Shock Graph for Representation and Modeling of Posture

Nooritawati Md Tahir, Aini Hussain, Salina Abdul Samad, and Hafizah Husain

Skeleton transform of which the medial axis transform is the most popular has been proposed as a useful shape abstraction tool for the representation and modeling of human posture. This paper explains this proposition with a description of the areas in which skeletons could serve to enable the representation of shapes. We present algorithms for two-dimensional posture modeling using the developed simplified shock graph (SSG). The efficacy of SSG extracted feature vectors as shape descriptors are also evaluated using three different classifiers, namely, decision tree, multilayer perceptron, and support vector machine. The paper concludes with a discussion of the issues involved in using shock graphs to model and classify human postures.

Keywords: Skeletonization, medial axis, shock graph, human posture, decision tree.

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I. Introduction

Abstraction of shape information is an important requirement for any automated or computer assisted environment for shape representation and modeling. The level of abstraction varies, depending on the task for which the shape information is required. Skeleton and medial axes have been extensively used for characterizing objects satisfactorily using structures that are composed of line or arc patterns. Skeletonization is an image processing operation which reduces input shapes to axial stick-like representations. It has many applications ranging from preprocessing for optical character recognition or as a shape descriptor in complete object recognition systems. Skeletonization in a plane denotes a process that transforms a two-dimensional (2D) object into a 1D-line representation, comparable to a stick figure.

For example, a skeleton of a rectangle, drawn based on [1], is shown in Fig. 1. It is most important that the skeleton combine the information contained in the outline of the shape with information about the region circumscribed by the outline. Next, it must preserve the initial connectivity of the shape. The study of skeletonization is motivated by the need to convert a digital image into a linear form in a natural manner. The skeleton emphasizes certain properties of the image; for

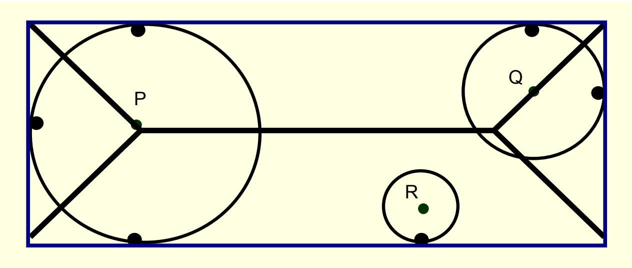


Fig. 1. Both points P and Q are skeletal, but point R does not belong to the skeleton (Thick black line segments mark the skeleton).

instance, curvatures of the contour which correspond to the topological properties of the skeleton. Concisely, medial axis representation introduces a new quality of shape descriptions, in which it encodes important visual cues such as (local) diameter and symmetries. Our shape descriptor is somewhat similar to shape contexts since both are feature-based. However, in this work, our shape descriptors are used directly in classifier development without having to find correspondences between point sets as described in [2], [3].

II. Medial Axis Transform

The medial axis transform (MAT) is described through a medial axis and a radius function. The medial axis (MA), or skeleton of set D denoted by M(D), is the locus of points inside D, which lies at the centers of all closed discs, which are maximal in D, together with the limit points of this locus. A closed disc is said to be maximal in a subset D of the 2D space if it is contained in D but is not a proper subset of any other disc contained in D.

The radius function of the medial axis of D is a continuous, real valued function defined on M(D), whose value at each point on the MA is equal to the radius of the associated maximal disc or ball. The MAT of D is the MA together with its associated radius function. Figure 2 shows the boundary and the corresponding MA of an object based on [2], [7], [8]. If the boundary segments of the object consist of only points, straight line segments, and circular arcs, then the MA segments will be one of the conic sections. An important characteristic of the MAT is that it can be used to simplify the original object and retain the original object's information. The 2D MAT defines a unique, coordinate-system-independent decomposition of a planar shape into lines. The MA of a figure is, therefore, also called the skeleton or symmetric axis of a part or shape.

