

Using Ground Reaction Forces from Gait Analysis: Body Mass as a Weak Biometric

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Abstract. Ground reaction forces generated during normal walking have recently been used to identify and/or classify individuals based upon the pattern of the forces observed over time. One feature that can be extracted from vertical ground reaction forces is body mass. This single feature has identifying power comparable to other studies that use multiple and more complex features. This study contributes to understanding the role of body mass in identification by (1) quantifying the accuracy and precision with which body mass can be obtained using vertical ground reaction forces, (2) quantifying the distribution of body mass across a population larger than has previously been studied in relation to gait analysis, and (3) quantifying the expected identification capabilities of systems using body mass as a weak biometric. Our results show that body mass can be measured in a fraction of a second with less than a 1 kilogram standard deviation of error.

Keywords: body mass, biometric, ground reaction forces, gait.

1 Introduction

Body mass is one of several weakly identifying biometrics used for classification. For example, descriptions of wanted criminals almost always include their height and build, both of which contribute to the helping rule in or rule out suspects. When applying for a driver's license, most states require the applicant to give information such as weight, height, and other physically identifying characteristics. In each of these cases, the body mass biometric is used less to identify the person individually and more to rule out other individuals. How would the weakly identifying ability of body mass change if it could be measured accurately to the kilogram, within a fraction of a second, and without requiring the active participation of the person being measured?

This study addresses just how this measurement can be taken and explores the expected identification capabilities of using such a measure. Results indicate that the standard deviation of measuring body mass while the person is walking is less than 1

kg. Moreover, this measure can be taken in a fraction of a second and over a small footprint (two 0.5 x 0.5 meter force plates). Two methods are developed for obtaining this body mass. The gait cycle method is restricted to acting on the ground reaction forces experienced during normal gait. The steady state method can be applied more generally to other patterns of forces experienced such as those generated by people passing over the force plates in wheelchairs.

The remainder of this paper will be organized as follows. Section 2 will describe the related work which uses ground reaction forces during gait for identification. Section 3 will describe some of the benefits and drawbacks of using body mass as a biometric. Section 4 will describe two methods which can be applied to actual ground reaction force data to extract the body mass feature. Section 5 evaluates these methods to determine the level of precision and accuracy obtained on a set of clinical walking trials. Section 6 will quantify the expected identification power on three different populations. Section 7 will describe potential future work and section 8 will conclude.

2 Related Work

Gait analysis is emerging as a promising biometric identification technique [8]. A wide range of media and techniques have been developed to classify gait sequences. The two categories of gait analysis most directly related to the work presented in this study are those which are based at least in part body size and/or shape, and those which analyze ground reaction force patterns.

In the system by Bobick and Johnson [10], three body measures are obtained from video: overall height, leg length, and torso length (including head). These measures are combined with a stride length parameter to create a feature vector. In the system by BenAbdelkader et al [11], stride length, cadence, and height are used as the features extracted from video sequences.

Ground reaction forces measured using force plates have also been used in a variety of gait recognition systems. The ORL Active Floor [1], the Georgia Tech Smart Floor [2], and the floor developed by Middleton et al at the University of Southampton all use only the impact of footsteps for identification purposes. In the biometric identification system developed by Cattin [12], data collected from force plates is combined with video recordings in order to improve the recognition rate over using ground reaction forces alone.

The Active Floor uses hidden Markov models to identify individuals. This system was able to achieve a 91% identification rate on 15 individuals. In later experiments the ground reaction forces were scaled by the inverse of the average force experienced during one footstep. This normalizing procedure was aimed at removing the influence of body mass on the identification rate. With the scaled data, the identification accuracy dropped below 50%. The Active Floor paper suggests that using different segments of the gait cycle may produce more accurate identifications.

The Smart Floor extended this work in many ways. The testing using the Smart Floor was much more extensive because the experiments involved the same people wearing different shoes in order to evaluate the effect of footwear on the recognition

rate. Their results indicated that different footwear had a negligible effect on the identification rate. Nearest neighbor applied to ten different features of ground reaction forces for a single footstep was able to achieve a 93% identification rate on 15 individuals.

In the floor developed by Middleton et al, three gait features unrelated to body mass were examined for their identifying capabilities [3]. This system used 1536 pressure switches arranged on a 3-meter long by 0.5-meter wide floor mat. Fifteen people walked up and down the mat 12 times each. The features extracted from these trials were the stride length, stride cadence, and time on toe to time on heel ratio. The third feature alone, the toe to heel ratio, was able to achieve 60% identification accuracy on 15 individuals using four footsteps. When all three features were combined, the identification accuracy rose to 80%.

