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Contactless Abnormal Gait Detection

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Abstract— **We present a new method to detect abnormal gait based on the symmetry verification of the two-leg movement. Unlike other methods requiring special motion captors, the proposed method uses image processing techniques to correctly track leg movement. Our method first divides each leg into upper and lower parts using anatomical knowledge. Then each part is characterised by two straight lines approximating its two borders. Finally, leg movement is represented by the angle evolution of these lines. In this process, we propose a new line approximation algorithm which is robust to the outliers caused by incorrect separation of leg into upper / lower parts. In our experiment, the proposed method got very encouraging results. With 281 normal / abnormal gait videos of 9 people, this method achieved a classification accuracy of 91%.**

I. INTRODUCTION

The human body motion is made possible due to bones, muscles and articulations. For gait, the movements of the lower limb articulations are fundamental, particularly knee flexion. To detect or quantify the level of an injury, different works were done to measure the knee angle during gait. Those previous work used different kinds of sensor like opto-electronic systems (e.g. Vicon or Optitraks) to localize markers directly placed on the skin or on an exo-skeleton to reduce artifacts generated by skin motion [6]. Those systems are very accurate but are unfortunately expensive and could not be used in daily clinical life due to the large space needed and long and tedious manipulations for marker placement. Another proposal used flexible electro-goniometer to record knee flexion during daily life [5]. However, these systems are still subject to positioning error and need time and expert people to manage them. To lessen all these problems, markerless methods were proposed using more or less complex video camera setups and computer vision techniques [7]. Methods using one camera such as the one in [8] permit to measure angles between major body segments. However, in case of a pathological leg, symmetrical gait analysis by comparing the two leg movement could not be done because the two legs parameters are not recorded at the same time. This limitation is caused by the occlusion of one leg by the other during the gait cycle.

The question is: is it possible to measure gait symmetry with one camera even if one leg is occluded by the other during a period of the cycle. To answer this question, in this paper, we propose a new method for measuring leg parameters as soon as legs are sufficiently distinct during the gait cycle. To evaluate the ability of this method to detect abnormal gaits, a pathological asymetric gait was simulated with a knee orthesis that affects knee flexion.

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In section II, we present the overview of our approach. Then, section III describes how we define the gait features and the algorithm to detect these features. After that, the experimentation is presented in section IV. Finally, section V presents the conclusion and future works.

II. SYSTEM OVERVIEW

In our system, to analyse the gait of a person, this person will walk perpendicularly to a camera capturing his side view. Then the video from this camera is processed by a background subtraction algorithm [3] to detect the person in the video. The output of the background subtraction algorithm is a sequence of binary images with the white region indicating the region occupied by the person (figure 1). From these binary images, the images belonging to each step are grouped. Then the system compares the movement of each pair of consecutive steps in which each leg (right and left) starts. The final comparison results are the average difference of all pairs of consecutive steps.

To compare the movement of two consecutive steps, gait features are extracted from binary images. These features are the angles of different parts of the two legs. Then the movement of one leg is described by the angle evolution of its parts. Finally, a human gait is classified as normal if the angle variations of one leg are similar to those of the other leg.

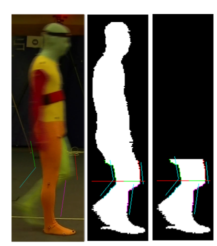

Fig. 1. From video, the person is extracted and the lower part containing two legs is segmented (white region). The magenta lines are approximation lines of borders of different leg parts.

Section III-A presents how we define the beginning and the end of a step and the features used to describe different leg parts in each binary image. In section III-B, we present the algorithm to detect these features. The algorithm to compare the angle evolution is presented in section III-C. The algorithm to classify normal / abnormal gait is presented in section III-D.

III. FEATURE EXTRACTION

A. Gait feature

In each binary image, the feature extraction works as follows:

- The lower part of human body from the point below the pelvis to the feet are extracted (figure 1).
- From the extracted region, the region corresponding to each leg is separated.
- Then, each leg is further divided at the knee level into two parts: upper leg (thigh) and lower leg (leg per se).
- Each part of one leg is then characterised by two sequences of front and back border points (figure 2).
- Finally, each sequence of border points is approximated by a straight line. The set of lines approximating the borders of the upper and lower parts of the two legs constitutes the feature set representing the two legs' position in each image.

