novel method to determine texture feature and color feature of images for CBIR. Also, they defined this low-level feature using two color histogram function in addition to a combining of color, texture and shape descriptors to retrieve images. In [19], the classifier of fuzzy KNN is explored to retrieve image. They assign an initial semantic state for dataset images, in which the allocated state to image is changed using significance feedback. Many measures, which relied on similarity used three types of visual features. The authors in [20], explored the Neural network of back propagation learning for CBIR. It is being noted that the classified images are divided into background and foreground images. The region of objects is provided using region-based segmentation technique. Additionally,

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the wavelet transform is to extract the texture feature to retrieve shape based.

The authors in [21], extract the features from image accurately and then retrieve the desired image effectively using Support Vector Machine (SVM). In [22], an Riis image is retrieve using hierarchical methodology. This approach is relied on the ground-breaking indexing technique to the iris dataset. In addition, two dissimilar features are extracted for the contents of iris images. The image texture is to recognize the target imaged using indexed iris dataset in which iris color is employed to build the indexing of images. Then the un-looked image is filtered out by color features. Also, an image has not similarity with the query of image color is filtered out. So, this technique is estimated for raucous iris image. In [23], a new method based on algorithms of moments invariants, texture and color histogram is investigated. They are to capture the regularity edges of image. Here, Gabor filter is used to extract texture feature in addition to shape feature is extracted using color and moment invariants of the images. The major drawback is due to a low in quality which in turn make the detection, recognition and retrieving processes be hard. Additionally, the use of low resolution of the camera and the environmental factors make a low quality of surveillance images too.
The main contribution is to propose a novel framework to retrieve semantic images based on shape symmetry, ontology-base and Hidden Markov Model. The region of interest is localized using an adaptive Gaussian model to model the background subtraction. In addition, the symmetry features for an object is extracted and then quantized using k-means procedure for learning or retrieving processes by Hidden Markov Model (HMM). Query Engine, Matching Module and Ontology Manger are to retrieve the semantic image using SPARQL language on input text or image query. The left-right Hidden Markov Model topology using Viterbi algorithm for retrieving and Baum-welch for learning is investigated. The outcome of our proposed framework is empirically tested against the mammals Benchmark. The paper is prepared as follows; For Section 2, the suggested framework is explored in three subsections. Section 3 carries out our experimental results. Section 4 is to conclude the proposed framework.

2. PROPOSED FRAMEWORK

Our proposed framework contains three key stages; preprocessing, shape features and ontology-base. The subsequent subsections clarify these stages as in Figure 1.

2.1 Preprocessing: Background Subtraction

The technique of background subtraction is an agreeably used to segment the unfamiliar patterns in a sequence scene. Each new frame is compared against to the designed model of background. It is worth declaring that, Gaussian Mixture Model (GMM) is a case of larger brand for density models, which have numerous functions by way of united components [24]. Properly tongue, in current frame, let X_t is a pixel, as well as K represents a distribution number. Then, every pixel can be classified distinctly using Gaussian mixture K (Eq. 1).