Cattin improves upon the ground reaction force only systems by capturing video simultaneously with the force plate data. This approach is more robust than other approaches which synthetically combine different biometrics by assuming they are independent. The model used by Cattin does not need to make such a claim because any correlation between the video sequence identification and the force plate identification will be present in his identification algorithm. Through fusing three video sequences with force plate data, a recognition rate of 99.74% is achieved when using 6 walking sequences as the training set and 4 walking sequences in the test set from 17 individuals. The force plate recognition rate alone (not fused with the video sequences) was 93.4%.

All four of these ground reaction force studies confirm that gait has some degree of identification information when measured by floor sensors. What is not clear from the above studies is how much influence body mass has on the level of identification. The Active Floor makes very clear that body mass is indeed a significant part of their identification scheme, but it does not fully characterize the amount of identifying information that remains after the body mass factor has been removed, nor does it address how accurately the body mass biometric can be measured. The Smart Floor incorporates features related to body mass, but it does not evaluate the degree to which these features contribute to the identification rate. The system by Cattin et al attempts to avoid using body mass as a biometric by focusing instead on the dynamic aspects of gait present within the force plate signatures.

Our work focuses on characterizing the contribution that body mass can provide for identification purposes. We neither promote nor dissuade from using body mass as a biometric. Instead, we provide a detailed analysis of how body mass can be obtained from ground reaction forces, how accurate and precise this extracted body mass feature is, and how accurately the body mass feature identifies over larger populations than are typically examined with respect to gait recognition. This analysis may be independently evaluated to examine the potential gains of using body mass as a biometric within different systems with different needs.

3 Benefits and Drawbacks of Using Body Mass as a Biometric

While body mass does not share the strongly identifying characteristic with other biometrics such as fingerprints and iris scans, the body mass biometric does have characteristics that make it an attractive feature to obtain within the context of a biometric fusion system. One of the strongest benefits of measuring body mass as opposed to other more identifying features is that body mass can be measured without the active participation of the person being measured. Simply walking over the force plates registers the person's body mass. While some methods of measuring this body mass require that the person be walking normally over the plates, other methods exist which can measure the body mass regardless of the manner of traversing the plates (these methods will be described in the next section.)

One of the greatest disadvantages of using body mass as a biometric is that the person can easily alter his or her body mass to some degree by carrying or depositing objects. If the typical mass of objects carried (or deposited) is much less than the typical differences in body mass, then a reduced identifying power remains even when using the altered body mass. Such changes in body mass by carrying or depositing objects are difficult to characterize generally and tend to be more domain specific. For example, people entering and exiting a classroom will likely carry in about the same load as they carry out but people entering a grocery store are likely to be carrying larger loads upon exiting than they were upon entering. Section 6 will describe how these differences in the expected load people will carry can affect the expected accuracy of the body mass biometric.

Finally, actual body mass has the property that it can gradually change over time. The amount of time between readings is a good indicator as to the amount of expected change that can occur. For example, over the course of 12 hours, it is very unlikely that a person will be able to gain or lose 5 kg, but this amount of change becomes more and more feasible when the time is extended to weeks or months. For this reason, the body mass measure must be regularly taken in order to remain accurate. Including body mass as a static biometric on documents such as passports will have a weaker ability to identify because of the long duration these documents remain valid. If however the passport were to contain a chip which could be regularly and securely updated, body mass could prove a useful biometric.

4 Methods for Extracting Body Mass

This study examines two basic methods for extracting body mass from the forces produced while walking. The gait cycle method assumes that walking is a periodic motion in which the forces produced are roughly identical for each period. One period of the cycle is observed and the average force over this period is divided by the acceleration of gravity in order to calculate the mass. The steady state method assumes that over a long enough duration of time, the average force generated by any object with any behavior will come to a steady state. This steady state force is then divided by the acceleration of gravity to again yield the mass. The steady state method has the advantage of being able to calculate mass over a broader set of

scenarios such as people traversing the force plates in wheelchairs or people using crutches while passing over the force plates. The gait cycle motion method would have to incorporate more complex patterns in order to identify these patterns and appropriate periods.

