

A CONVENIENT PHOTO-BASED APPROACH FOR ASSESSING BODY POSTURE

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ABSTRACT

Good body posture is important because it helps to reduce the risk of musculoskeletal injuries and permanent distortions which may interfere with efficient functioning of the body. Individuals need to be aware that good body posture is vital for a healthy quality of life, especially as one ages. However, an individual's ability to detect poor posture can be difficult as a faulty posture tends to feel normal after continuous practice. Moreover, consulting a physician about one's posture may not always be feasible. As such, we propose a convenient photo-based approach for assessing body posture from a side profile image of an individual. Shape features extracted by processing these images, such as the curves from an individual's back are used to train a Support Vector Machine and a Naïve Bayes classification models to predict good or poor posture. Results from the experiments conducted with 144 participants demonstrate the effectiveness of our approach.

Index Terms— body posture, image processing, shape features, support vector machine, classification, feature extraction

1. INTRODUCTION

Poor body posture is associated with musculoskeletal disorders, uneven pressure at joints and ligamentous strain [1]. It can be caused by certain force or repetition of activity during work and other activities without any breaks [2-5]. Poor posture can result in many physical disabilities including spinal and joint dysfunctions. Poor posture also raises the risk for several types of musculoskeletal injuries

[2-5]. Good posture is closely associated with neutral spine which refers to three natural curves in sagittal view of a healthy spine including the anteriorly convex cervical region, the posteriorly convex thoracic region and the anteriorly convex lumbar region [6]. Some visual cues of poor posture can be a rounded and elevated shoulders, pushed-forward head position, forward tilting of the hips and increased curvature in the lumbar spine or a protruding stomach. Practitioners with expertise in the musculo-skeletal systems can analyze these biomechanical disorders by visually examining the patient's body shape or by analyzing data collected using techniques such as radiology, magnetic resonance or 3D imaging [1, 7]. However, for the general public self-assessment of poor posture can be difficult as even a faulty posture tends to feel normal after significantly long and continuous practice. Consulting a physician about one's posture may not always be feasible due to cost or contraindications for radiation exposure. As such we have proposed a convenient photo-based approach for assessing body posture from a single side profile image of an individual. Our approach relies on the visual cues and shape analysis of an individual's back to assess posture.

We start by marking 5 significant joints in the side profile photograph and obtaining a side body mask. Then using image processing techniques we extract several shape features including three major curvatures from an individual's back curve and the head tilt angle. Feature extraction is followed by feature selection where we select only those features that can accurately describe the shape of the back and distinguish between good and poor posture. The selected features are included in the feature vector that represents the shape of the back curve. Our training samples include side profile photographs of 144 participants in a standing position. Two experts (OA and DKP) visually inspected and classified these photographs as either good or poor posture. Based on this ground truth, we train a Support Vector Machine (SVM) [8, 9] and a Naïve Bayes [10, 11] classification models to predict good/poor posture. Experimental results after only considering the back curve

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have yielded an accuracy of 74.3%. This demonstrates the potential usefulness and effectiveness of our approach.

The remainder of this paper is organized as follows. Section 2 presents some related work. Section 3 describes the overall work flow of our approach. Experimental results and analysis are presented in Section 4. Section 5 presents a brief discussion. Finally some future work and conclusion are presented in Section 6.

2. RELATED WORK

Photography has been frequently used for postural analysis in different tools and experiments. Perry and Smith explored the reliability of sagittal photographic spinal posture assessment in adolescents [12]. Eight spinal postural angles and four distance measures were derived from photographs and tested for spinal pain in adolescents. They concluded that photographic analysis of adolescent posture has fair inter-rater reliability. Our work does not focus on the inter-rater reliability but rather on predicting good or poor posture by analyzing the shape of the back curve. Our study is based on large, diverse population of adults ranging from age 19 to 52 years. Our sample also included a wide range of body composition (body fat %: 9.8% to 60.4%).

A biologically relevant measure determined by digitization of images was used to test the reliability of standing spine postures within subjects by [13]. Sagittal and posterior views of normal upright standing participants were taken in different sessions. The landmarks were digitized, and cervical, thoracic and lumbar angles were measured to assess the detection of postural changes resulted from clinical treatment. Unlike evaluating intra individual reliability across sessions presented in this work, we use only one view, i.e. the side profile photograph of the participant, and predict the quality of body posture. These studies also report the potential error for using angles due to sway and lateral shifting of the participant’s position. As such, we also explore the use of other features extracted from the back curve profile.

