Gait Recognition for Children over a Longer Period

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Abstract: In this paper a comparative investigation into the effects of time on gait recognition in children's walking has been carried out. Gait recognition has attracted considerable interest recently; however very little work has been reported in the literature which is related to gait recognition in children. It has been suggested ([Kyr02])that the gait of children does not stabilize before they are 11 years old. In this papers we will provide arguments that support this suggestion. When looking at the performance of gait recognition, which serves as an indicator for the stability of gait, we found a relationship between performance improvement and aging of children. The gait of a group of children was measured twice with a 6 months period between the two measurements. Our analysis showed that the similarity between these two measurements is significantly lower than the similarity within each of the measurements. Finally we also report the effect of gender on performance of gait recognition.

1 Introduction

Even though gait analysis has a long history dating back to the time of Aristotle, who studied animal locomotion using artistic works, it was much later that work on the biomechanics of human walking was carried out at the end of the 19th century [Ari04, Pit09]. In recent years gait analysis has progressed rapidly with the development of more sophisticated electronics, advanced computer technology and more accurate sensors [GHS06]. A major interest in gait analysis involves its applications to bioengineering, physiotherapy, rehabilitation, the management of medical problems affecting the locomotor system and sports performance [YSS+07, SR09, JMOdG05, YMH+06]. More recently, it has also attracted considerable attention of researchers in identification and recognition for security and safety purposes [MLV+05, BS10]. Gait has a number of advantages over other forms of biometric features. For example, it is unique as each person has a distinctive walk, it is unobtrusive as gait avoids physical contact whilst collecting data unlike most other methods which involve physical touching; data can also be collected at a distance without the need for close proximity [CHH07, BCND01].

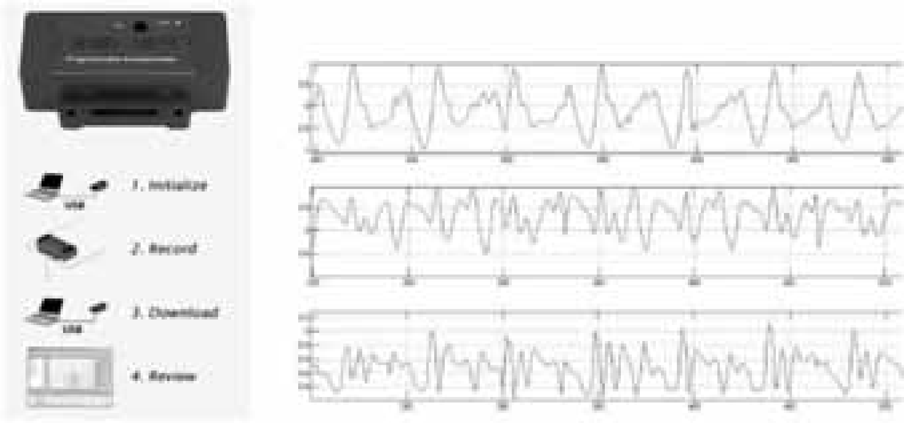
For improved security, gait analysis is being used for biometric authentication and identification [GSB06]. Currently, there are three types of systems being employed, which are machine vision based (MV), floor sensor based (FS) and wearable sensors (WS). Each type has its own unique advantages and disadvantages depending on the specific application being considered. The MV systems can be used remotely without any user interaction; however it is expensive and involves the use of background subtraction. FS based is very accurate but it is expensive to install and maintain. WS are simple, small and inexpensive devices and are not location dependent [GSB07]. These can be readily incorporated into mobile devices such as the popular i-Phone.

For adults of both genders, considerable research has been done on gait recognition and medical applications [DBH10, YTH$^+$09, BS10, BN08]. However, with children very little work has been reported in the literature [PPW$^+$97, OBC$^+$99]. In previous studies we have reported an analysis of gait performance in children compared to adults [BDB$^+$11b] and gait analysis under special circumstances [BDB$^+$11a] such as variations in walking speed and carrying objects. In this paper we present a study on the effects of time on gait patterns in children and its relationships to gender and age. The accelerometer sensor was placed on the left side of hip. A comparative analysis of gait patterns in children and adults both male and female for the purposes of recognition and identification is presented.