In order to evaluate the accuracy and precision of these two methods, ground reaction force data were acquired from clinical gait trials [4]. This data contains anthropometric, kinematic and force plate data from 62 children walking normally across two consecutive force plates. Three trials are available per child and the mass of each child is reported directly. To the authors knowledge this database is the largest publicly available collection of ground reaction forces with corresponding body mass measurements.

The force plates used to collect the data for this study are OR6-7 Force Platforms manufactured by Advanced Mechanical Technology, Inc [13]. These force plates are specially designed for use in a clinical gait analysis setting and retail for approximately \$10,000 each [14]. Much more appropriate and less expensive force plate designs are described in the Active Floor and Smart Floor papers. Data collected using these custom plates is not readily available, but the complete ground reaction force and body mass data used in this study are well documented [4].

4.1 Gait Cycle Method

The pattern of ground reaction forces during the gait cycle is shown in Figure 1. The first part of this cycle is called *double support*. This is when the vertical force is split between the feet. At the start of the recorded forces one foot is on the force plate and the other is off the force plate. When the weight is transferred onto the heel, this is called the *load response*. Sometimes before the weight is entirely transferred, there is a transient force experienced just before the load response. The force during the load response is typically a force exerted which exceeds the normal standing force. Between the heel coming down and the toe pushing off is what is called the *midstance*. Typically the vertical ground reaction forces experienced during the midstance are below that of normal standing force. When the toe pushes off, this is called the *terminal stance* because this is the last part of the gait cycle where the person's weight is entirely on one foot. Following the terminal stance is another period of double support and the cycle repeats itself.

Ideally, each gait cycle would generate identical ground reaction forces when walking on level ground at a constant pace [4]. If this were the case, then two complete footsteps would be sufficient for characterizing the walking pattern (assuming the period of time of double stance is symmetric). In addition, the average of the left and right foot ground reaction forces over each period would be the same. Since there is no net rise or fall over time during normal walking, this average ground reaction force is the same as the force which would be experienced if the individual were standing still. The gait cycle mean in Figure 1 and 2 would be computed using the forces from time a to d. By dividing this force by the acceleration of gravity, the body mass can be determined. Figure 2 shows this force over 1.5 gait cycles (3 steps).

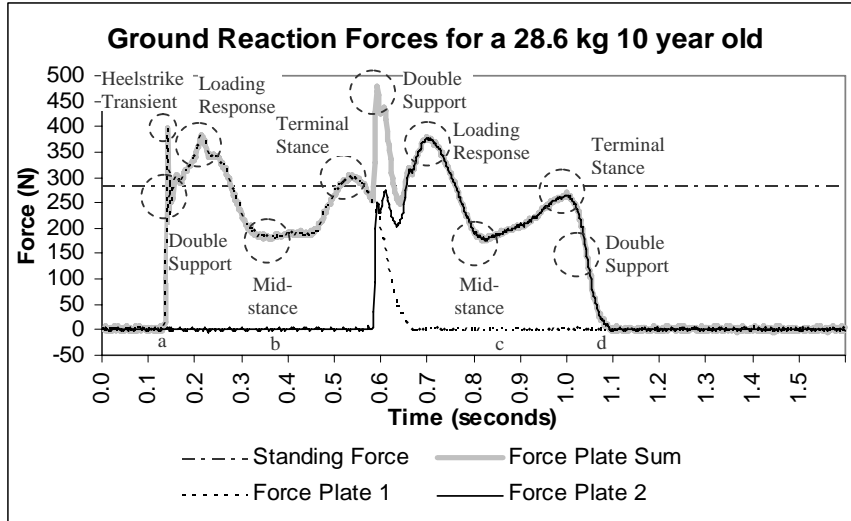


Fig 1. The ground reaction forces represent two steps from dataset aa_10_01 in [4]. The first step fell directly on the first force plate and the second step fell directly on the second force plate.