Smith et al. [14] explored to determine whether posture subgroups based on photographic assessment are similar to those determined clinically using radiography in association with spinal pain. They concluded that meaningful classification for thoraco-lumbo-pelvic alignment can be successfully determined from sagittal photographs. Kuo et al. [15] studied and compared spinal postures in standing and sitting positions and concluded that the angular relationship between the spinal regions can be objectively quantified using image-based analysis. These studies support our use of 2D photographs for posture analysis.

Niekerk et al. [16] experimented with photographs taken by Photographic Posture Analysis method (PPAM) and Radiographs taken using LODOX system and concluded that photographs provide valid and reliable indicators of the position of the underlying spine in a sitting position. However, this study used photographs to measure

only the angles on the back that have known problems as reported in [10], while our proposed method intends to automatically extract more shape features and build a training model that can accurately classify a given side photograph of an individual into good or poor posture. Unlike [13], our proposed method also does not require any expert assistance sophisticated hardware.

3. OUR APPROACH

As shown in Figure 1, our photo-based approach to assess posture consists of the preprocessing, feature extraction, feature selection, and training and classification phases.

3.1. Preprocessing

The side profile photographs were taken in a standing position with a green background. A side body mask as shown in Figure 2(b) is obtained by using image segmentation based on color thresholding. This process is followed by a normalization process to represent the correct relative size of the participant in our image dataset. We used

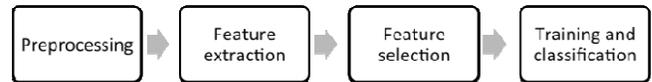


Fig. 1. The work flow of our approach

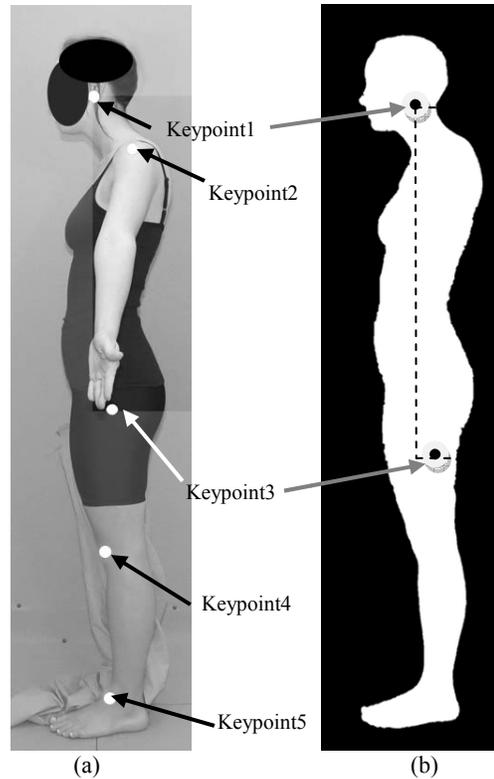


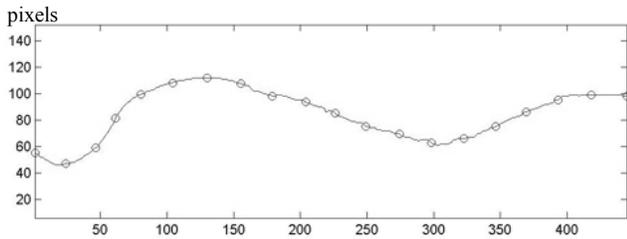
Fig. 2. Key points and the side body mask.

one particular photograph of a medium height participant (e.g., 172cm) as the reference photograph and normalize the size of all the other photographs and body masks with respect to this reference photograph using Equation 1, where R is the reference photograph and P is the photograph being currently processed.

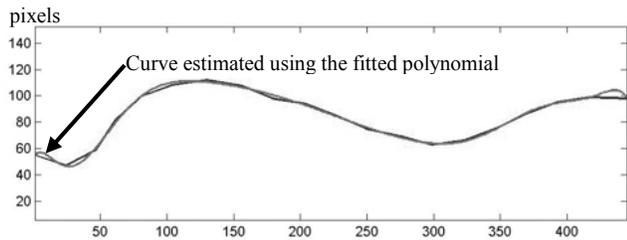
$$P_{\text{new pixel height}} = \left(\frac{P_{\text{height in cm}}}{R_{\text{height in cm}}} \right) \times R_{\text{pixel height}} \quad (1)$$

We then mark the approximate locations of five key points in the photographs at the ear (*keypoint1*), the center of the glenohumeral joint (*keypoint2*), the center of the acetabulum (*keypoint3*), knees (*keypoint4*) and the tarsal bones (*keypoint5*) as shown in Figure 2(a). This process can be easily automated by using colored stickers while the participant is photographed and detecting the locations of these stickers during image preprocessing.