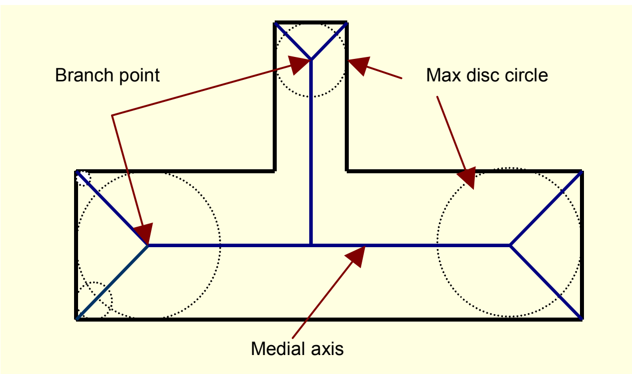


Fig. 2. Boundary of an object and its medial axis.

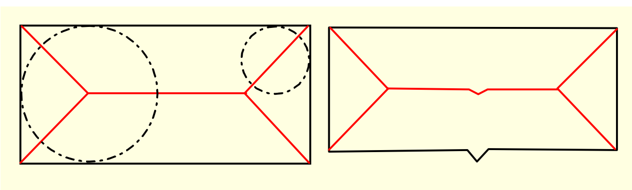


Fig. 3. Medial axis in 2D.

Figure 3 gives an illustrative 2D example of how a small change in an object's shape can generate a large change in the medial axis based on [1], [7], [8].

1. Properties of MAT

The MAT has the following properties.

- Uniqueness: There is a unique MA for a given object.
- Invariant under isometric transformations: Given an isometric transformation T, the skeleton of the transformed object should be the same as the transformed skeleton of the original object.
- Decomposition (dimensional reduction): The dimensionality of an MA is lower than that of its object. A 2D MAT transforms planar figures into lines.
- The MAT has no interior.

2. Applications of Skeleton MAT

The original application for which MAT was proposed was biological shape measurement [1]. Since then, MAT has been proposed and used for feature extraction and reduce-model formulation. It has played a central role in computer vision and shape analysis research. The medial axis is an attractive shape feature; however, its high sensitivity to boundary noise hinders its use in many applications. A small change in an object's shape can generate a large change in the medial axis, and it will often fail to deliver a useful shape descriptor. Boundary smoothing represents a routine remedy against noise, but it does not solve the problem in general. It is difficult to distinguish a large artifact from a salient feature at an early stage of shape analysis. Assembly parts or shapes of natural objects are often characterized by a rather complex or jagged outline; consequently, they yield a great number of spurious branches that clutter the skeleton. Therefore, techniques that allow the gradual extraction of salient subsets of the medial axis should be integrated into every skeletonization algorithm. Many algorithms have been developed to extract the skeleton. The straightforward procedure to accomplish such a transformation involves an iterative process which shrinks the object region step-by-step until a one-element thick figure is obtained.

III. Previous Shock Graph Studies

Basically, a shock graph is a shape abstraction that decomposes a shape into a set of hierarchically organized primitive parts. Shokoufandeh and others [4] combine shock graphs with an indexing and matching framework for hierarchical structures. Sebastian and others [5] use shock graphs to represent 2D shape silhouettes sampled from the object's viewing sphere. The authors, however, propose a hierarchical partitioning of the database, in which shapes are grouped into categories. A small number of exemplars from each category are chosen to represent the grouping, thus forming a database of prototypes used to index into the larger model database. Cyr and Kimia [6] explore the problem of how to partition the view sphere of a 3D object using a collection of shock graphs. However, they do not address the shock graph indexing problem. They resort instead to a linear search of all views in the database in order to recognize an object. Inspired by Blum's original idea of using directed graphs to define equivalence classes of shapes, Siddiqi and Kimia define the concept of a shock graph [1] as an abstraction of the skeleton of a shape onto a directed acyclic graph (DAG). The skeleton points are first labeled according to the local variation of the radius function at each point. Shock graphs have also led to a number of successful silhouette-based recognition systems based on graph matching [1], [4]-[12]. A careful examination of the shock graph literature shows that most, if not all, approaches are typically applied to unoccluded shapes, with only a few approaches tested on occluded shapes [1], [4]-[12]. Shock graph researchers have focused more on shape description and matching problems than on the representation or modeling of shapes. This paper specifically proposes a technique for shape representation and the modeling of human shape. The efficacy of the proposed human shape representation technique is further tested and subjected to a human posture recognition task. Achievement of this task will lead to a broad range of safety system applications such as intruder alert systems, pedestrian detection, and action recognition for surveillance applications.