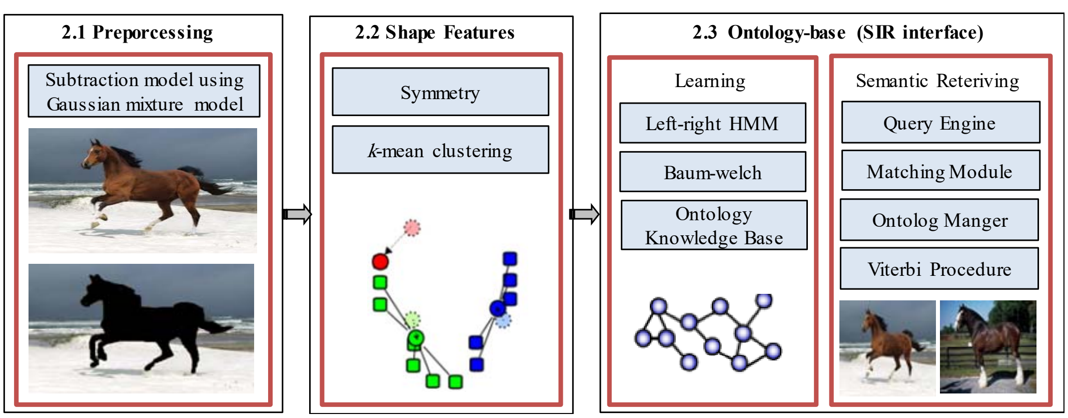

Figure 1: Framework of Semantic Image Retrieval.

$$p(X_t) = \sum_{i=1}^{K} \omega_{i,t} \cdot \eta(X_t; \mu_{i,t}; \Sigma_{i,t}) \quad (1)$$

where η is to the probability density function of Gaussian. $\mu_{i,t}$, $\Sigma_{i,t}$ and $\omega_{i,t}$ are to mean, covariance and an estimate of the prior probability (i.e.

weighting function) of the i^{th} component, respectively. In addition, a constructive algorithm decides automatically the number of components using the criteria of maximizing a likelihood function [24]. Then the background is optimized relied on the minimization of error function E as in Eq. 2.

$$E = -\sum_{n=1}^{N} ln\Big(\sum_{i=1}^{K} \eta(X;\mu_i;\Sigma_i)\cdot\omega_i\Big) \quad (2)$$

Such that N is the data points number X_n. Using a threshold γ = 0.5, the background distribution with smallest variance always run on top. As a result, all pixels X with no components are candidate to be foreground representation. Furthermore, EM procedure is a superior circumstance technique of Maximum Likelihood (ML) [25], such that mixture model parameters fit the best for the given dataset in ML sense. In Figure 2, the horse pattern in left image is segmented with respect to the right image source using background subtraction technique. For additional details, the reader can refer to [26].

Figure 2: The result of horse segmentation using background subtraction technique.

2.2 Shape Features

Using a totally different basis to determine shapes, the discrete symmetry operator is automatically very attractive and has associations with human observation. It locates shape features using their symmetrical properties somewhat the border of shape. The operator principally builds points accumulator, which measure the symmetry among points of image. The pairs points of an image, which are determined by a phase weighting function, distance weighting function and edge magnitude are attributed symmetry values. The phase weighting function is demonstrated at the time edge vectors for points pair that refer to each other. In addition, the function of distance weighting controls the scope of this function, in which the weather points with more distance underwrite in an equivalent manner to those that are near together. Thereby, the accumulation of symmetry occurs at center for each pair point. Formally speaking, distance weighting function D is;

$$D(i,j,\sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{|\mathbf{P}_i - \mathbf{P}_j|}{2\sigma}} \quad (3)$$

Such that i and j represent two image points index p_i and p_j respectively. Here, a deviation σ is to function scope using the scaling distance among all points at exponential function. When the deviation assigned with small value, it was referring to detect local symmetry and local operation. When the value of σ is large, the points subsidize to accumulation process supplementary and they are close together. Mathematically, the affection of σ value on the weighting function of scalar distance is expressed as;

$$Di(j,\sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{j}{\sqrt{2\sigma}}} \quad (4)$$

Such that, the phase weighting function P is

$$P(i,j) = (1-\cos(\theta_i+\theta_j-2\alpha_{ij}))\times(1-\cos(\theta_i-\theta_j)) \quad (5)$$

where θ refers to the direction of edge at target two points. αij is to measure direction of a line that join the two points.

$$\alpha_{ij} = \tan^{-1}\left(\frac{y(\mathbf{P}_j)-y(\mathbf{P}_i)}{x(\mathbf{P}_j)-x(\mathbf{P}_i)}\right) \quad (6)$$