In our system, the position of the pelvis and the knee are estimated based on anatomical knowledge [1]. According to [1], if the height of a standing person is H then the heights of his pelvis, knee, and ankle are $0.72H$, $0.285H$, and $0.039H$ respectively.

To remove the upper body, the height of the line separating the lower part from the upper part of human body is set to $0.5H$ like in [2]. This line is between the pelvis and the knee so that the lower part does not include hands which are difficult to separate from legs.

With the feature set defined above, two problems emerge.

Firstly, the anatomical knowledge only gives an average height of different parts of the human body when a person stands up. Therefore, the approximative height provided by anatomical knowledge is incorrect when this person walks. Consequently, the border of the upper part extracted by the anatomical knowledge often contains the border of the lower part and vice versa as illustrated in figure 2. In this case, the problem of approximating border by a straight line becomes more difficult. In section III-B, we propose an algorithm which takes into account this problem.

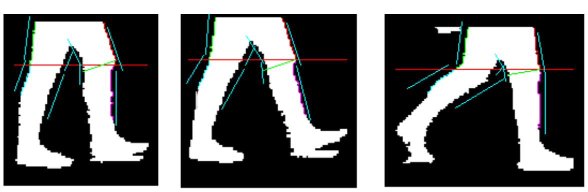

Fig. 2. The system starts analysing gait when the lower part of the leg in front is perpendicular to the horizontal line (left image). It stops analysing gait when this part becomes perpendicular again (right image)

Secondly, when one leg is occluded by the other (figure 1), it is impossible to extract the border of each leg using only binary image. To avoid this problem, the proposed algorithm skips the period when the two legs cross each other. We notice that, when two legs cross each other, the angle between the horizontal line and the line approximating the front border of the lower part of the leg in front is smaller than 90 degrees. Therefore, to avoid this period, the proposed algorithm only analyses human gait when this angle is larger than 90 degrees as illustrated in figure 2.

B. Line approximation algorithm

In the literature, there are several approaches to approximate the border of each part of an object by a line.

In [1], [2],the authors used linear regression or orthogonal regression methods. These methods have good results when there is no outlier. However, because the anatomical knowledge is incorrect in the case of walking, the extracted border may contain the border of other parts of the leg (outliers). Consequently, due to these outliers, the lines provided by these methods are often deviated.

Another approach is to use the Hough transform. The Hough transform can deal with outliers but for this algorithm it is difficult to select the correct parameter value among the background noise.

In this article, we propose a simple but still effective algorithm which can deal with outliers specific to this problem.

The proposed algorithm has two main steps:

- Generate a set of candidate lines.
- Select the best approximation line among the candidate lines.

Based on the three-group resistant line method [4], the algorithm to generate a list of candidate lines works as follows:

Input: a sequence S of border points, each point is determined by an index value i

Output: a set of candidate lines

Begin:

1) Divide the sequence S into three equal parts: S_l (low index values) , S_m (middle index values), and S_h(high index values).
2) Create the line l^* going through the end of S_l and the beginning of S_h.
3) For each part, compute the distance from each border point to l^*. For S_l, take the border point M_l having the median distance to l^*. Similarly, take M_m of S_m, and M_h of S_h.
4) Create the line l^{ml} going through M_l and M_m, the line l^{hm} going through M_m and M_h, and the line l^{hl} going through M_l and M_h.
5) Create variations of these lines by rotating these lines a little bit. l^*,l^{ml}, l^{hm}, l^{hl} and their variations constitute the candidate line set.

End

In step 3, to ensure that the candidate lines are not going through noise border points, the points with the median distance to l^* are selected. Then, if we construct lines going through these points (and slight variations of these lines), it is likely that at least one candidate line will not be influenced by outliers at the end of the process.