IV. Shock Graph

In this paper, the aim is to develop a framework to model human posture efficiently using shock graphs as our shape descriptors. The shock graph of a shape is the medial axis, the locus of centers of circles which are at least bitangent to the boundary, endowed with dynamic and geometric information. Shock graphs are a richer descriptor of shape than the boundary by itself. Shock graphs encode information about the interior of the shape by pairing shape boundary segments. The shock graph has emerged as a powerful, generic shape description possessing these properties, and is based on a labeling partitioning of the skeleton points (shocks) making up the MAT of a shape.

Shock graph is an image transform and a thinning algorithm,

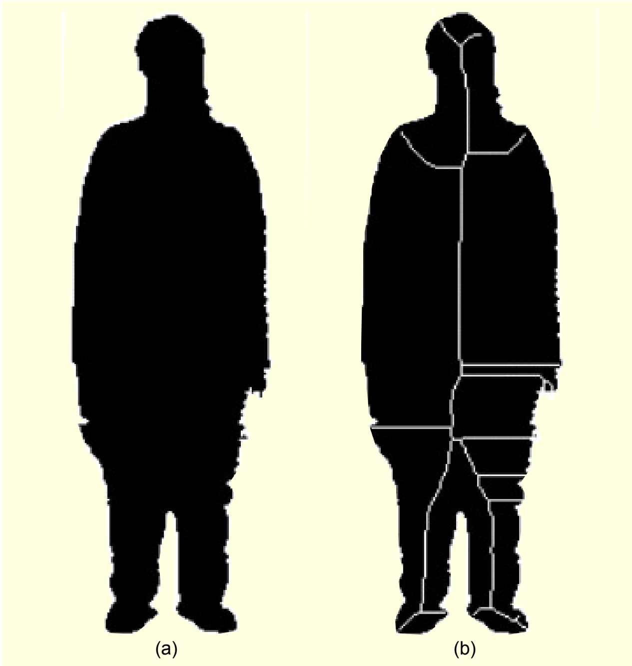


Fig. 4. Illustrative example of shock graph extraction: (a) original segmented image and (b) its shock graph.

which requires an already segmented image. Intuitively, the result of this process yields the skeleton of an object, encoding in it additional information. For instance, when the algorithm processes an image as shown in Fig. 4(a), a shock graph as in Fig. 4(b) is produced. Here, the black color serves as an indication of the shape of the input object. The white 'skeletal' line is the shock graph itself.

Skeletonization on its own is not sufficient to describe a shape in a satisfactory way. Blum's MAT encodes, for every point belonging to the skeleton, the shortest distance from that point to the object contour. A shock graph is a shape abstraction which decomposes a shape into a set of hierarchically organized primitive parts. The novel shock graph we propose in this work is a human posture representation algorithm, which yields a simplified shock graph (SSG). In addition, we demonstrate that the framework is effective in classifying human posture shapes. Such primitives arise from a labeling of the singularities along the medial axis of the shape.

1. Thinning and Its Application

Thinning has become a fundamental preprocessing technique and was used in many digital image analyses years ago. It has been applied in many fields such as inspection of printed circuit boards, electrical schematic and logic diagram interpretation, classification of fingerprints, recognition of characters, and so on. Thinning in image processing and pattern recognition has two main advantages. First, the reduction of the amount of data for an input binary image helps decrease the data storage and transmission time. Second, the preservation of the fundamental skeleton, which is topologically equivalent to the original object, facilitates the extraction of fundamental features of the object [13]. In general, the thinning algorithm is an iterative edge-point erosion technique, where a small window (such as a 3 × 3 window) is moved over the entire image with a set of rules applied to the contents of the windows.

