An Improved Shock Graph for an Improved Object Recognition

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Abstract—**Converting a binary image to a skeleton or medial axis form is often used to preserve the shape details efficiently. The medial axis is converted to a shock graph which has structure like a tree. Shock graphs are derived from the skeleton and have emerged as powerful 2-D shape representation. A skeleton has number of branches. A branch is a connected set of points between an end point and a joint or another end point. Every point also called as shock point on a skeleton is labeled according to the variation of the radius function. The labeled points in a given branch are to be grouped according to their labels and connectivity, so that each group of same-label connected points will be stored in a graph node. Edges are added between the nodes so as to produce a directed acyclic graph. Binary images with different shapes have different skeleton and different tree structure. Number of features of the graph can be extracted which facilitate comparison of shapes using these features. Comparison of shapes using their Shock graphs provides a very effective way of object recognition. An object recognition frame work by comparing the subgraphs has been presented here. A novel concept has been implemented in the presented work for inserting a node in Shock branch whenever there is a sharp direction change. Addition of node improves the object recognition results.**

Keywords— **Directed acyclic graph, MAT, Radius function,Skeleton,Shock graph, nodes, labels, shock graph grammar.**

1. INTRODUCTION

In the field of pattern recognition robust shape matching and object recognition are two very important issues. Any recognition process requires comparing a query object with the objects present in the data base one by one until the matching object is obtained. The proposed frame work of object recognition using Shock Graphs starts with converting every object in the data base to a binary image and its skeleton [1,2,3,4,5,6,7] is obtained by performing morphological operations on them. Skeleton is a representation of a 2D object which preserves the details of the silhouette of an object. Skeletons are converted to shock graph. Shock graph is a shape abstraction that groups skeleton points according to the local variation of a radius function. These groups are called as Shock groups and are labeled as 1, 2, 3 or 4.Such a grouping will provide a decomposition of a skeleton into parts, whose interrelation will confirm to a well-defined grammar [8,9,10].The shock graph is a directed acyclic graph and is obtained from these Shock groups which are the constituent primitives of the Shock Graph. The arrangement of primitives for graph generation is according to the Shock Graph grammar. Shock Graph is generated for each image in the data base and is compared with the shock graph of the query image very efficiently and leads to an efficient technique for pattern matching.

Kaleem Siddiqui, Ali Shokoufandeh, Sven J. Dickinson, W. Zucker in their paper 'Shock Graph & Shape Matching [10] presented the shock graph theory and grammar. They also gave a graph matching algorithm by characterizing a shock graph as an Eigen value sum. They represented a shock tree as a (0, 1) adjacency matrix. Any shock sub tree is a sub matrix of the adjacency matrix. The two shock sub trees whose Eigen value sums are closest represent an approximation to finding the largest isomorphic sub tree. They further use the largest matching sub trees to calculate the topological similarity between two shock trees.

Rahmati and Zaboli [13] have proposed a simpler approach for shock graph. They have given priority to branch points of the skeleton. All branch points where more than two shock branches meet are treated as the starting nodes of the shock tree. They even proposed a new set of grammar rules where type 2 and type 4 shocks have been excluded.

Thomas B. Sebastian, Philip N. Klein, and Benjamin B. Kimia [12] have developed a coarse level matching strategy in which they find a coarse-scale approximate similarity measure which relies on the shock graph topology and a very coarse sampling of link attributes. They developed an exemplar-based indexing scheme which discards a large number of non-matching shapes solely based on distance to exemplars. P. Klein et al [11,16] proposed edit operations like delete, prune, contract etc on a graph structure to make it isomorphic with another graph. They attached cost to every edit operation and calculated the overall cost. Pedro F. Felzenszwalb et al [14] developed a matching scheme based on hierarchical description of shape boundaries. Two curves are matched by building a shape-tree for curve A and looking for a mapping from points in A to points in curve B such that the shape of curve A is deformed as little as possible. Total amount of deformation is a sum of deformations applied to each node in the shape-tree