Here, $x(P_i)$ and $y(P_i)$ represent coordinates (x, y) of point Pi. When the the edge of the two points have the same direction ($\theta_j = \theta_i$), the function is the minimum. But the function in maximum status when direction of the edge is gone from each other, ($\theta_j = \theta_i + \pi$), lengthwise the line that join the two points ($\theta_j = \alpha_{ij}$). Then the relation of symmetry in-between two points is expressed as follows;

$$C(i,j,\sigma) = D(i,j,\sigma)\times P(i,j)\times E(i)\times E(j) \quad (7)$$

where E refers to edge magnitude as follows;

$$E(i) = \log(1+M(i)) \quad (8)$$

Such that, M is to the edge magnitude which is determined by using an application of an operator of edge detection. At the line midpoint, the symmetry gathered and join each two points. Therefore, S_{Pm} that assigned to total symmetry at point Pm is equal to the sum of measured

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symmetry for every points pairs (i.e. with their midpoint at P_m,). So, points $\Gamma(P_m)$ is computed as;

$$\Gamma(\mathbf{P}_m) = \left[(i,j) \middle| \frac{\mathbf{P}_i + \mathbf{P}_j}{2} = \mathbf{P}_m \wedge i \neq j \right] \tag{9}$$

Then the accumulated symmetry which used as a feature to retrieve semantic image after quantization using k-means procedure is computed as;

$$S_{\mathbf{P}_m}(\sigma) = \sum_{i,j \in \Gamma(\mathbf{P}_m)} C(i,j,\sigma) \tag{10}$$

The main motivation behind use k-mean is constructed by Euclidean distance between the all cluster points and cluster center point. Here, at first each point is allocated with one initialized cluster. Then, the center point of each is recalculated based on the capable cluster mean points. Therefore, the processes are again repeated till convergence. Figure 3 summarizes the processes of k-means algorithm as follow;
By using some heuristic, the clusters are initialized with random values. The k-means algorithm relies on two major processes: assignment process and update process. For the assignment process, every point is classified into a specific cluster, which has a closest mean. Therefore, the obtained mean point is calculated for every cluster based on their instance in update step. During two steps, EM algorithm computes the maximum likely estimation for the unknown mixture parameters iteratively [27]. Thus, the subsequent steps are well prepared to sight k-means in a motivating characteristic.

- Step 1: Initializing and assigning the set of clusters K randomly using data set. For instance, red, blue and green are to three clusters as in Figure 3.
- Step 2: Every point is classified to its cluster of the closest mean.
- Step 3: The mean of each cluster will take place with the mean of all points with respect to learned vector.
- Step 4: Step 2 & step 3 are iterated till no changes between two successive repetitions (i.e. convergence verification).

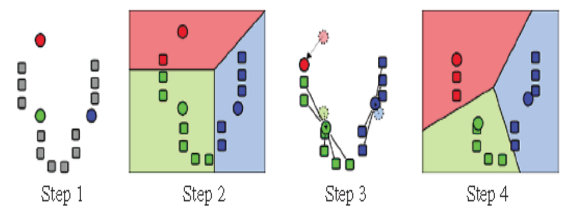

Figure 3: Demonstration of k-means clustering algorithm [27].

2.3 Ontology-base

There is no one can deny that the success of retrieving semantic images depends on a suitable selection of classifier technique which carries out the forceful view-invariant task. The aim of this section is to address and carry out the retrieving process using the classifier HMM that capable for real-time applications. The next two subsections momentarily assessment the processes of learning and semantic retrieving.

2.3.1 Hidden Markov Model

In learning process, the shape feature of pattern symmetry is normalized and employed to suggested classifier to construct ontology knowledge base of mammal's dataset. The record extensively used classification algorithm for image retrieving is Hidden Markov Model (HMM), which capable for real-time applications [28, 29]. Hidden Markov Model is a mathematical typical with specification of stochastic process that produces emissions sequence with respected to warehoused information previously. The main motivation behind using HMM is to rich mathematical framework, decoding method, powerful learning, flexible topology and good sequences handling capabilities. The drawback is to the unfortunate discrimination among models and idealistic expectations, which should be made for concepting the theory of HMM. There are succeeding reasons to call the states of HMM be hidden. First, the next process is based on the emitting pattern decision. Second, HMM emitter emits the observed instance only (i.e., pattern). Finally, since the current state is based on previous state, the emitted states are unknown. Furthermore, HMM is more flexible and very well-known its stochastic nature. Three issues switch the use of HMM. They are topology, emitted features and emissions probability. In addition, there are three types of HMM problems, which based on three parameters to be solved. The parameters are initialization state vector, transition state matrix and emission (i.e., observation) matrix. For real-world application, these problems be:

- Evaluation problem: compute the $P(O|\ \lambda)$. In which O is to observation sequence (emitted features) and λ refers to the model parameters (i.e., transition state matrix and observation matrix).
- Decoding problem: estimate the best path during λ (i.e. best clarifies an observation), which produces the observation sequence $O = (o_1, o_2, \ldots, o_T)$ with maximum likelihood.
- Estimation problem: perform the learning process by re-estimation (i.e., adjusting) the model parameters λ to verify the observation $O = (o_1, o_2, \ldots, o_T)$ with maximum likelihood.

In our approach, Baum-Welch algorithm is to learn the initialized parameters of HMM (π, A, B) to create an ontology knowledge base. An image is retrieved by matching the tested image compared to ontology database (i.e., reference HMM models) to classify it into a belonged class. So, the semantic image is classified (i.e., retrieved) using Viterbi procedure, which matching it to maximal likelihood of all reference models. A maximal score among all references HMM models is defined as a retrieved image (Figure 4).

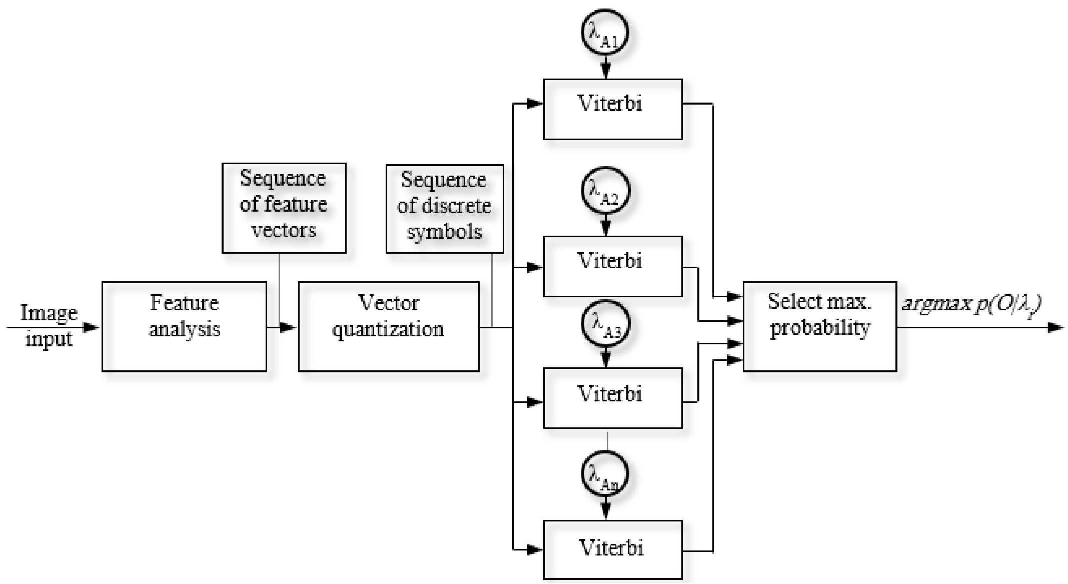

Figure 4: Retrieving image block diagram using HMM Viterbi retriever.