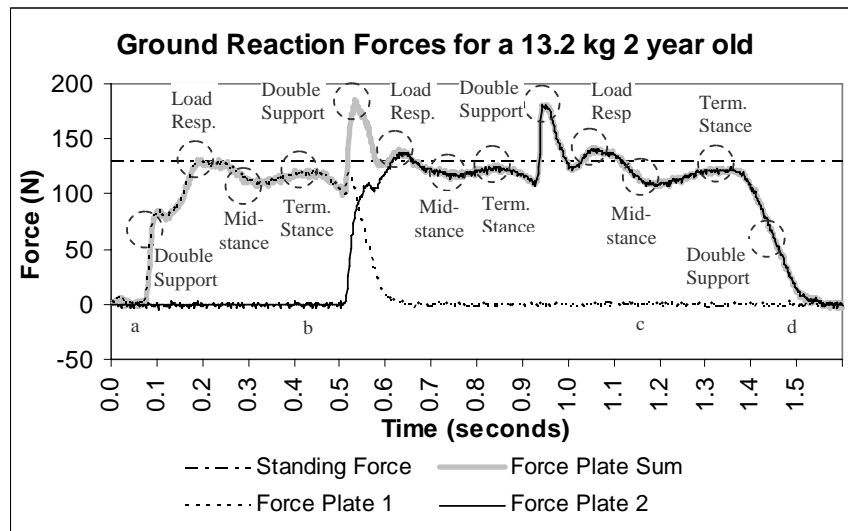


Fig 2. The ground reaction forces represent three steps from dataset am_02_01 in [4]. The first step fell directly on the first force plate and the second two steps fell directly on the second force plate.

4.2 Steady State Method

During the gait cycle, the sum of the left foot and right foot ground reaction forces vary above and below the force that would be experienced if the person were standing still. Typically, the load response, the terminal stance, and double support experience forces above average standing force and the midstance experiences forces below average standing force. However over time, the average force must tend toward the average standing force regardless of the pattern of forces unless there is a net vertical change in the center of gravity.

When the person steps onto the plate and off of the plate, he or she is transferring forces which may not be measured because they are off the measuring area. This can be seen in Figure 1 where the sum of the forces for the first and last double support is much lower than the middle double support when the person is entirely over the force plates. For the period of time the forces exerted by the person are entirely over the measurement area, average force experienced should be the same as the average standing force if there is no net vertical change in the center of gravity.

There are two competing potential sources of error when using this method to calculate the average force. The first potential error is to start taking measurements before the person is entirely over the measurement area. This would lead to measuring an average force below the standing force. In order to avoid this potential error, as many of the measurements when transitioning onto and off of the force plates should be discarded. The second potential error can occur if there is asymmetry with respect to the gait cycle when the measurements begin and end. Because there is normal rise and fall during walking, if the measurements begin and end at different phases of the gait cycle, then there may be a net vertical change in the center of gravity. This error can be minimized by making the reading range as large as possible so as to make insignificant the contribution of this error to the mean force experienced. Thus the minimizations of the two errors compete. The minimization of the first error requires as many of the start and end of the measurements to be discarded while the second potential error requires as large of a read area as possible. For this reason a balance must be reached between how many of the beginning and ending measurements to discard and how many to retain. As the area of the force plates increases, each source of error becomes easier to minimize. For Figure 1 and Figure 2, the steady state mean would be computed by discarding the first and last quarters of the measurements (time a to b and c to d) and retaining the middle half of the measurements (time b to c).

4.3 Implementing the Methods

The gait cycle method requires the segmenting of the force signals into footsteps. If every step were to directly fall onto the center of each plate then segmentation of the footsteps would be a simple task. However, there are many occurrences of individuals stepping more than twice (such as in Figure 2), stepping partially on a force plate, and stepping between force plates. While this complicates the segmentation, this type of activity must be handled if the force plates were to actually be deployed in a commercial application.

The two consecutive periods of activity in the force plates are considered an integral number of footsteps with no footstep falling between the force plates. For example, in Figure 2, the first force plate receives one footstep while the second force plate receives 2 footsteps. The period of time when both the first and second force plates have active readings is considered the double stance phase. The beginning and end of the signal are also considered part of the double stance phase in which one foot is on the force plate and the other is off the measurement area. Therefore, if the gait cycle is symmetric, then the sum of the beginning and ending of the signal would correspond to a single double stance phase while the other parts of the measure are directly over the force plate. In this way, the sum of all forces over both plates includes one less double stance phase than actually occurred. Therefore, to compute the gait cycle mean, the sum of the forces is divided by the period of activity less the period of time both force plates are active.

The problem of segmenting the forces into footsteps does not exist in the steady state method because there is no assumption about the pattern of signals experienced. The only requirement is that the forces begin and end measurements when the vertical center of gravity is the same upon starting to measure and finishing the measures. Determining this duration of the beginning and ending to discard and how much of the center to keep must be found experimentally. For the purposes of this study, the first and last 27.5% of the active measures were discarded for all individuals. This amount to discard reached a balance between discarding the forces when they are being transferred onto the plates and retaining an amount which makes changes in the vertical center of gravity insignificant with respect to the duration of measures taken.