2. Brief Description of Thinning

Thinning is a morphological operation, which is used to remove selected foreground pixels from binary images, somewhat like erosion or opening. It can be used for several applications, but is particularly useful for skeletonization [13]. In this mode, it is commonly used to tidy up the output of edge detectors by reducing all lines to the thickness of a single pixel. Thinning, which is normally applied to binary images, produces another matchstick-like binary image as an output. Like other morphological operators, the thinning operation is determined by a structuring element. The thinning operation is calculated by translating the origin of the structuring element to each possible pixel position in the image, and at each such position, comparing it with the underlying image pixels. Figure 5(a) shows a portion of the skeleton plot prior to thinning, while Fig. 5(b) depicts the skeleton plot after thinning. The skeleton figures shown are reproduced from [14].

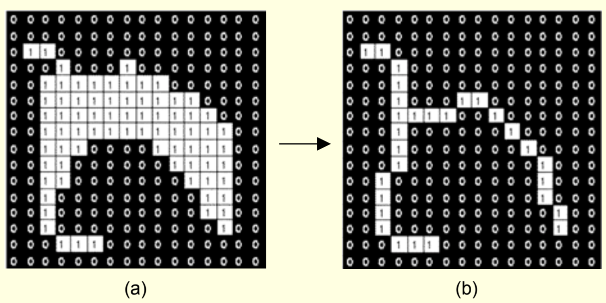


Fig. 5. Portion skeleton plots of (a) pre-thinning and (b) post-thinning.

V. The Proposed SSG Algorithm

In this work, we implement a skeletonization process based on Blum's skeleton and incorporate the thinning method mentioned above. The next stage is the identification of end points and intersection points which are present in every region of the shock graph. In our proposed SSG, we set a limit of two intersection points and four end points. The next subsections outline the following algorithms: end point detection procedure, intersection point detection procedure, and shape modeling. In the last two subsections, we present pruning and the SSG.

1. End Point Detection

The algorithm for end point detection in a given skeleton is as follows:

```
START
 Extract all skeleton coordinates;
 Set border vector to all eight-sides;
 for 1: length of skeleton coordinates extracted
       select current coordinate to be tested as end point;
       generate eight neighboring pixels around current
       coordinate;
      for 1: each surrounding pixel
       /* test if any pixels that are on the opposite side of
          the current pixel is/are present */
       /* check for existence of nearby pixels (immediate
          neighbor) */
          if present
          then this pixel is not an end point pixel;
          break;
          else
          it is an end point; save it;
          /* repeat loop */
           end;
 end;
/* all terminating points detected */
STOP
```

2. Intersection Point Detection

For intersection points, detection is performed using the following algorithm:

```
START
 Extract all skeleton coordinates;
 Create 3 by 3 kernel;
 Convolve kernel with the skeleton;
 Multiply result of convolution with the original skeleton
    image;
 Select all pixel values > 3 to be tested as intersection
    points;
 for 1: length of intersection points to be tested
       select current coordinate to be tested as intersection
         point;
       generate 8 neighboring pixels around current
         coordinate;
        /* determine if any of result is/are member of
           neighboring pixels */
       perform Euclidean distance;
       select intersection point;
       store it;
        /* repeat loop */
   end;
/* all intersection point detected */
STOP
```

3. Modeling of the Shape

Once the end points and intersection points are determined, the next step is to perform the human posture modeling using the following algorithm:

```
START
Find first intersection point;
 /*searching from top to bottom of the image */
first intersection point detected;
 save it;
Exclude it from the intersection points detected in 2;
 /* this is the branch point of head of the human posture */
Find the protrusions from this intersection point; save
   them;
/*these are the first two end points detected*/
Exclude both from the end points detected in 1;
Find the third and fourth end points at bottom part of the
   skeleton;
perform Euclidean distance; save them;
Compare end points detected in 1 with all 4 end points
   marked as the end points of the skeleton;
All end points unmarked, prune them;
Detect second intersection point; save it;
 /*This is the branch point of the lower posture of the
  skeleton*/
 STOP
```

4. Pruning and Simplified Shock Graph

Pruning methods are incorporated in many skeletonization and thinning algorithms. Practically, all skeletonization algorithms designed for shapes implement some form of pruning. The main goal of this paper is to introduce a standard framework for pruning, which consists of an application specific pruning paradigm. The pruning strategy is to delete superfluous axis branches. In this work, the pruning hierarchy is obtained as follows: after the detection of all four end points of the skeleton shape, the pruning process is initiated on every remaining end point detected and progresses inwards until it reaches the medial axis of the skeleton. As such, our pruning strategy aims to produce a simple shock graph comprising of only two intersection nodes and four end nodes. This simpler looking shock graph is what we term an SSG. The two intersection nodes lie within the boundary of the shape, and the end nodes lie on the boundary itself. Nevertheless, if both feet are not positioned at the same level, the third and fourth end points will be detected from the lower foot.