David Lowe [15] proposes that features can be efficiently detected through a staged filtering approach that identifies stable points in space. He presented a method for image feature generation called as scale invariant feature transform (SIFT). This approach transforms image into a large collection of local feature vectors which are invariant to translation, scaling & rotation. Andrea Torsello et al [17] in their paper present a geometric measure that can be used to gauge the similarity of 2D shapes by comparing their skeletons. The measure is defined to be the rate of change of boundary length with distance along the skeleton. This measure varies continuously when the shape undergoes deformations.

Sibel Tari et al [20] present a similarity-based approach for classifying 2D shapes based on their Aslan skeletons. The coarse structure of this skeleton representation allows them to represent each shape category in the form of a reduced set of prototypical trees providing alterernative solution to the problem of selecting the best representative examples. The ensemble of these category prototypes is then used to form a similarity-based representation space in which the similarities between a given shape and the prototypes are computed using a tree edit distance algorithm.Support vector machine (SVM) classifiers are used to predict the category membership of the shape based on computed similarities.

Nooritawati et al[21] evaluate the effectiveness of decision tree as classifier for recognition of four main human postures (standing, sitting, bending and lying). They used decision trees because good success has been achieved for prediction, recognition and classification task in data mining problems. Firstly, the eigen features of these postures are optimized via Principal Component Analysis rules of thumb specifically the KG-rule, and Cumulative Variance Test. These eigen features are statistically analyzed prior to classification. In doing so, the most relevant eigen features termed as eigen postures are ascertained. Decision tree is then classified for posture recognition. In this paper, posture classification using Simplified Shock Graph as feature vectors based on two machine learning techniques namely Artificial Neural Network along with Support Vector Machine are investigated. Initial results showed that both classifiers are able to classify the four main postures with high recognition rate. Superior Performance of Support Vector Machine (SVM) as classifier is confirmed based on the Kappa Score calculated. Also simplified SHOCK Graph has been found as very suitable for Posture recognition.

II. THE MEDIAL AXIS TRANSFORM AND SHOCK GRAPH CONSTRUCTION

The skeleton of a shape is like a stick diagram. One of the first formal definitions of the skeleton is that of Blum, who defined the medial axis of a shape as the locus of center points of all the maximal circles contained within the shape boundary. Blum called the shape's skeleton as the Medial Axis Transform (MAT). [1,2,3]

In order to reconstruct the original shape from the skeleton points, we need the information provided by the radius function, R(s), so as to map every skeleton point s, to the radius of the maximal inscribed circle centered at s. The original shape can be reconstructed by the union of all disks of radius R(s) centered at s

Shock graph is a directed acyclic graph representing the decomposition of a skeleton into primitive parts. A Graph contains finite set V of objects called vertices and finite set of edges E and a function γ that assigns to each edge a subset {v,w} where v and w are vertices. Hence Graph G= (V,E, γ). Shock Graph in addition is directional and has no cycles or loops. Fig. 1 (c) shows the Shock Graph of the binary image which is shown in fig.1 (a) and which has been derived from the skeleton in fig. 1(b). In the Shock Graph the first number is node number and the second number is the Shock type.

Every node has a unique number and it is followed by the number which denotes the Shock Type of that node.