2 Experiment Design

In this study a programmable sensor (Model GP1, see Figure 1(a)) purchased from Sensr (USA, `http://www.sensr.com`) was programmed and used to record the motion of the children in several walking cycles. The GP1 measures the acceleration in three perpendicular directions which will be referred to as x, y and z. Figure 1(b) is an example of the output obtained from the GP1 sensor and shows the signals obtained in the x, y and z directions. These signals provided the raw data for the subsequent analysis reported in later sections of this paper. It is converted into a unique pattern for each individual for comparison. The GP1 can collect acceleration data up to $10g$ and has a sampling rate of 100 Hz per axis. Acceleration data is filtered inside the GP1 by a 2 pole Butterworth low pass filter with a cut-off frequency of 45 Hz [Sen07]. The device has a USB interface for transferring data and a 1 Mbyte memory for storage purposes. An overview of the specification of the Sensr GP 1 is given in Table 1.

In this study, 46 children (31 boys and 15 girls) with ages ranging between 5 to 16 years participated. Ethical approval was obtained from the school principal, the university's ethical approval committee and parents of the children. For each child, the parents formally approved participation in the study by signing a standard University approval consent form prior to volunteering. The criteria set for the child to take part of this study were that they should have no previous history of injury to the lower extremities within the past year, and no known musculoskeletal or neurological disease.



(a) (b)

Figure 1: *Left*: SENSR GP1 Device, *Right*: (x,y,z) Acceleration Output

Item	**Specification**
Size	3.935" x 2.560" x 1.140"
Weight with batteries	8.25 oz
Connectivity	USB
Accelerometer type	Programmable 3 axis MEMS
Accelerometer range	Programmable $\pm 2.5g$, $\pm 3.3g$, $\pm 6.7g$, $\pm 10g$
Sampling rate	100 Hz per axis
Memory type	Non-volatile EEPROM
Memory size	1 MByte
Device Temperature Range	$-20^{o}C$ to $+80^{o}C$

Table 1: Partial Specification of the GP1 Sensor.

The Sensor was attached to left side of the hip (see Figure 2(a)) because previous studies have shown that the hip is the most stable position compared to leg, arm and other body positions. Volunteers were told to walk normally for a distance 17.5 meters in a carpeted hall on a flat surface in bare feet (see Figure 2(b)). At the end of the hall section the volunteers waited 5 seconds, turned round, waited 5 seconds and then walked back again.

This procedure was repeated twice and the data recorded was transferred to a PC for storage and analysis. The detailed sequence is as follows.

1. Connect to PC and initialise
2. Attach to the belt on the left hand side of the hip
3. Press the start recording button
4. Wait for 5 seconds

(a) (b)

Figure 2: *Left*: The Sensor Position, *Right*: Walking Hall

5. Walk 17.5 meters from one end of hall section to the other
6. Stop and wait for 5 seconds
7. Turn around and wait for 5 seconds
8. Walk back 17.5 meters wait for 5 seconds and turn around
9. Repeat procedure

After walking twice the sensor was detached from the volunteer, connected to the computer and the data inside the GP1 device was downloaded and stored and the filed was named appropriately.

The main experiment was carried out over a time period of 6 months. First experiment was performed in September 2010 and the second was performed in March 2011. There were 20 volunteers who participated in the long term experiment out of an initial group of 46. In September 2010, each subject did 2 sessions, whilst 16 sessions were performed in March 2011. This means that each subject participated in 18 sessions in total.

3 Feature Extraction

The raw data retrieved from the Sensr sensor needs to be processed in order to create robust templates for each subject. The feature extraction steps are based on the work of [DBH10].

Preprocessing: First we apply *linear time interpolation* on the three axis data (x,y,z) retrieved from the sensor to obtain an observation every $\frac{1}{100}$ second since the time intervals between two observation points are not always equal. Another potential problem is that the acceleration data from the sensor includes some noise. This noise is removed by using a *weighted moving average* filter (WMA) . The formula for WMA with a sliding window of size 5 is given in Equation 1.

$$\frac{(a_{t-2}) + (2a_{t-1}) + (3a_t*) + (2a_{t+1}) + (a_{t+2})}{9}, \tag{1}$$

where a_t is the acceleration-value in position t. The current value we are located at are given weight 3, the two closest neighbors weight 2 and the next two neighbors weight 1.

Finally we calculate the resultant vector or the so-called magnitude vector by applying the following formula,

$$r_t = \sqrt{x_t^2 + y_t^2 + z_t^2}, t = 1, ..., N$$

where r_t, x_t, y_t and z_t are the magnitudes of resulting, vertical, horizontal and lateral acceleration at time t, respectively and N is the number of recorded observations in the signal.