The learning Baum-Welch procedure is identical efficient. After 5-10 iterations, an optimal model is achieved often. To signify a new test for given sequence correctly, the learned model must be sufficiently flexible. Here the new test never arisen during training process. Until no change in emission and transition matrices (i.e., convergence verification), the learned stage is repeated. The convergence is reached when the change is less than tolerance ϵ with 0.001 or reaching to the maximum number for iterations (i.e., experimentally 500 iterations) as in Eq. 11.

$$\sum_{i=1}^{N}\sum_{j=1}^{N}|\hat{a}_{ij}-a_{ij}|+\sum_{j=1}^{N}\sum_{m=1}^{M}|\hat{b}_{jm}-b_{jm}|<\varepsilon \quad (11)$$

Thereby, the used tolerance is to control in the steps number that required for Baum-welch procedure to carry out their objective positively. In addition, the learning process is terminated for three following reasons with tolerance less than 0.001. Firstly, given an observation sequence O, the likelihood is obtained based on the estimation value of transition matrix and emission matrix. Secondly, performing adjustment in a normalized transition matrix. Finally, performing adjustment in a normalized emission matrix. It is being noted that an increasing in tolerance value will decreases the steps number, which needed for Baum-welch procedure for completing before terminating. We remark that the termination be arisen with warning when the procedure of Baum-welch runs 500 iterations with no scope the definite tolerance. To alleviate that problematic, the maximum number of iterations should be increasing to desire the tolerance before finishing.

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2.3.2 Semantic Retrieving

The semantic image is retrieved either by text-based or image-based with respect to the proposed framework of Semantic Image Retrieval (SIR). Figure 4 summarize the main processes, which carry out the result of retrieving. The road map of these processes is detailed in the following subsequent.

A. Query Engine

In our proposed framework the semantic image is retrieved either by text-based or image-based query, in which the Query Engine (QE) is responsible for these two separate methods. For the text-based method, the search process is started when the user enters the text input in the dialogues box of our Sematic_image_retrieve system. Here, the search engine is to Bing, Alta Vista Google and Yahoo. The principal motivation is to afford likelihood to workers to certainly learn and test with Sematic_image_retrieve interface. For instance, text query like "Ox", "Deer", "Giraffe" and "Tiger" etc. is entered via a user. Then the QE for Text-based is build the input text query directly. For the second input method of image-based, the Sematic_image_retrieve system will hold object with some elective options description.

Shortly, QE builds a Query for input image using SPARQL language based on ontology knowledge base. Here the high-level ontology feature of symmetry is extracted and employed to SPARQL, which creates the object parameters to start flexible search. Legally speaking, the query of input image over symmetry feature take the form;

Query. Find the image of mammals with $(F_{symmetry})$

SPARQL FROM: SELECT?M?N
WHERE {?N rdfs:subClassOf:mammals.?
M: $F_{symmetry}$

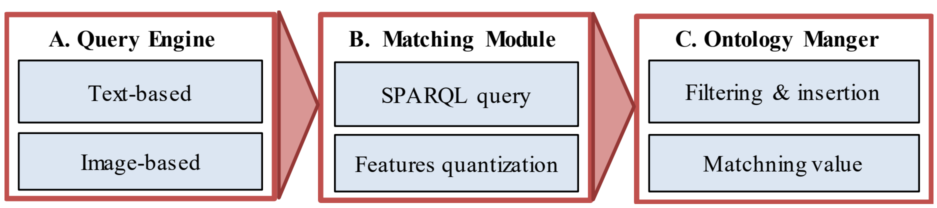

Figure 5: Text or image query-based road map of retrieving semantic images.

B. Matching Module

In Fig. 5, the second process is to Matching Module (MM), which retrieves semantic image according to SPARQL query of QE in situation of successful access. But in case of failure for retrieving relevant image, the MM performs three main processes. At the begin, MM surfs for the relevant images in query search engine like Google. Then the obtaining images are approved by the processing module to organize their content verification. Also, the obtained images are tested against relevant of user query (Fig. 5). If this has not happened, they are proved rely on the features of symmetry that converted to high level ontology features. At end, SPAEQL is constituted relies on high level ontology with respect to ontology base. As an outcome, we well-thought-out for retrieving relevant images when they matched a user search query; else they are cast-off.