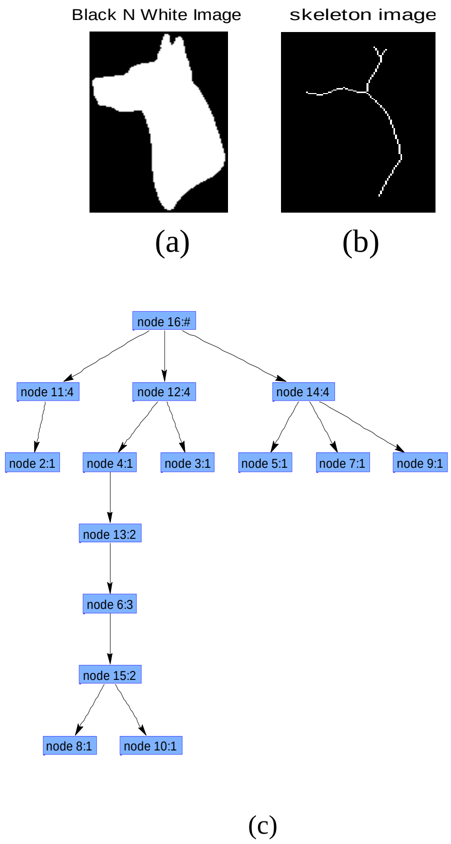


Fig. 1 a) Binary image b) Skeleton c) Shock Graph.

After obtaining the skeleton of an image the next step is to label skeleton points according to the local variation of the radius function at each point. The label given to a skeleton point which is alternatively also called as a shock point can be 1, 2, 3, 4 according to the nature of shape. Type 1 label is given to that particular segment of the skeleton which has the radius function continuously increasing or decreasing however each of them will have different sign. Type 2 label is given when the shape reaches local minima and on either side the radius function is incremental. Type 3 label is given to that skeleton segment where radius function remains constant. Type 4 label is given to a point where radius function has reached local maxima.

Every skeleton branch and joint where number of skeleton branches meet contributes one node in the graph. Sometimes one skeleton branch can give rise to more nodes in the graph. This happens when the segment has deep curvature. The curved segment is then modeled as number of small straight line segments.

The construction of the graph can be mathematically explained as follows.

We will consider the set of skeleton points S to be a continuous and connected set of the medial axis points of a closed curve. Two points in a set are said to be connected if they can be joined by a continuous path of points also in the set. We define $N(s, \in)$ to be a set of shocks in $S \setminus \{s\}$ within distance $\in$ from s, and N(s) as the set of the largest connected sets of points in $S \setminus \{s\}$.

Labeling of each point in a skeleton branch is defined according to its time of formation. The radius function of a skeleton point has connotation of time. Skeleton points with higher radius function are later to form as skeleton is formed by thinning that is peeling of the object surface iteratively.
A skeleton branch is formed by all the connected medial axis points between two end points. Next, the labeled points in a given branch are to be grouped according to their labels and connectivity, so that each group of same-label connected points will be stored in a graph node. One skeleton branch will give rise to one or more nodes. Finally, we will specify how to add edges between the nodes so as to produce a directed acyclic graph with edges directed according to the time of formation of the shock points in each node.

Definition 1 (labeling) R(s) is the radius function $R : S \rightarrow R^+$, and l(s) be a shock labeling function $l : S \rightarrow \{1,2,3,4\}$, where S is the set of continuous medial axis points (i.e., shocks) of shape X. Alternatively, this definition can be regarded as specifying how to label the skeleton points as per whether R(s) is: monotonically increasing/decreasing (type 1), a strict local minimum (type 2), constant (type 3), or a strict local maximum (type 4).

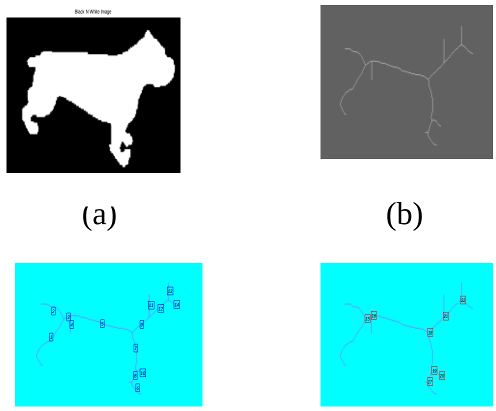
Definition 2 (grouping) Let $B_1 \ldots\ldots B_n$ be the largest groups of connected shocks in S s.t. $\forall s; s' \in B_i$; $l(s) = l(s')$ and $\forall s \in B_i$, either $|N(s)| \le 2$ or if $|N(s)| > 2$, then s must be a terminal point of B_i (i.e., $B_i \setminus \{s\}$ is connected), for $1 \le i \le n$. Let the group's label, $l(B_i)$, be the label of the shocks in Bi, and similarly, let the time of formation of the group, $t(B_i)$, be the interval [min (R(s)); max(R(s))] defined by the time of formation R(s) of all $s \in B_i$.
In other words, the shock groups are skeleton segments in which all the shocks have the same label and belong to the same branch. Moreover, each bifurcation point will belong to more than one group if the point's label is the same than those of the groups of points meeting at the bifurcation