Finally, we crop the body mask vertically and horizontally at *keypoint1* and then horizontally at *keypoint3* to obtain the body mask of the back as shown in Figure 2(b). We also take 20 equidistant points from the back curve as shown in Figure 3(a) and fit a polynomial of degree 12. We use this polynomial to estimate a smoother back curve. This process removes small irregularities in the obtained back curve mask as can be observed in Figure 3(b). From this smoothed curve the two local minimum (*min1* and *min2*) and two local maximum (*max1* and *max2*) points can be discovered, as shown in Figure 4.



(a) Twenty equidistant data points extracted from the back curve of the participant



(b) The smoother curve estimated by the fitted polynomial overlapping with the original curve

Fig. 3. The extracted back curve of the participant

3.2. Feature extraction

We started by extracting various shape features that could describe the back curve of a participant. The list of all the extracted features is shown in Table 1. The first in this list are the angles in radians viz. *angle1*, *angle2*, *angle3* and *angle4*. As shown in Figure 5, *angle1* is the angle formed by the line between *keypoint1* and *keypoint2* with the horizontal line. *Angle2* is the angle formed by the line between the points *min1* and *max1* with the horizontal line. *Angle3* is the angle formed by the line between *max1* and *min2* with the x-axis. *Angle4* is the angle between the line joining *min1* and *max2* and the line joining *max1* and *min1*. These angles are presented in Figure 5.

In addition, we also extract the ratios between a set of body measures from the back profile. These measures are shown in Figure 6(a). Feature *backratio1* is the ratio between measures *a* and *b*. The ratio between *a* and *c* is represented as *backratio2*. Feature *backratio3* is the ratio between *c* and *d*. Similarly *backratio4* is the ratio between *d* and the height of the person.

Variance_keypoints is the variance in vertical alignment of the three key points. *A1_by_A2* is the ratio of the areas *A1* to *A2* as shown in Figure 6(b). We also extracted the curvatures of the back curve at *min1*, *max1* and *min2*. Curvature can be viewed as the amount by which a geometric object deviates from being flat. In a given curve C and a point P on it, there is a unique circle or line that most closely approximates the curve near the point P . This is called the osculating circle. The center of this circle lies in the normal drawn at P and the curvature of this circle is the curvature of the curve at P . Thus, the curvature can be calculated by taking the reciprocal of the radius of these circles at P . The radius of this circle is also called radius of curvature. The radius of curvatures at *min1*, *max1* and *min2* in the back curve is presented by the bar plots in Figure 7.

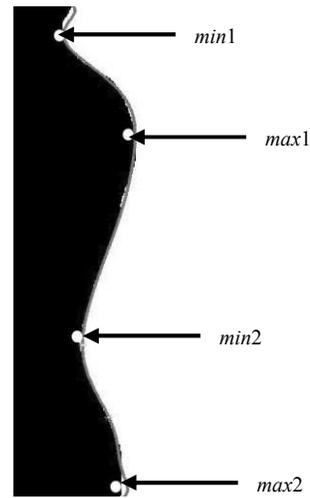


Fig. 4. Local minimum and maximum points on the back curve

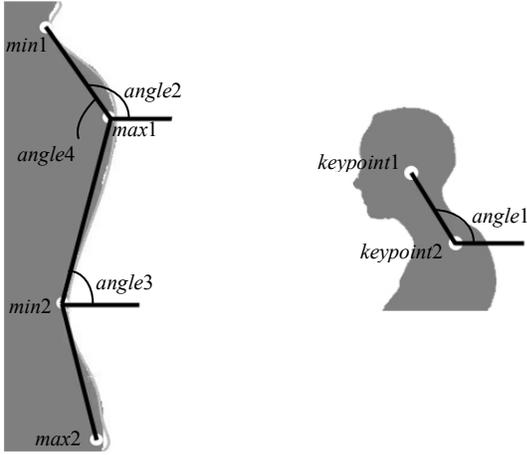


Fig. 5. Angles considered to describing the back curve.