C. Ontology Manger

According the Fig. 5, the final process is to Ontology Manger (OM), which conveys three main tasks of filtering, insertion and ranking. Using the instance properties of ontology knowledge base, the obtained relevant images be filtered. The second task constructs the semantic description of retrieved images and inserts the images resultant in ontology knowledge base. Then third task is to rank, which depended on matching value. This value is calculated using a summation of user query reference and matched ontology symmetry feature. The result is obtained by sorting the resulting images in descendant order with respect to matching value. Then the obtained images with higher ranking are carefully chosen as a user request.

3. EXPERIMENTAL RESULTS

In our work, we used the dataset of mammals, which is built by Z. Malki [30]. He gave us the

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dataset to compare the proposed work with him. The comparison is thus fair where the same dataset conditions are available. This ontology knowledge base includes 25 various mammals. Each mammal has 50 different frames. In other word, the dataset contains 1250 frames for various mammals as Horse, Elephant, Panda, Ox, Deer, etc. (Fig. 6). We decided to divide the ontology knowledge base into two thirds for training HMM classifier using Baum-welch algorithm and one third for testing using Viterbi algorithm. It being noted that the sample of training process is entirely divergent testing process. Furthermore, we build the proposed system by Matlab language to retrieve the relevant semantic image either by text or image as in Fig. 7 and Fig. 8. For instance, the user runs proposed Matlab program and then browsing the Fox image as input in Sematic_image_retrieve interface (Fig. 7). As a result, the QE builds the image's query with respect to ontology knowledge base. The MM retrieve the relevant images in case of positive response. Therefore, the processes of ontology and filtering well done. Then OM begins to rank the resulting images and retrieves the highest ten semantic images in descendant order. If the response is negative, the searching process will come to pass in Web images. After that, the filtering process in addition to ontology contents updating are done to retrieve the result. Another case, we can retrieve the relevant semantic images by the text as input in text query of Sematic_image_retrieve interface (Fig. 8). When the user writes the text "Tiger" for example, QE will build the corresponding "Tiger" query and then the relevant images is retrieved by MM. In addition, they filtered and ranked with respect to ontology knowledge base and OM.

Figure 6: Some Sample Frames from mammal's dataset.