Definition 3 (Shock Graph) The shock graph of a 2-D shape is a labeled graph $G = (V,E,\gamma)$ such that: vertices $V = \{0,\ldots\ldots\ldots n\}$, corresponding to the groups $B_1\ldots\ldots B_n$, and 0 denoting a root node;
edges $(i, j) \in E \subseteq V \times V$ directed from vertex i to vertex j if and only if $i \neq j$, and $i \neq 0 \wedge t(B_i) \ge t(B_j)^5 \wedge B_i \cup B_j$ is a connected set of shocks, or $i = 0 \wedge \forall k \neq 0\ (k, j) \notin E$;
labels $\gamma : V \rightarrow \{ \#,1,2,3,4\}$ s.t. $\gamma(i) = \#$ if $i = 0$ and $\gamma = l(B_i)$ otherwise.

From the above definition, it can be seen that the shock branches act as the shape's primitive parts which, in turn, are represented as nodes in the graph. The edges are directed according to the relative time of formation of each part such that the last shocks to form are at the top of the hierarchy of dependencies. Thus, the central parts of the shape will be at the top, and the smaller shape extremities will be further down in the hierarchy. The skeletons are converted to Shock Graph as per grammar rules which lay constrain on the possible arrangement of graph nodes and edges.

III. SHOCK GRAPH FROM END POINTS AND JOINTS OF THE SKELETON

Following images were taken as test images for which skeletons, end points and joint points were evaluated and subsequently their directed acyclic graph representations were generated using shock graph theory [9].



(a) (b)

(c) (d)

Fig. 2 (a) Binary Image (b) Skeleton
(c) Shock branches (d) Joint Points

Table 1 Coordinates of Joint points for Dog for Dog's skeleton

X Coordinate	Y Coordinate
142	153
134	174
302	365
177	366
274	380
287	406
136	419
95	478

End Points and Joints also called as branch Points are vital in plotting the shock graph of the object. Every branch point and skeleton segment contributes one node in the tree structure.
These points were found by observing the neighbors of the pixel under consideration. If more than two neighbors are '1' then the pixel is a branch point. An end point has only one neighbor as '1'.

Coordinates of Skeleton end points for each skeleton branch and 8 joint points for the Dog image are evaluated (refer Table 1 and Table 2 and are given unique numbers and are shown in the Fig. 2 .

Table 2 .End Points of Curve Segments, length, type of Shock and Segment Number for Dog Image.

x1	y1	x2	y2	Length	Shock type	Seg. No.
235	67	144	152	61	1	1
105	83	140	151	60	1	2
142	155	134	172	60	1	3
136	174	178	174	51	1	4
133	176	176	364	85	3	5
304	365	332	394	17	3	6
179	367	255	380	85	1	7
299	367	276	378	25	1	8
176	368	138	418	86	1	9
274	382	286	404	23	1	10
81	419	134	419	63	1	11
136	421	96	476	65	3	12
51	478	93	478	60	1	13
95	480	116	517	61	1	14

IV. IMPROVED SHOCK GRAPH

As a skeleton captures the details of a binary shape any subsequent conversion of the skeleton in another form should retain these details therefore as a skeleton is converted to a Shock graph it becomes imperative to add node in a Shock branch whenever there is a steep direction change otherwise loss of shape details occur. An original concept has been used to decide whether it is necessary to insert a node in a shock branch and the location at which the node should be inserted. The concept is discussed in detail below.