To model human posture, we extract relative body parameters from the SSG. Fig. 6 (a) depicts conventional shock graphs of two human postures while Fig. 6(b) shows examples of our SSG.

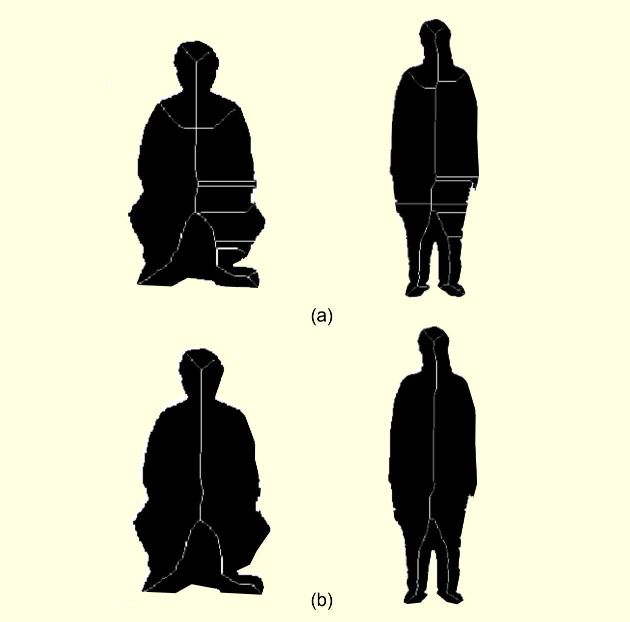


Fig. 6. Human postures models: (a) conventional shock graphs and (b) the SSG.

VI. The Algorithm in Action

1. SSG for Feature Extraction

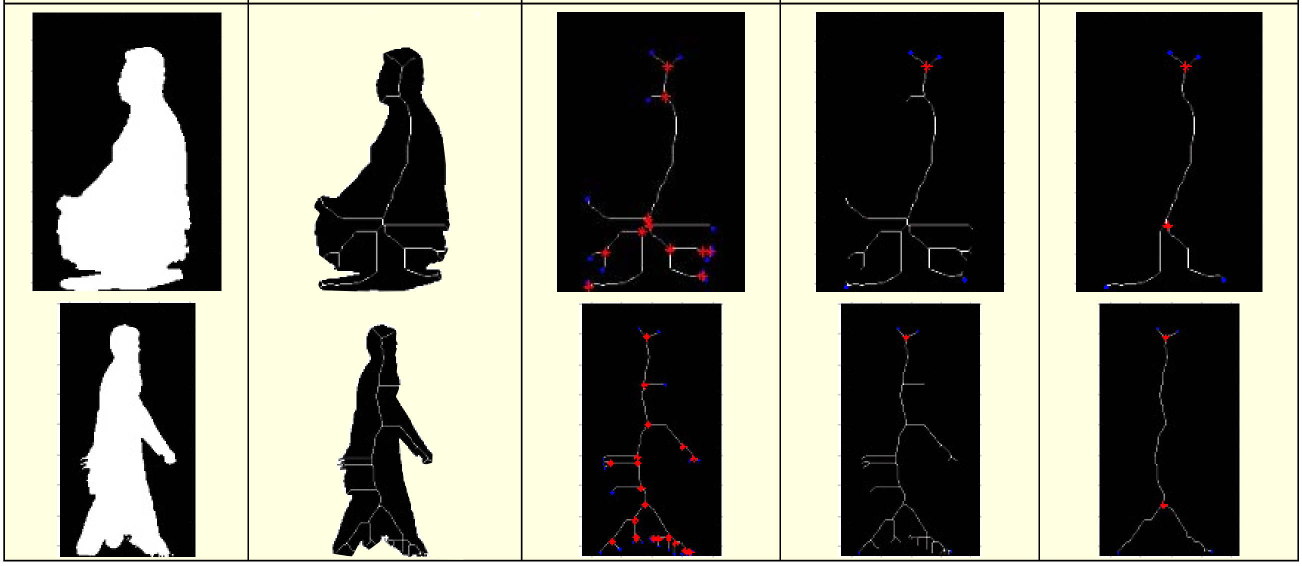
We tested the algorithm with several input images including a wide variety of 2D human shapes representing a range of postures. Table 1 delineates the systematic procedure using our algorithm. In each case, the algorithm determined all four end points and two intersection points and preserved them. As can be seen in Table 1, end points are represented by circles and intersection points by asterisks. In the third column of Table 1, the detection of the first end point, second end point, first intersection point, and third and forth end points are shown. Next is the pruning process of the shock graph, after detection of the end points. This is followed by detection of the second intersection point. These key points are important structural descriptions, which capture the topological information embedded in the SSG. Next, a set of body parameters comprising three measurements are extracted from the SSG to serve as feature vectors. The feature vectors are the distances d_1, d_2, and d_3 indicated in Fig. 7. Parameter d_1 covers the length from the upper intersection node to either of the lower end nodes, d_2 represents the distance between the upper and lower intersection nodes, and d_3 is the horizontal distance between the two lower end nodes.