After having the candidate line set, our algorithm must select the best approximation line. The best approximation line is the line to which the mean distance from border points is the smallest. However, border points may contain outliers due to the background subtraction algorithm or due to the incorrect separation of different parts of the leg. Therefore, to avoid the effect of these outliers, before computing the mean distance, n% of the border points farthest from the approximation line are discarded. In our experiment, n is equal to 20.

The effectiveness of this algorithm is illustrated in figures 1, 2.

C. Angle Comparison

Our goal is to verify if the movement of each part of a leg is similar to the movement of the corresponding part of the other leg. Each part is characterised by two lines approximating the back and the front borders of this part. Therefore, to compare the movement of one leg part, one needs to compare the evolution of the lines approximating the two borders of that part. In our system, instead of comparing lines, we compare the evolution of the (clockwise) angles with respect to the horizontal. This section presents the algorithm to compare two angle sequences.

The two angle sequences (one for the left, and the other for the right leg) to be compared have two characteristics.

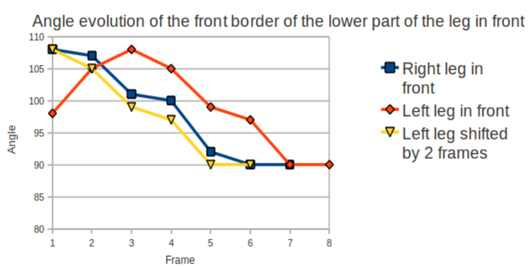

Fig. 3. The two angle sequences of the front border of the lower part of the leg in front. The first sequence is different from the second one because it starts at a higher angle but if we shift the second sequence by 2 frames, they become similar.

Firstly, because the two parts move similarly, the length of the two sequences should be nearly equal. Therefore, the comparison of the two sequences only requires the direct comparison of each element of the two sequences. The distance d in this case is the mean difference between the corresponding angles in the two sequences.

Secondly, although the length of the two sequences should be similar, the starting angle and the ending angle can be different. As defined above, the starting point of a step is defined as the point where the approximation line of the lower part of the leg in front is perpendicular to the horizontal. However, the camera cannot always catch this moment. Consequently, sometime the starting angle of a sequence is slightly higher than 90 degrees. Therefore, to correctly compare the two sequences, the algorithm shifts one sequence in both direction a few positions (figure 3). Then the final distance between the two sequences is the minimum distance obtained when we shift one sequence in both directions by p positions. In our experiment, p ranges from 0 to 2 frames. The frame rate was 30 fps.

D. Normal / abnormal gait classification

In our method, each leg is divided into upper and lower parts, and each part is characterised by two borders (back and front borders) with their respective angles with respect to an horizontal line. Beside that, to model the interconnection between the upper and lower part of one leg, our method also measures the angles between the upper back / lower back and upper front / lower front approximation lines. Therefore one step is characterise by 12 sequences of angles (figure 4).

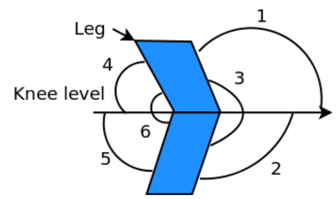

Fig. 4. For each leg we measure 6 angles.

These sequences are considered to be independent and each one can be used to construct a classifier to distinguish normal gait from abnormal one. Then, a video of human gait is classified as normal if and only if it is classified as normal by all of these 12 classifiers.

To construct one of these 12 classifiers, the videos of normal gait are collected. After that, for each two consecutive steps (one for the left, and the other for the right leg), the method computes the distance between the two corresponding sequences which is a single value d. From the set of videos of normal gait, the system construct a Gaussian distribution of d with the mean value $\bar{d}$ and the standard deviation σ_d. Then a video of human gait is classified as abnormal according to this classifier if the distance d^* between the two corresponding sequence does not satisfy the following conditions:

$$|\bar{d} - d^*| < m\sigma_d \tag{1}$$

.

In our experiment, m ranges from 2.5 to 3. With this range of standard deviations, assuming that the distribution of d is Gaussian, the classifier can cover from 98.75% to 99.74% of normal gaits.