A skeleton branch or a segment is

a) A curve or line connecting an endpoint of the skeleton to a joint.

b) A curve or line connecting a joint point to another joint point.

All the endpoints and joint points contribute one node to the tree or graph to which it is finally converted.

This segment is not always a straight line but is curved and can have number of changes in direction. Wherever there is a considerable change in direction a node must be inserted.

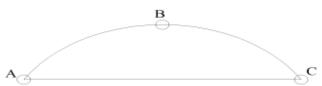
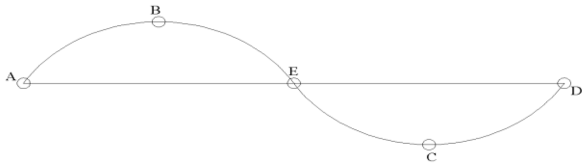


Fig. 3 Curved skeleton segment ABC



Consider the curved segment ABC in the above Fig. 3 we must have nodes at end point A, endpoint C and node at B. Also if ABECD curved segment is considered in Fig.4, node should be present at A, B, C and D, where A and D are the end points and B and C are the points where a significant change in direction has occurred.

Following algorithm was used to find:

a) Whether insertion of node in a curved segment is desirable by estimating the change in direction by setting a threshold.

b) the point at which node should be inserted

The steps are as follows:

1. Find number of pixels from point A to C if the two points are directly connected by a straight line.
2. Find the number of pixels actually present on curved segment ABC
3. Number of pixels on curved segment will be more than number of pixels on the straight line.
4. If the length ABC in terms of number of pixels on curved segment is 50% more than pixels on the straight line AC then, we need to insert an additional node between AC.
5. This setting of threshold as 50% can be changed and decided by trial and error so as to obtain good recognition results as well as complexity of the tree structure has to be kept in mind. Lowering the threshold can increase number of nodes and can make tree structure complex
6. Drop perpendiculars from pixels on the curved segment ABC to equal number of pixels on the line AC.
7. The length of each perpendicular dropped from curved segment ABC to the straight line AC is evaluated.
8. The perpendicular which has the longest length will decide the point of insertion of node as highest perpendicular length indicates point of maximum curvature.
9. The same logic can be applied for locating the nodes at B and C in Fig. 4 considering ABE as one curved segment and ECB as the other curved segment.

Following Fig. 5 shows few binary images, their skeletons and shock branches in the skeleton.

The first skeleton of each image has less shock branches where as there is greater number of shock branches in the 2nd skeleton because when ever there is substantial change in direction of a Shock branch additional shock branch has been added. This will also add new node in the Shock Graph.

Fig. 5(a), 5(b), 5(c) are three binary objects whose skeletons with their Shock branches having unique numbers are shown.
In Fig. 5(b) the entire neck of the dog image was treated as one shock branch where as in Fig. 5(c) the neck portion has three segments. In Fig. 5(e), the trunk of the Dog has only one with the graph of every object in the data base along with the shock type of each branch.

Matching is 100% if the number of levels is same and the shock type of nodes at each level matches. If the match is not perfect the extent of matching is expressed as a numerical value and is calculated using the formula given later
The steps involved in the algorithm are as follows:

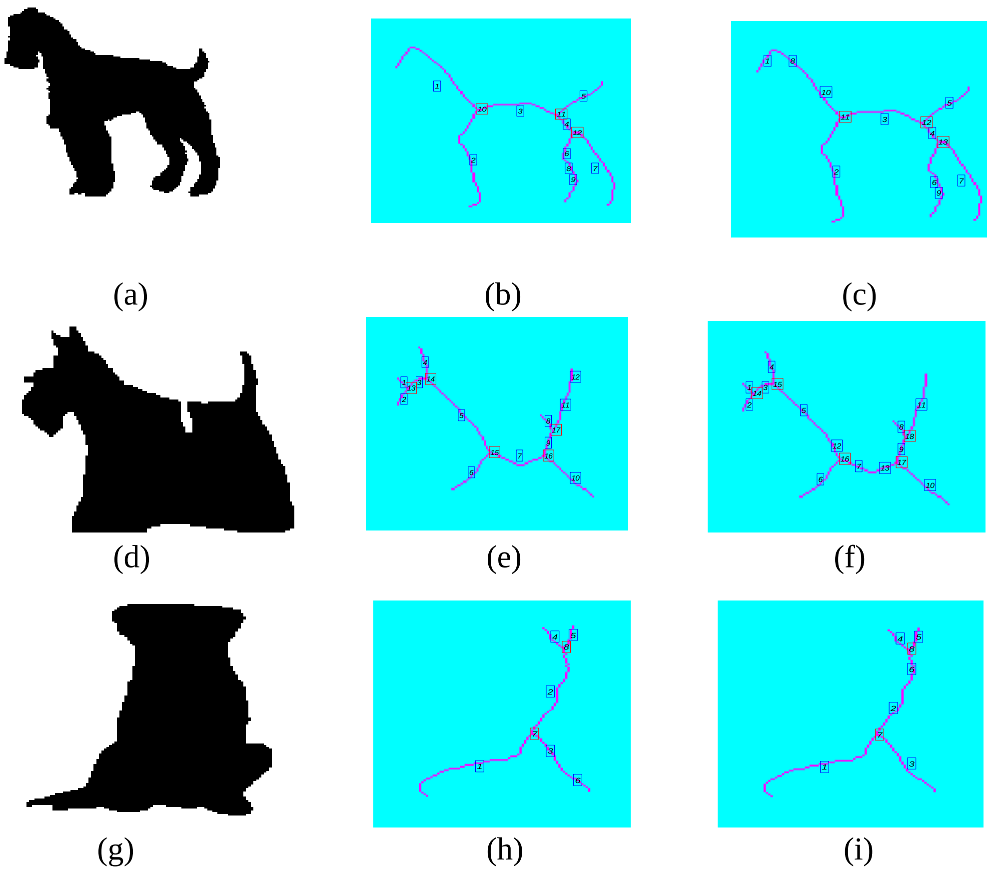


Fig. 5 (a)(d)(g) Binary images of Dogs from the Data Base
(b)(e)(h) Skeletons with Shock branches and end points allotted unique numbers written inside squares
(c)(f)(i) Additional shock branches created whenever there is a distinct change of slope in a branch and additional node inserted

In Fig. 5(h), the neck of the Dog has only one shock segment where as Fig. 5(i) has two segments due to sharp change in the slope. Graph for each object in the data base is obtained using the principles described above.
For object recognition following strategy has been implemented.
There will be two tree structures for the same image, corresponding to two skeletons. The first one will have fewer nodes where as the second one will have more nodes due to additional nodes

V. OBJECT RECOGNITION STRATEGY USING SUB GRAPH MATCHING METHOD

The trees to be matched are split into sub graphs and each sub graph of the query image is matched with each subgraph of the object image. The graph topology of query image is compared

1) Split the graph for an arbitrary query image and the graph for any arbitrary object from in the data base into sub graphs as shown in the Fig. below.