2. SSG Classification

In this study, the aim is to test the validity of SSGs as feature vectors of various postures. We used a collection of 500 images

Table 1. Results obtained after each procedure.

Original image	Result after skeletonization	Result after detection of all end and intersection points	Result after selection of 4 critical end points and the upper intersection point	Result after prunning and detecting the second intersection point (SSG)



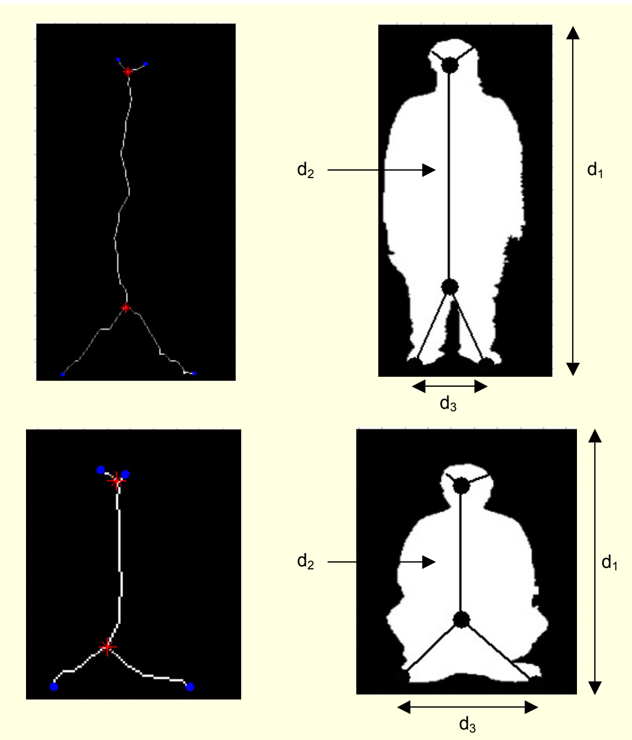


Fig. 7. Feature vectors extracted from the SSG.

of various human postures to generate the three feature vectors for this study. The various postures include both standing and non-standing positions, and the human subjects could be facing either to the front or to the side. No restriction was imposed on the type of clothing worn but there was a minimum distance requirement between the subject and the camera. To estimate the classifier generalization error, the training data set was re-sampled using the *k*-fold cross-validation method. A *k*-fold cross-validation divides the training data into *k* subsets. Then, *k*-1 subsets were used for training, and the remaining subset was used as the test data set to predict classification errors. The whole process was repeated *k* times until each individual subset was used once [15]. In this study, the classifier performance was estimated using a 5-fold cross-validation in which the posture data was divided equally into five subsets. Therefore, in each fold there were 100 postures in each subset representing the five posture classes. The efficacy of the proposed SSGs as feature vectors was evaluated using three classifiers namely, classification and regression tree (CART), artificial neural network (ANN), and support vector machine (SVM).