5 Accuracy and Precision of the Methods

In order to evaluate the ability of using body mass to identify, the accuracy and precision of the different measurements need to be characterized. The accuracy will determine how close to the true value the measures are, and the precision will determine how close consecutive measures are to each other. Both the accuracy and precision are important to evaluate independently. Because the true measure of body mass may be unavailable, the consistency of the body mass estimate determines in part how the measure may be used to classify individuals into groups. If the measure were for example, always 10 kg less than the true measure, it would have perfect precision but poor accuracy. This precision and a predictable accuracy though would be sufficient for classifying individuals. Of course, precision alone is not sufficient. Measuring all body masses as 1 kg would give perfect precision, but the accuracy of the measure is so far from the true value that it could not be used. In this way, it is also necessary to measure the accuracy of the body mass measure.

5.1 Accuracy of the Gait Cycle and Steady State Methods

To the author's knowledge, no previous study identifying individuals by the ground reaction forces has reported the body masses of the individuals. Because the true body mass is known for all of the 62 children from whom the ground reaction forces

were recorded, the accuracy of the body mass measure for the two methods can be evaluated. Each of the children made three passes over two consecutive 0.5 meter by 0.5 meter force plates. The mass measures were computed for both the gait cycle and steady state methods. The actual mass was then subtracted from the measured mass in order to determine the errors experienced.

For the gait cycle method, the mean error was -1.18 kg with a standard deviation of 1.78 kg. The maximum absolute error experienced was 11.32 kg below the actual mass and all measures were within a 14.45 kg range (from 3.13 kg above actual mass to 11.32 kg below actual mass). For the steady state method, the mean error was -0.67 kg with a standard deviation of 0.96 kg. The maximum absolute error experienced as 5.66 kg below the actual mass and all measures were within a 7.00 kg range (from 1.33 kg above the actual mass to 5.66 kg below the actual mass). Because the steady state mean experienced far better accuracy and would function across a wider range of force plate signal patterns (such as if a wheelchair would roll across the force plates), only the steady state method will be examined from this point forward.

In order to characterize more fully the errors experienced using the steady state method, the errors were examined to determine if the distribution of error is close to normally distributed. In order to do this, the Kolmogorov-Smirnov statistic was evaluated [5]. This statistic evaluates the maximum deviation from the expected order statistics for any fully specified distribution. For the statistic to be valid, the distribution parameters must not be drawn from the sample being tested itself. For this reason, the first two trials were used to compute the mean and variance parameters for the normal distribution, and the third trial was evaluated to see if there is evidence of deviation from this normal distribution. This experiment was repeated using the first and third trials to compute the parameters and test with the second trial, and finally with the second and third computing the parameters and the first being evaluated. The 90%, 95% and 99% confidence levels for this statistic are 0.155, 0.173, and 0.207 respectively when examined on a set of 62 samples. Values below these numbers indicate there is no strong evidence of deviation from the tested distribution while values above indicate there is evidence of deviation. The three Kolmogorov-Smirnov statistics computed for the errors of the steady state method were 0.124, 0.189, and 0.204. These results indicate that the distribution of error shows slight deviation from what would be expected from a normal distribution. Qualitatively, the errors tend to have a longer tail in the underestimating direction.

In order to evaluate the effect of body mass on the error, correlations between the actual body mass and the error were computed over each of the three trials. These correlations are -0.71, -0.65 and -0.47. They indicate there is a trend toward underestimating the mass more as the body mass increases. In addition, the correlation was computed between the actual body mass and the absolute error. These correlations are 0.67, 0.60, and 0.45. These positive correlations indicate there is a trend of increasing magnitude of error as the body mass increases. These correlations are important to heed because they indicate that the accuracy with which body mass can be measured may be slightly less in adults than it can be in children because of the increased average body mass. The correlations imply that further testing should be done in order to evaluate if this correlation is indeed causation.

5.2 Precision of the Steady State Method

While the accuracy of the steady state method evaluates to some degree the level of identification that measured body mass can provide, the precision of the measures also can influence the identification level. For example, it is possible to achieve the level of accuracy described in section 5.1 with every body mass measure coming out exactly the same per individual or vastly different per individual (constrained to achieve overall identical mean, standard deviation, max and min over the population).