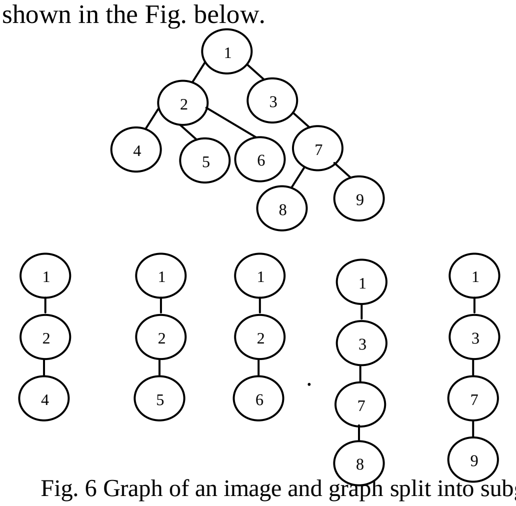


Fig. 6 Graph of an image and graph split into subgraphs

1) Compare every subgraph of the query image graph with that of the subgraphs of the object.
2) While comparing the subtrees, the type of shock of the nodes is also compared. If the type of shock does not match, it is considered as a mismatch.
3) For example : Following are two subtrees which are being matched

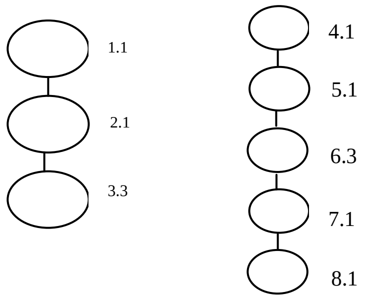


Fig. 7 Two subgraphs which are being matched

4) The 1st digit represents the node number & digit after the decimal point represents the shock type.
5) The nodes at different levels in a tree structure have different significance. Level 1 represents most significant part of the image and hence has highest weight. As we move down from the root node the significance reduces. The weight allotted to nodes at different levels is different and is calculated as shown below. Subtree 1 belongs to the query where as subtree 2 belong to the object. Since subtree 2 has nodes at 5 levels, the total weight of 5 levels put together is 1 with level 1 having highest weight and level 5 the least weight. The weights of 5 levels together are

$$x + \frac{x}{2} + \frac{x}{3} + \frac{x}{4} + \frac{x}{5} = 1$$

where x – weight of 1st level, x /2 – weight of 2nd level , x/3 – weight of 3rd level and so on.

$$\frac{60x + 30x + 20x + 15x + 12x}{60} = 1$$

$$\therefore x = \frac{60}{137}$$

$$\therefore 1^{st} \text{ level weight is } \frac{60}{137}$$

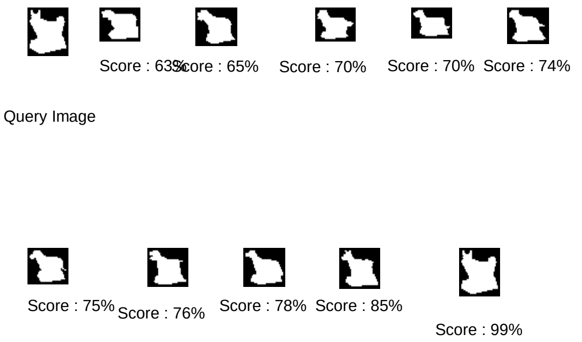
In the 2 subtrees given above, 3 nodes of subtree 1 match with 3 nodes of subtree 2 along with their shock types. The matching score is sum of the weights of level 1, level 2 and level 3¸ calculated as:

$$\text{Matching score} = x + \frac{x}{2} + \frac{x}{3}$$

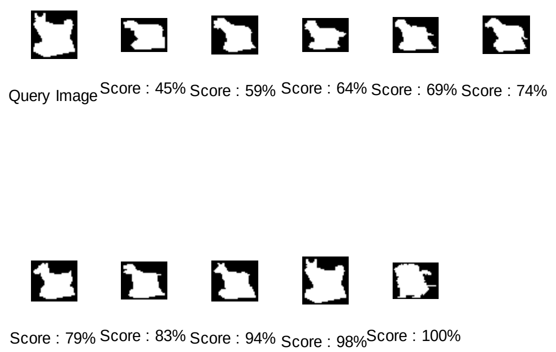
$$= \frac{60}{137} + \frac{30}{137} + \frac{20}{137} = \frac{110}{137}$$

The procedure for matching is repeated until every subtree of the query image is matched with every subtree of the image with which it is being compared. The total score of matching is the sum of all matching scores.