Cycle Detection: From the data it is known that one cycle-length varies between $80 - 140$ samples depending on the speed of the person. Therefore we need to get an estimation of how long one cycle is for each subject. This is done by extracting a small subset of the data and then comparing the subset with other subsets of similar lengths. Based on the distance scores between the subsets, the average cycle length is computed, as can be seen in Figure 3.

The cycle detection starts from a minimum point, P_{start}, around the center of the walk. From this point, cycles are detected in both directions. By adding the average length, denoted γ to P_{start}, the estimated ending point $E = P_{start} + \gamma$ is retrieved (in the opposite direction: $E = P_{start} - \gamma$). The cycle end is defined to be the minimum in the interval Neighbour Search from the estimated end point. This is illustrated in Figure 4. This process is repeated from the new end point, until all the cycles are detected. The end point in the Neighbour Search is found by starting from point E. From this point we begin searching 10% of the estimated cycle length, both before and after E for the lowest point. When the minimum point is found we store it into an array and we begin searching for the next minimum point by adding the length of one estimated cycle. When forward searching is complete we repeat this phase by searching backwards so all steps in the data are identified. We will therefore end up with having an array containing start/end index for each step. These points will therefore be used for the extraction of cycles, as illustrated in Figure 5.

Template Creation: Before we create the feature vector template, we ensure that cycles that are very different from the others are skipped. This is done by taking each cycle and calculating its distance compared to every other cycle by using dynamic time warping (DTW),

$$dtw_{i,j} = dtw(cycle_i, cycle_j)$$

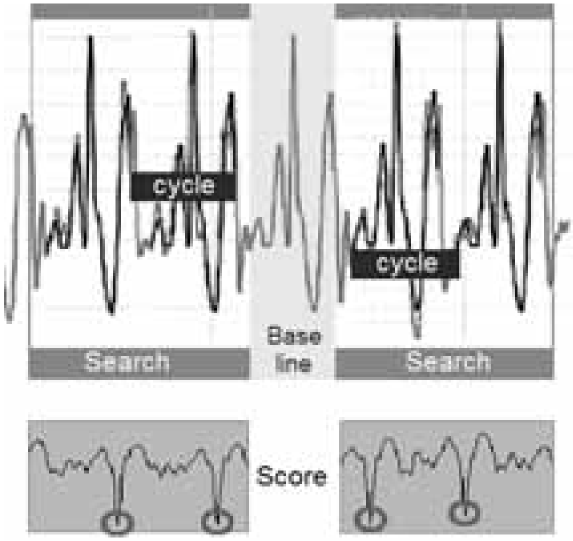


Figure 3: The yellow baseline area indicates the subset with 70 samples that are extracted, the green area is the search area where the baseline is compared against a subset of the search area. The 4 black subgraphs are the baseline at those points that has the lowest distance with the search area subsets, and the difference between them (blue area) indicate the cycle length [DBH10].

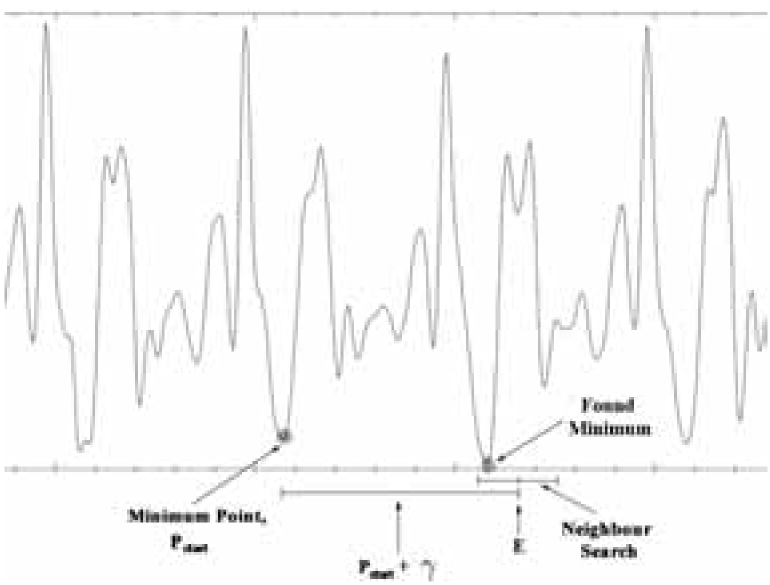


Figure 4: Cycle detection showing how each cycle (i.e the steps) in the resultant vector is automatically detected [DBH10].