For each individual, the range of the three values was computed (maximum measure minus minimum measure). The average range of body mass measures over the 62 children was 0.91 kg and the standard deviation of this range was 1.00 kg. The maximum range experienced was 5.05 kg. In addition, the correlation of errors between trials was computed. The correlation of first and second, first and third, and second and third respectively are 0.58, 0.38 and 0.38. This seems to indicate that there is some level of clustering of the errors which will make the measures more precise than the standard deviation of the overall accuracy indicates.

6 Identifying with Body Mass

There are two primary factors that influence the ability to identify using body mass – the distribution of body mass within the population, and the combination of precision and accuracy with which this measure can be obtained. The distribution of body mass in the population will not only affect the overall identification performance, but this distribution will also affect how identifiable each individual is. For example, uniformly distributed body masses provide the greatest overall level of identification due to the maximal dispersion and every individual is equally identifiable (with the exclusion of those at the extremes). If the body masses were instead normally distributed, then the individuals with masses in the tails will be the most identifiable and there would be a lesser overall identification accuracy when compared to uniformly distributed masses. This overall and individual identification level needs to be exposed in order to understand fully the amount of identification information provided by body mass.

The precision and accuracy achieved in clinical trials was explored in Section 5. The actual experience in the field may be quite different. People may carry more or less load on their person causing the body mass measure to experience greater magnitudes of error. Moreover, behavior outside of controlled trials may introduce other unexpected errors. For this reason, the identification power of body mass must be explored in a manner which addresses these domain specific sources of error apart from the measurement error.

These interactions of the distribution of body mass in the population and the model of error are explored in Figures 3-6. Figures 3-5 describe the level of identification on individuals with a given mass while Figure 6 describes the overall expected identification power given a continuous range of error models. Figure 3 shows the percentage of other children in the clinical trials who have an actual body mass within a given range. For example, the solid black line shows that there are

about 5% of the children between 19 and 21 kg (a 2 kg range centered at 20 kg). If children being identified were rejected when the measured mass was more than 1 kg different from what is expected, then there would be a 5% false accept rate for a 20 kg child. However the false accept rate under the same scenario but for a 50 kg child would be near 0%. In both cases, if the body mass measures were within ± 1 kg 90% of the time, then the false reject rate for all children would be 10%. Figure 4 explores this same interaction, but over a larger population of children the same age as those in the [4]. Figure 5 explores this interaction over about 4000 adults [6].

Figure 6 explores the overall expected identification power for a continuous set of ranges for the three populations in Figures 3-5. This graph can be used to describe the percentage of the population that would be expected to be in the given range if a person were selected randomly from the population. Stated another way, this is a mapping of the expected false accept rate for a given false reject rate and given a measurement error model. For example, if 90% of the masses measures are ± 5 kg from the true body mass (a 10 kg diameter of range), then approximately 30% in the child population would be accepted in this range. This roughly translates into mapping a 10% false rejection rate to a 30% false acceptance rate for the population described. Figures 3-6 are all functions of the distribution of body mass within the population, but they can be used to estimate the expected false rejection and false acceptance rates under general measurement error models so long as the error is symmetrically distributed around the true measure.

For the purposes of directly evaluating the identification power of the ground reaction forces in the child database in particular [4], the following experiment was performed. For each of the three trials, the steady state mass was computed. The body mass measures for the first two trials per child were averaged to create a baseline mapping of body mass to child. The body mass computed in the third trial was then ranked as to how close to the baseline measure it was. A rank of 1 would mean the baseline measure for the child who generated the ground reaction forces was the closest to the measured mass in the third trial. A rank of 2 would mean the baseline mass was second closest to the measured mass of the child. The procedure was repeated for the remaining pairs of trials generating the baseline measure and testing against the measure left out.

The results from this experiment are shown in Figure 7. Of the 62 children, 39% of the time, the correct child was the one with the baseline body mass closest to the measured mass. 85% of the time, the correct child was within the 4 closest baseline body masses. The Active Floor and Smart Floor studies have shown approximately 90% identification accuracy on 15 individuals. The identification accuracy is defined as when the person who generates the footstep is the rank 1 individual. The trials in the Active Floor and Smart Floor studies clearly segmented individual footsteps by requiring the participants to place each step directly onto the center of the force plates. 19 of the 62 participants in the trials examined in this study had at least one trial where at least one footstep did not fall directly on a single force plate. The remaining 43 participants had footsteps that could be clearly segmented in the same way the footsteps were segmented in the Active Floor and Smart Floor studies.