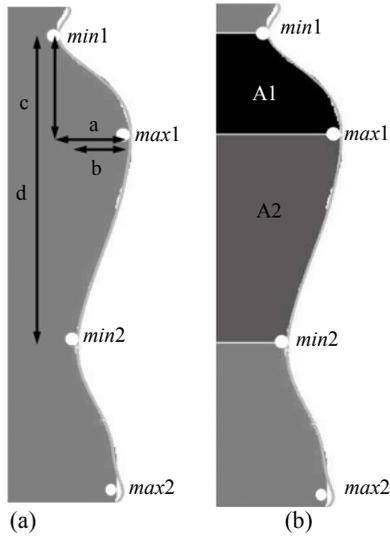


Fig. 6. Back measures.

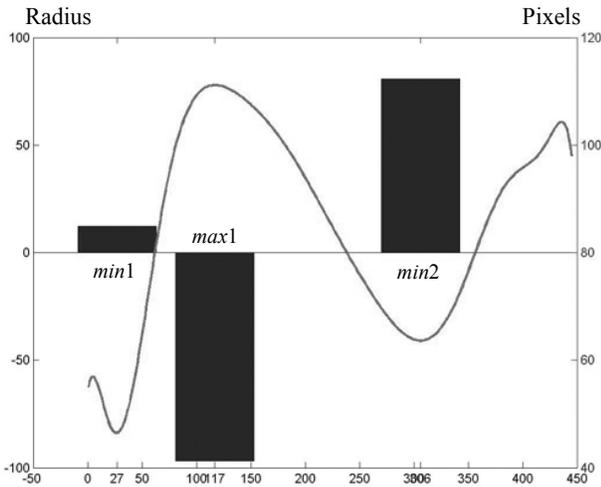


Fig. 7. Radius of curvatures at $min1$, $max1$ and $min2$.

Table 1. Extracted Features

No.	Features
1-4	$angle1$, $angle2$, $angle3$ and $angle4$
5-8	$backratio1$, $backratio2$, $backratio3$ and $backratio4$
9	$Variance_keypoints$
10	$A1_by_A2$
11-13	$C1$, $C2$ and $C3$
14-33	Fourier Coefficients

Table 2. Selected Features

Rank	Features
1	$backratio4$
2	$backratio3$
3	$C3$
4	$C1$
5	$angle3$
6	$keypoint1$
7	$Variance_keypoints$
8	$keypoint4$
9	$keypoint5$
10	$keypoint3$

Feature $C1$ is the ratio between the radius of curvatures at $max1$ and $min2$. $C2$ is the ratio between the radius of curvatures at $min1$ and $min2$. $C3$ is the ratio between the radius of curvatures at $min1$ and $max1$. Besides these features we also take the 20 points on the back curve as presented in Figure 3(a) and calculate the Fourier Coefficients by performing Fast Fourier Transform (FFT) [17]. We also use these coefficients as features to describe the back curve. The values of all the attributes are normalized to a scale of 0 to 1 before any further data analysis.

3.3. Feature selection

During the feature extraction phase we extracted many features that could be used to describe the shape of the back curve. However, we would want to select the most effective features. Otherwise we might be adding unnecessary inefficiency to the training and testing models. As such, we use the attribute selection functionality of WEKA [18, 19]. Out of the many options available we chose chi squared attribute evaluation using $ChiSquaredAttributeEval$ class. This class evaluates the attributes individually by measuring the chi-squared statistic with respect to the class. We then rank the attributes according to their worth using the Ranker filter class and finally selected the first ten features with the highest ranks. The selected features are listed in Table 2.

3.4. Training the classification models

After the feature selection phase, our feature vector consists of only 10 attributes. The output classes for all the curve instances were either good or poor posture. This ground truth was based on the classification of the 144 photographs by two domain experts. We used this dataset of 144 back curves to train and build an SVM classifier and a Naïve Bayes classifier. To build and train the SVM classifier we used the LIBSVM library [8]. We used a nu-SVC type SVM and a radial basis kernel function. The cost and gamma parameters were obtained by iterating over a range between 2^{-10} and 2^{10} in order to discover the best set of parameters. To build and test a Naïve Bayes classifier we again used WEKA [18, 19]. 5-fold cross validation was performed to assess the classification results.