Decision tree (DT) classifiers are powerful and popular tools used for classification. The DT learning method involves approximation of discrete valued functions. It is robust to noisy data and is capable of learning disjunctive expressions [16]. Typically, it takes a set of known data and induces a DT from that data. The tree is then used as a rule set for predicting the outcome from known attributes or feature vectors. The initial data set, which induces the tree, is known as the training data set. The DT takes a top-down form. There is a variety of algorithms for building DTs. In this work, we use the CART algorithm. This classifier generally attempts to predict the values of a continuous variable from one or more continuous and (or) categorical predictor variables. In this study, we want to classify human postures using the three feature vectors extracted from the SSGs namely d_1, d_2, and d_3. This dataset contains numerical attributes. Therefore, the splitting process is performed by choosing the threshold value. It minimizes the impurity measure and is used as a splitting criterion. The CART algorithm uses the Gini index to measure the class diversity in the nodes of the DT [17] and produces five categorical outcomes. To be specific, the categories are standing (side view, facing front, or walking) and non-standing (facing front or side view).

The second classifier is the ANN. The ANN classifiers are well known for their ability to express highly nonlinear decisions. This make them appropriate for recognition of complex patterns. They also possess the ability to maintain accuracy even when some input data is inappropriate and/or inadequate. In this study, the feedforward multilayer perceptron (MLP) neural network was used as the second classifier to test the efficacy of the extracted SSG feature vectors in the human posture recognition task. A three-layer NN with weights adjusted using the scaled conjugate gradient (SCG) algorithm [18] was trained to learn the relationship between SSG features and the respective posture class. The MLP had an input layer consisting of three neurons corresponding to the input features, one hidden layer and an output layer with five neurons to represent the five posture classes.

The SVM, developed by Vapnik [19] as an implementation of structural risk minimization (SRM) was also considered. The idea behind SRM is that given a sequence of hypothesis spaces of increasing complexity, one needs to choose the hypothesis space that minimizes the training error. Then from this same sequence of hypotheses, one must again choose the hypothesis that minimizes the upper bound of the generalization error. The SVM approximates the upper bound by performing these two tasks simultaneously and by controlling the size of the feature weights. This principle formulation of weight decay is used in neural networks to improve generalization [15]. In terms of geometrical interpretation, this is when an SVM chooses the optimal separating surface [20] (see [19]). First, the SVM method was outlined for the linearly separable case. Kernel functions were then introduced to deal with non-linear decision surfaces. Finally, for noisy data, slack variables were introduced when complete separation of classes cannot be achieved [20], [21]. In this study, we applied the multiclass SVM.

VII. Classification Results

The extracted SSG feature vectors were used as inputs to the classifiers for validation purposes. Figure 8 displays the CART generated with 11 maximum tree depth for classifying the five possible outcomes which are the posture positions categories, namely, standing oblique (SO), standing facing front (SF), non-standing oblique (NO), non-standing facing front (NF), and walking (W). The CART algorithm selects all three as attributes and picks d_1 as the top node in the discrimination process. Beginning from the top node, the rule of "$d_1 < 210$" classifies the test image attributes accordingly into one of the eleven possible leaf nodes. If the top rule is satisfied, the decision takes the left path or vice versa. Ultimately, a decision is reached when a leaf node assigns the test image or observation as NO, NF, SO, SF, or W. In this