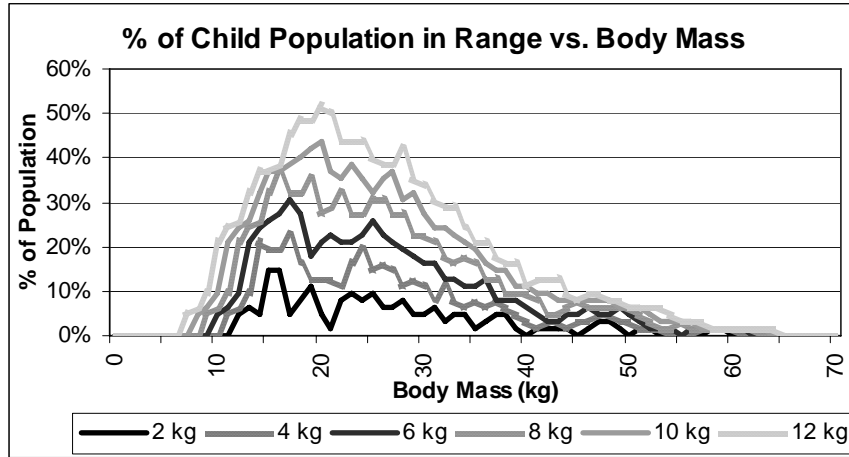


Fig 3. This graph covers the population for which ground reaction forces were available. The horizontal axis represents the center of the range and different lines represent the range magnitudes.

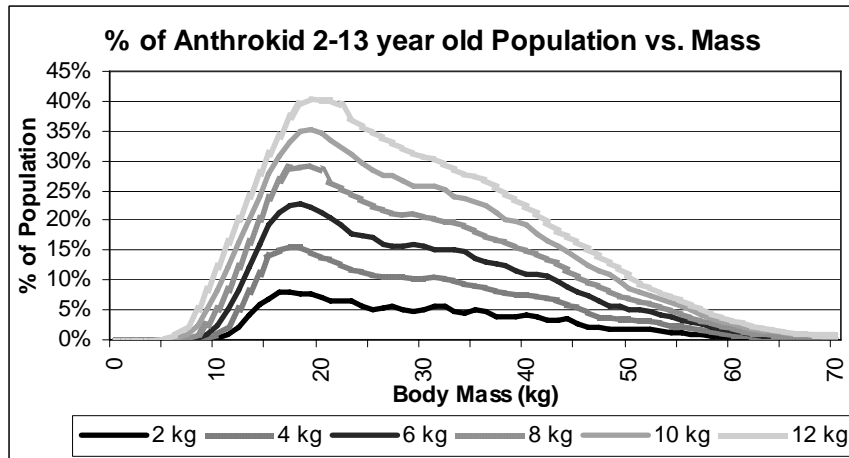


Fig 4. This graph shows the distribution of body mass over 2924 children the same age as those in Figure 3. The data is drawn from a publicly available anthropometric database [7].

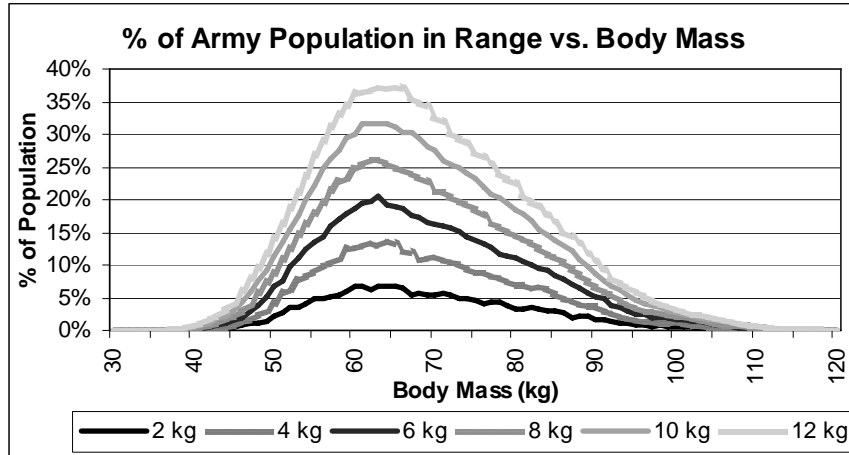


Fig 5. This graph covers a 1988 anthropometric survey of 3982 men and women in the United States Army [6]. To the author's knowledge, this is the largest public domain database of adult anthropometric data.