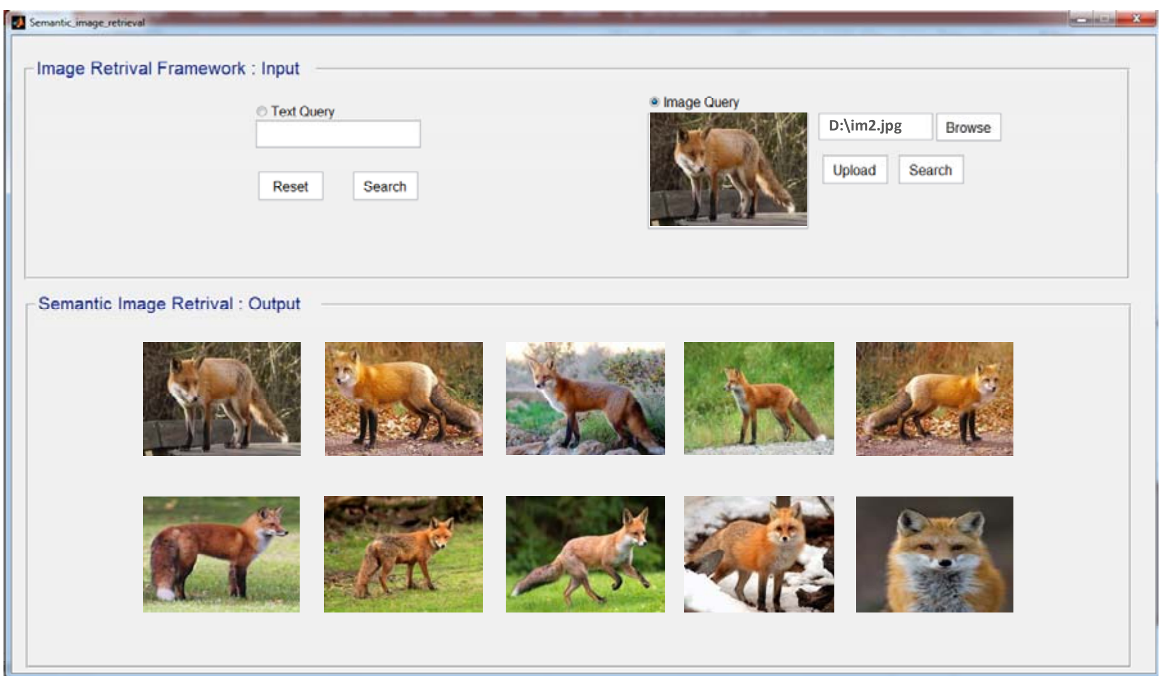

Figure 7: Image query to retrieve relevant Fox images by ontology knowledge base.

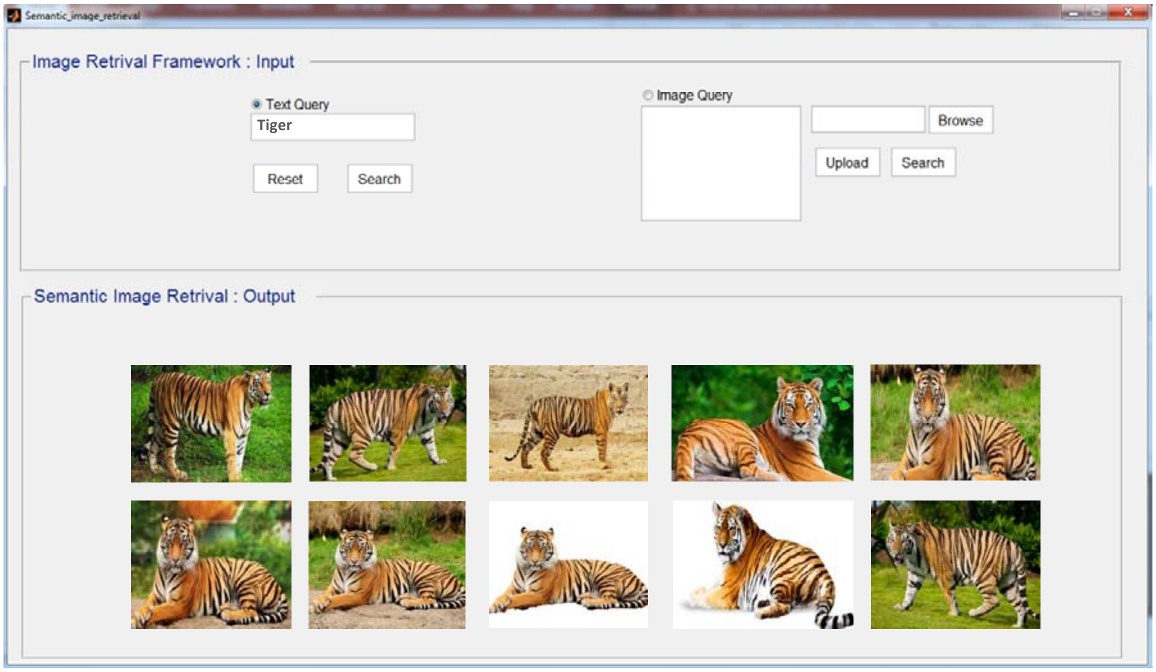

Figure 8: Text query to retrieve relevant Tiger images.