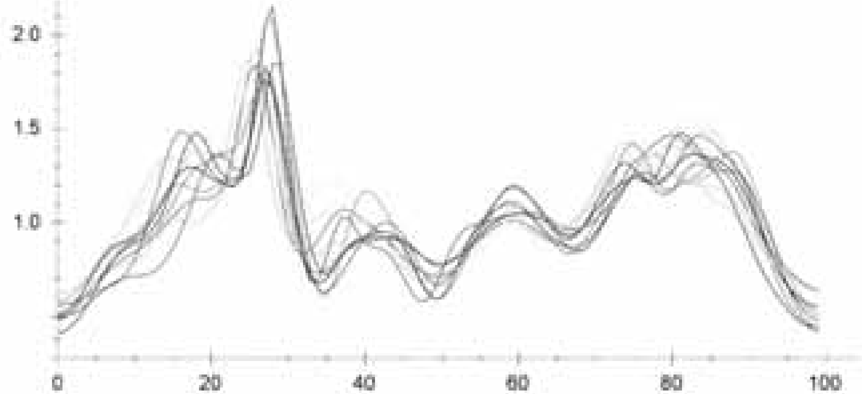


Figure 5: The cycles have been extracted by taking starting and ending point for each step. Both these points are minimum points from the resultant-vector data set.

where i = 1..N and j = 1..N, which means that we will get a symmetrical N × N matrix. From this point, we calculate all the averages of one specific cycle to all others.

$$d_i = \frac{1}{N-1} \sum_{j \neq i} dtw_{i,j}$$

Thereafter we calculate the average of the calculated averages,

$$\mu = \frac{1}{N} \sum_i d_i$$

which therefore will be the total average. Now we will have the opportunity to see how much deviation exists from one cycle to another. Thus, the standard deviation, μ, is calculated and to use a realistic border we will accept cycles that are within 2σ of difference from the total average

$$d_i = [\mu - 2\sigma; \mu + 2\sigma]$$

The 2σ is used to process trial and error. If a lower limit was chosen, we might have ended up skipping too many cycles, while a higher limit would lead to accepting too many cycles.

When all odd cycles are removed, we create the feature vector. In previous work [GSB07], researchers used the average cycle as a feature vector. That was computed by combining all the cycles (which were normalized) into one average median cycle. In this paper all of the extracted cycles are stored as a template for one subject, denoted $C^S = \{C_1^S, ..., C_N^S\}$ where each cycle i = 1..N is normalized to a length of k observations; in our case $k = 100$.

4 Feature Vector Comparison

A distance metric, named the cyclic rotation metric (CRM) with small changes, is applied [DBH10]. This metric cross-compares two sets of cycles with a cyclic-rotation mechanism to find the best matching pair:

Cross Comparison: is used to find the most optimal and best distance score when cross-comparing two set of cycles, denoted $C^S = \{C_1^S, ..., C_N^S\}$ and $C^T = \{C_1^T, ..., C_M^T\}$. This simply means that each cycle in the set C^S is compared to every cycle in the set C^T. The comparative distances are calculated by the cyclic rotation metric (CRM). From the total number of N $\times$ M distance scores calculated, the minimum score is selected,

$$d_{min} = min\{CRM(C_i^S, C_j^T)\}$$

where i=1..N and j=1..M. The pair of cycles with the most minimum similarity score is considered the best matching pair. Thus, this best (i.e. minimum) similarity score, d_{min}, is used as the similarity score between set C^S and C^T.

Cyclic Rotation Metric (CRM): is a metric that compares a reference cycle and an input cycle with each other. The reference cycle, i.e. C_i^S, which is compared against the input cycle, i.e. C_j^T, is stepwise cyclical rotated. After each rotation the new distance is calculated using the Manhattan distance. This is repeated until the input template has done a full rotation, then the lowest distance value is kept:

$$d(C_i^S, C_j^T) = min_{w=1..k}\{Manh(C_i^S, C_{j(w)}^T)\}$$

The reason why we use the Manhattan distance when rotating is due to the fact that Manhattan runs fast. Furthermore the cyclic rotation is done to minimize the problem when local extremes among the cycles we create for each input are located at different locations.