Two more features namely the skeleton segment length in terms of number of pixels on the segment and slope of the segment calculated from it's end points as (y2-y1) / (x2-x1) where x1,y1 and x2,y2 are the coordinates of end points, were extracted and evaluated for each segment These features for each segment of the skeleton which is represented as a node are compared while matching shock Graphs. When sub graph of the query and that of the object were found to be matching then we compare the length and slope and give additional weight to them by adding to the matching score.

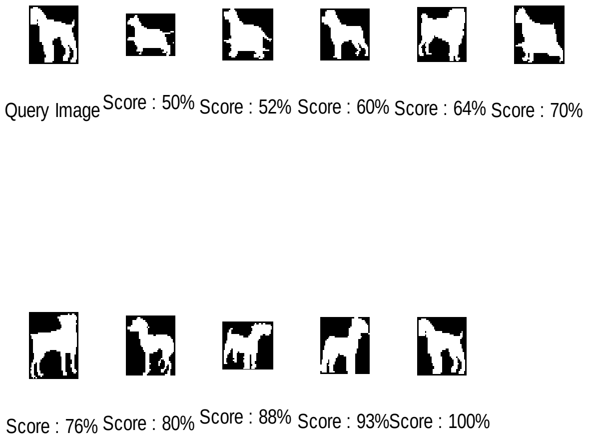


(8a)

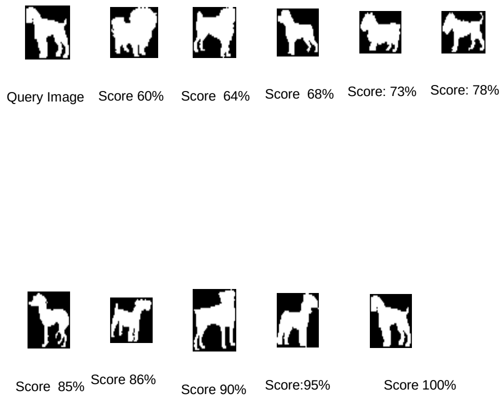


(8b)

Fig. 8 (a) Ten Closest matching objects to the Query along with matching score
8 (b) Ten Closest matching objects to the Query with improved Shock Graph



(9a)



(9b)

Fig. 9(a) Ten Closest matching objects to the Query along with matching score
9(b) Ten Closest matching objects to the Query with improved Shock Graph

The above matching technique was used to find ten closest matching objects to the query image by generating Shock graphs of the objects plotted in two different ways. The first matching results are with normal Shock Graph and the second matching results are for Shock Graph with proposed method. Matching results using Subgraph Comparison Method are shown in Fig. 8(a) and 9(a).

The results using Proposed Method with improved Shock Graph are shown in Fig. 8(b) and 9(b).

VI. CONCLUSION

A new concept for insertion of additional node in a Shock branch at the place of significant change in direction has been proposed. This changes the Shock graph topology. The object identification strategy called as Sub Graph matching method is used for Object recognition and ten closest matching objects to the query image are shown. The experiment is repeated by changing the query image. This experiment is performed for an object data base in which all objects are represented by their Shock Graphs which are generated from the end points and branch points of the object's skeleton. The same experiment is performed with the modified Shock Graph generated using proposed method. It was observed that the performance of recognition improved due to the new improved shock graph. Improvement in result is not significant when the Skeleton does not have many curved segments but improvement is significant when the skeleton has greater number of curved segments. The ten most matching objects selected were more relevant and nearer to the query object with the proposed strategy as can be seen with the sample results. The method was tested on large binary data bases The same was verified when more number of images were tested. A large database of closed binary shapes collected by the LEMS Vision Group at Brown University [18] has been used for testing the results of the designed algorithms

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