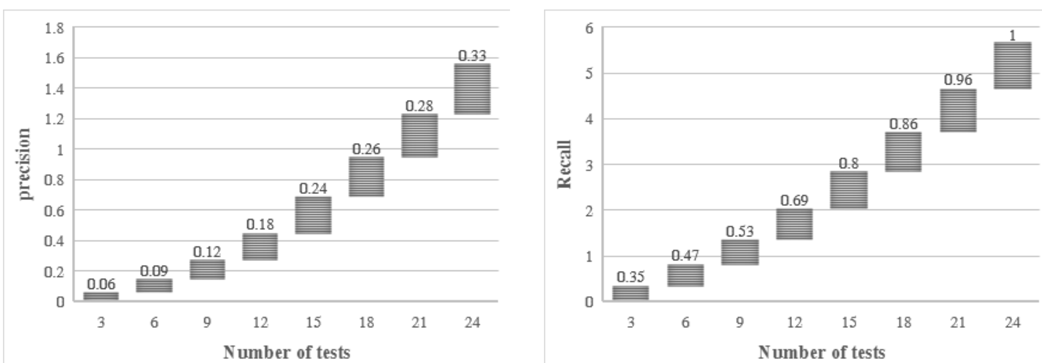

Figure 9: Precision and Recall metrices of proposed framework.

Table 1. Comparison with our previous work

Method	***Classifier***	***Feature type***	***Retrieving rate***
Our method	HMM	Symmetry features	97.76 %
Zohair Malki [30]	CRF	CLF and color features	93.50 %
Zohair Malki [31]	Multi-SVM	Shape and geometric	96.33 %

To estimate the evaluation of our proposed framework to retrieve semantic images, we usage Precision and Recall system based on metrics in International Relations World. Precision (i.e., true positive) measures the system performance for retrieving relevant images (Eq. 12). Here, all truthful information does not provide the system performance that because it is not brilliant all retrieved semantic images. On the other hand, recall (i.e., false negative) retrieves the relevant semantic images using the total number of associated images that have been regained (Eq. 13). It is not well-thought-out the distinct images. Thus, Precision and Recall are computed using Eq. 12 and Eq. 13, in which we tested 25 gathering classes of 415 various images.

It is being noted that the obtained results yield efficient results. In Fig. 9, x-axis is to number of

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tests and y-axis represents either Precision or Recall. Thereby, the value of Precision/Recall from the waterfall chart in Fig. 9 is in the range of concluded 0.33/0.96. The higher value of Precision/Recall is in the range of (0.06 over 0.33)/(0.35 over 1.0), respectively. The proposed framework can retrieve semantic images with 97.76 % precision.

$$\text{precision} = \frac{\text{true positive}}{\text{true positive} + \text{false positve}} \quad (12)$$

$$\text{Recall} = \frac{\text{true positive}}{\text{true positive} + \text{false negative}} \quad (13)$$

We make a comparison between our proposed framework with have used similar experimental setups and dataset to achieve the fairness principle. The obtained results have been compared with [30, 31] to measure the framework effectiveness (Table 1). In [31], the author used Chord length shape Features and color feature in combination with Conditional Random Filed (CRF) for retrieving. The drawback is to very much complex since the color feature has high dimensionality. But in [31], the author used two various type of features as shape feature and geometric feature for the classifier of Multi support vector machine. The shape feature is to Zernike moments, but the geometric features are circularity and rectangularity. Here, the drawback is to the component, which dependent on the image position and effective for natural objects.

4. CONCLUSION

A new framework for retrieving semantic image based of on shape symmetry, ontology-base in conjunction with Hidden Markov Model is proposed. An adaptive Gaussian model is to localize the region of interest using background subtraction mechanism. Furthermore, the symmetry feature is quantized using k-mean algorithm to build ontology knowledge base by Baum-welch procedure. Three main processes of Query Engine, Matching Module and Ontology Manger are employed to retrieve relevant images from building ontology dataset or from Web images. The Viterbi algorithm over left-right topology is used to perform the retrieving images. Our experiment on Benchmark mammals of 25 different mammals had been carried out to conclude the retrieving framework. Additionally, a comparison between our proposed framework with have used similar experimental setups and dataset had done. The results yield efficient retrieving with 97.76 % precision than previously reported.

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