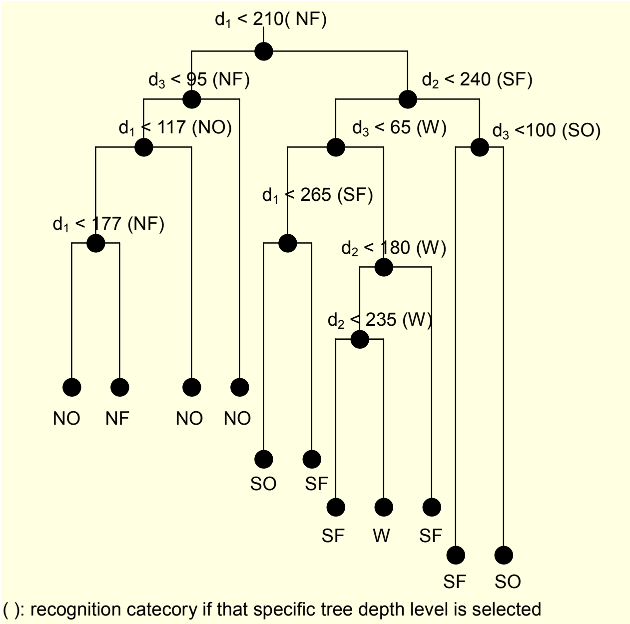


Fig. 8. Decision tree used for posture recognition.

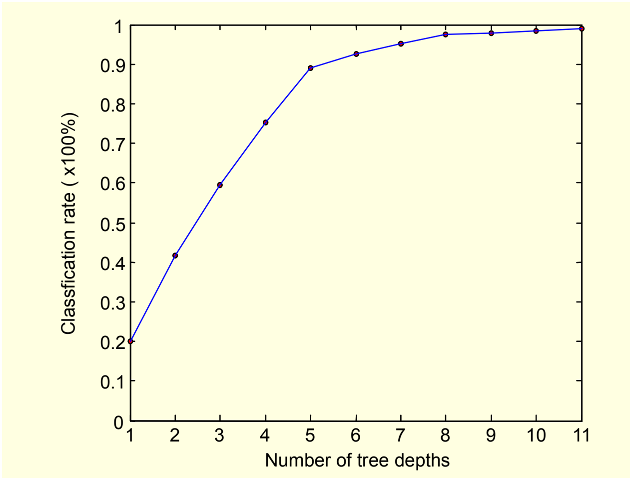


Fig. 9. Accuracy rates at different tree depth levels. The best performance is at maximum tree depth.

Table 2. Confusion matrix for posture recognition.

Actual category	Predicted category														
	DT					MLP					SVM				
	NF	NO	SF	SO	W	NF	NO	SF	SO	W	NF	NO	SF	SO	W
NF	**100**	0	0	0	0	**98**	2	0	0	0	**100**	0	0	0	0
NO	0	**100**	0	0	0	4	**96**	0	0	0	0	**100**	0	0	0
SF	0	0	**100**	0	0	0	0	**100**	0	0	0	0	**100**	0	0
SO	0	0	0	**99**	1	0	0	0	**100**	0	0	0	0	**100**	0
W	0	0	1	3	**96**	0	0	5	6	**89**	0	0	0	3	**97**

work, the DT perfectly discriminates between standing and non-standing postures. Further discrimination into 5 subsets yields 99% efficacy. Figure 9 shows the relationship between the classification rate and the number of tree depths used. The best classification rate attained was 99% when all tree depths were used. At the levels of five and seven tree depths, the classification accuracies attained were 90% and 95%, respectively. Table 2 tabulates the DT, MLP, and SVM classification results. The radial basis function kernel was opted in this study, based on [22], [23]. Again, both MLP and SVM distinguished well the two main postures of standing and non-standing as observed in the DT classifier. The MLP achieved above a 96% recognition accuracy rate for all categories except the walking posture category, for which it only achieved an 89% recognition rate. The SVM performance was very similar to that of the MLP but with higher accuracy. Overall, and as expected, the SVM showed the best performance with an average recognition rate of 99.4%. One interesting fact is that the walking posture was the most difficult to recognize. The DT classifier performance was also encouraging with overall recognition accuracy of 99%.

VIII. Conclusion

We introduced and demonstrated the efficacy of a method which uses an SSG to model human posture. We used three different classifiers to confirm the efficacy of the extracted SSG feature vectors as input features. Based on the classification results, it is clear that the SSG-based feature vectors are robust, accurate, and computationally efficient. Therefore, the SSG is recommended as a feature extraction technique to represent human posture in a more compact form than other shape descriptors such as the Fourier descriptor.

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