IV. EXPERIMENTATION

To test our method, we used the videos of 9 people walking perpendicularly to the camera axis. To make videos of normal gait, each person walked normally several times in front of the camera. Then, to make videos of abnormal gait, these people wore a knee orthesis to make their gait asymmetric and walked several times in front of the camera again.

These videos were then split into shorter videos, each of them showing a person walking in front of the camera once. Among these short videos, there were 135 videos of abnormal gaits and 146 videos of normal gaits. As the proposed algorithm only models the normal gait, all the videos of abnormal gaits were used in the testing set. For

TABLE I

THE CLASSIFICATION RESULTS OF NORMAL / ABNORMAL GAIT

m	Accuracy	TP	TN	FP	FN
2.5	0.918	126.33	12.56	3.67	8.67
2.7	0.903	123.33	13.33	2.89	11.67
3	0.88	118.78	14.33	1.89	16.22

the videos of normal gait, we applied leave-one-out cross validation (9 rounds corresponding to 9 people). In each round, the normal gait videos of 8 people formed the training set. The videos of the last person were grouped with the abnormal gait videos to form the testing set. These training and testing sets were used to test the performance of our method. The final results were the average results of 9 rounds.

To measure the performance of our method, we used the following metrics in the experiment:

- True Positive (TP): the number of abnormal gait videos correctly classified.
- True Negative (TN): the number of normal gait videos correctly classified.
- False Positive (FP): the number of normal gait videos misclassified as abnormal.
- False Negative (FN): the number of abnormal gait videos misclassified as normal.
- Accuracy = (TP + TN) / (TP + TN + FP + FN)

The final results after 9 rounds of cross-validation are shown in table I. This table shows that, at $m = 2.5$ (equation 1), most of the abnormal gait videos were correctly classified but a high number of normal videos were classified as abnormal. When m increased, FP decreased but TP also decreased. When $m = 3$ most of the normal gait videos were classified correctly ($FP = 1.89$) while a still high number of abnormal gait videos was detected. Therefore, depending on specific requirements (low FN or low FP) we can change m accordingly.

When we used the color to better distinguish legs from hands, the accurracy increased to 0.96 while FP decreased to 3.33.

Analysing FP, we see that there are three main reasons for high FP. Firstly, because the system takes only a few steps (between 4 and 5) from each video, noise may interfere with the classification results. This effect was quite strong especially when the sequences were too short as in the case of the upper border points between the two legs. Secondly, different people walked at different speeds and faster speeds led to higher variability. Finally, when a person walked, the relative view point between the person and the camera changed leading to variability in the comparison.

These problems can be alleviated if people walk on a treadmill. Then instead of taking only a few steps, the system could take more steps and average the differences between these steps which would reduce the noise influence. Also with the treadmill, the walking speed can be controlled and the viewing angle remains the same.

V. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

In this article, we propose a new image processing-based method to detect abnormal gait. This method distinguishes the abnormal gait from the normal one using the movement symmetry of the two legs. Our method has two main advantages. Firstly, by not analysing the whole gait cycle, this method can avoid the period when the two legs cross. Secondly, the line approximation algorithm is designed specifically to be robust to the outlier caused by incorrect separation of upper and lower parts of the leg. However, as shown in the experiment section, the proposed methods still suffer from several problems such as the short length of the upper border sequences between the two legs, the variation of walking speed among different people, and the change of relative view point between the walking person and the camera. Despite these problems, the proposed method achieved a high classification accuracy (90%) in distinguishing normal / abnormal gaits.

B. Future Works

In the future, to overcome the problems presented in the experiment, we will apply our method with the videos of people walking on a treadmill. In term of algorithms, we also want to find a better way to combine different classifiers corresponding to different sequences. For example, instead of producing positive / negative outputs, the classifier could produce the probability that a gait video is normal or abnormal. Then by combining all the classifiers, the classification results could be improved. Finally, we want to try new line approximation methods robust to outliers such as RANSAC line fitting [9].

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