4. EXPERIMENTS AND RESULTS

Our dataset consists of photographs of 144 adults ranging from ages 19 to 52. There are 71 men and 73 women. Their postures were classified into 64 good postures and 80 poor postures. Compared with other existing works, our data set also had racial/ethnic diversity consisting of Black (37%), White (57%) and others (6%) adults. They also varied in shape and size with body fat percentages ranging from 9.8% to 60.4%. 5-fold cross validation was performed to evaluate the accuracy of both classification models. Good and poor instances of curves were uniformly distributed over each 5-fold cross validation was performed to evaluate the accuracy of both classification models. Good and poor instances of curves were uniformly distributed over each fold to reduce the bias in the training and testing. We exhaustively tested all the combinations of the selected features in classification and found that the combination of *backratio4*, *backratio3*, *C3*, *C1*, *angle3*, *keypoint1* and *keypoint3* produced the best result.

As a result, we achieved an overall accuracy of 74.30 % for both the SVM the Naïve Bayes classifier. The Rand Index (RI: http://en.wikipedia.org/wiki/Rand_index) was also calculated for both of these classifiers. The Rand Index penalizes both false positives and false negative decisions. The RI for the SVM classification was 0.582, and that for the Naïve Bayes classification was 0.575.

We further examined the Precision and Recall values of both classification models. Since there is more than one class ('good' and 'poor'), we have to redefine Precision and Recall. In this case, a true positive (TP) is the correct grouping of two 'good' postures or two 'poor' postures. For example, in the results of SVM classification, 50 good postures were correctly classified as good, and 23 poor postures were incorrectly classified as good. Therefore, the number of TPs in the detected 'good' cluster is equal to $C_{50}^2 + C_{23}^2$. The number of TPs in the detected 'poor' cluster can be calculated in the same way.

		Predicted	
		Good	Poor
Actual	Good	50	14
	Poor	23	57

(a) Confusion Matrix for the SVM classifier

		Predicted	
		Good	Poor
Actual	Good	55	9
	Poor	28	52

(b) Confusion matrix for the Naïve Bayes classifier

Fig. 8. Results for the SVM and the Naïve Bayes classifiers.

Together the sum of TPs from both detected clusters is the total number of TPs. A false positive (FP) is an incorrect grouping of one 'good' and one 'poor' postures into one cluster. A false negative (FN) is an incorrect separation (or miss-grouping) of two 'good' or two 'poor' postures into different clusters. According to this definition, the precision of the SVM classifier was 0.55, while that of Naïve Bayes classifier was 0.53. SVM classifier yielded a recall of 0.58 while Naïve Bayes classifier had a recall of 0.59. The precision and recall values may not appear to be that high, and this is because there are many more (C_N^2) possible pairwise grouping of two participants' postures than there are participants (or the total number of postures N). Therefore, both the numerators and the denominators in calculating precision and recall exhibit a much larger range of value, making the precision and recall values spread out more on the lower side. The confusion matrices for each of the classifiers are shown in Figures 8(a) and (b), respectively.

5. DISCUSSION

We successfully demonstrated that shape analysis of the back curve from a 2D photograph can be effectively used to assess body posture. Initially we tried to extract many shape descriptors but the chi squared test on all the individual attributes revealed that *backratio4*, *backratio3*, *C3*, *C1*, *angle3*, *keypoint1*, *Variance_Keypoints*, *keypoint4*, *keypoint5* and *keypoint3* were the most effective features (in decreasing order of their worth) for our classification. The classification results show that there is no significant difference in performance between the SVM classifier and the Naïve Bayes classifier in terms of overall accuracy, rand index, and precision or recall. Our experiments were mostly based on local descriptors extracted from the back curve.

These local features alone look promising, but posture also depends on the overall orientation of the body. Features like the tilt of the body and the orientation of the back with respect to the whole body, can be exploited to achieve higher classification accuracy. The features we extracted primarily focused on the curves from the upper back. Lower back may also contribute useful features for the classification of postures.

Posture analysis using photographs naturally tend to have some potential flaws as we are estimating the arrangement of the health and performance of the underlining spine based on external measurements and observations [16]. However, there can be other possible sources of errors such as misidentification or potential bias while labelling the ground truth by the experts or inconsistent placement of markers (key points) during image preprocessing.

6. CONCLUSIONS AND FUTURE WORK

In this paper we have presented a photo-based approach for posture assessment. This method is simple and easy to use as we only need one side profile image to assess posture quality. Results from our experiments verify the effectiveness of our approach. We are thus highly encouraged and motivated to further explore and improve this methodology.

In our future work, we want to explore more shape features that might better describe the back curve and differentiate between good and poor posture. As referenced in the above discussion, the overall orientation of the body and the orientation of the back with respect to the whole body are yet to be explored. So our future work will focus more in the global features and global shape descriptors.

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