5 Analysis and Results

In this section we will present the analysis performed and results. Three different tests have been performed and these are as follows:

1. The first test analyzes the performance of gait and how it varies with the age of the children.
2. The second test analyzes the performance of gait and studies its variations over time, with a 6 months interval measurements.
3. The third test analyzes and compares the performance of gait between boys and girls.

As mentioned in a previous study by [Kyr02], it was suggested that the gait of children does not stabilize before they are 11 years old. In order to test this hypothesis, we have split the set of the 46 children into three groups. The first group consisted of 17 children that are at most 10 years old. The second group consisted of the 11 children in our experiment that are only 10 years old, whilst the third group consisted of 18 children that were between 11 - 16 years old. The split was done in this way because the size of the three groups is more or less equal. We do realize that the number of children in each of the three data sets is rather small, which influences the statistical significance of the results negatively. Nevertheless we want to present the results of our analysis on all three groups as an indication of the performance.

The data used for the analysis is the collected gait data from March 2011, i.e. all of the participants contributed 16 data samples for the analysis. The resulting EER values are given in Table 2 for each of the three age groups. We also included the analysis results for the case where the group of 46 children was not split. The resulting EER can be found in the columns "All against All".

	5-9 years	**10 years**	**11-16 years**	**All against All**
Manh.+Rotation	16.12	13.74	13.21	14.23

Table 2: EER Performance results in % on the collected dataset due to age.

From the results in Table 2 we see that with increasing age the EER value decreases, indicating an increase in the stability of the walking of children with increaing age. This seems to confirm the suggestion from [Kyr02]. In order to test this suggestion further we tested how the walking of children would change over time. As mentioned in Section 2 do we have gait data samples from 20 children who participated in the experiment in both September 2010 and in March 2011. In September 2010 each of the 20 children provided only 2 gait data samples, but in March 2011 each of them provided 16 data samples. Of these 20 children, 18 were below 11 years old, one was exactly 11 years old and one who was 14 years old.

We have determined the EER for each of these periods separately and we see in Table 3 that the resulting EER values are rather similar: 18.88% for September 2010 and 18.94% for March 2011. In order to see if the gait has developed over time we also added a test where the template was created with the September 2010 data, while the test data came from the March 2011 data. From Table 3 we see that the EER value increases significantly from approximately 18.9% to 34.02%. This indicates a major change in the way of walking of these children, confirming the suggestion from [Kyr02] once again.

	September 2010	**March 2011**	**6 Months**
Manh.+Rotation	18.88	18.94	34.02

Table 3: EER Performance results in % on the collected dataset due to time.

Although the number of participants in the tests is rather low, we can still clearly see a change of performance over time. We see that one group of children measured twice, with 6 months interval between measurements, has a large change in their way of walking, while we on the other hand there is also an increased stability in walking with growing age. Both these facts support the suggestion that the walking of children stabilizes around 11 years as Kyriazis suggested in [Kyr02].

A final test was performed to see if there are differences in gait recognition between boys and girls. The results can be found in Table 4. We know from Section 2 that the number of boys was more than twice the number of girls in the experiment conducted in March 2011. In order to make the results comparable we have used the gait data from all 15 girls and randomly selected 15 boys. The distance metric used was again the Manhattan with Rotation metric. The slightly lower EER for girls (13.44% compared to 14.86%) indicates a that the gait of female subjects is slightly more stable than the gait of male subjects.

The result in Table 4 for the boys is based on a random selection of 15 out of the available 31 boys. In order to make the result independent of the selected boys, this random selection has been performed 100 times and the presented performance is the average over these 100 results.

	Males	**Females**
Manh.+Rotation	14.86	13.44

Table 4: EER Performance results in % on the collected dataset over time due to gender.

6 Conclusions

As far as we know there are no published results on the stability of gait for young children, except from the suggestion in [Kyr02]. In this paper we have given evidence indicating the correctness of that suggestion. It has been shown that as the children get older their gait becomes more stable and that there is a large difference between the gait of a group of 20 young children measured six months apart; this indicates that the gait of children is still developing at these young ages.

In addition, a comparison was carried out between the stability of gait from girls and boys and it was found that the female gait was slightly more stable as indicated by a lower EER.

Whilst the results presented in this study are interesting and in line with previous suggestions, a more comprehensive study with a higher number of participants is required to confirm the results described in this paper. In addition, research on the stability of gait from adults over a longer period of time is needed to compare against the results presented in this paper.

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