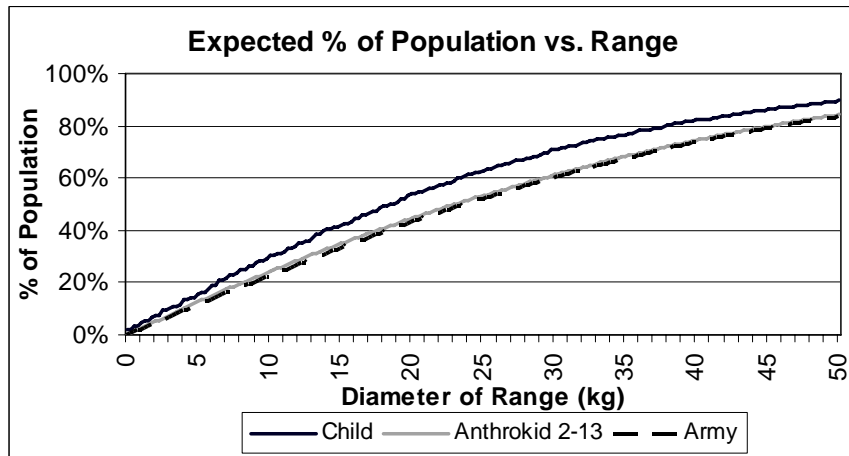


Fig 6. This graph represents the expected percent of the population whose body mass would fall in the given range. The three populations shown are the same as the ones used in Figure 3, 4, and 5 respectively. Given a distribution of the error in determining a person's body mass, this graph can be used to approximate the interaction between the false accept and false reject rates.

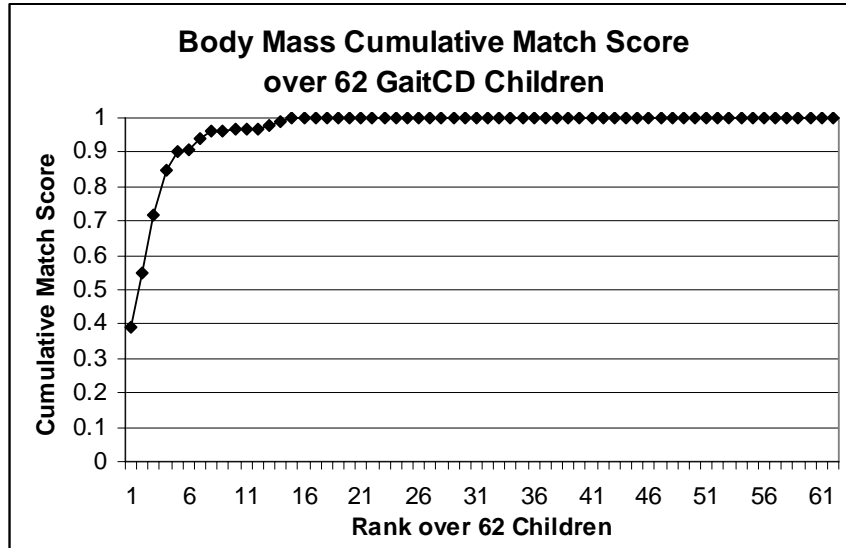


Fig 7. This shows the identification rank of the 62 children when identified by body mass only. The cumulative rank is how much of the population was ranked at that level or less. No person was ever ranked higher than 15.

The identification algorithm used in the Smart Floor was applied to the data from the 43 participants who had clearly segmented footsteps. The steady state method for measuring the body mass was also evaluated on these same 43 individuals. The Smart Floor recognizes individuals using a single footstep whereas the steady state method uses a single pass over the two force plates. For this reason, the distance measures for each footstep described in the Smart Floor algorithm were combined in four different ways in order to match a pair of footsteps to an individual. The measures were combined by taking the minimum of the two measures, maximum of the two measures, sum of the two measures, and product of the two measures. The identification accuracy reported is the best performing combination of the steps per trial. The Smart Floor algorithm was also tested when the forces were scaled by the inverse of the average standing force in order to remove the effect of differences in body masses between individuals.

Figure 8 shows the cumulative match curve for the steady state body mass method and the Smart Floor algorithm. The steady state body mass method outperforms the Smart Floor algorithm at all ranks. In addition to computing the ranks, the correlation between the Smart Floor feature distance and the difference between body masses is 0.93. This seems to indicate that the majority of the identification in the Smart Floor algorithm is due to differences in body mass. The correlation between the measured mass via the steady state method and the actual mass is nearly 1.

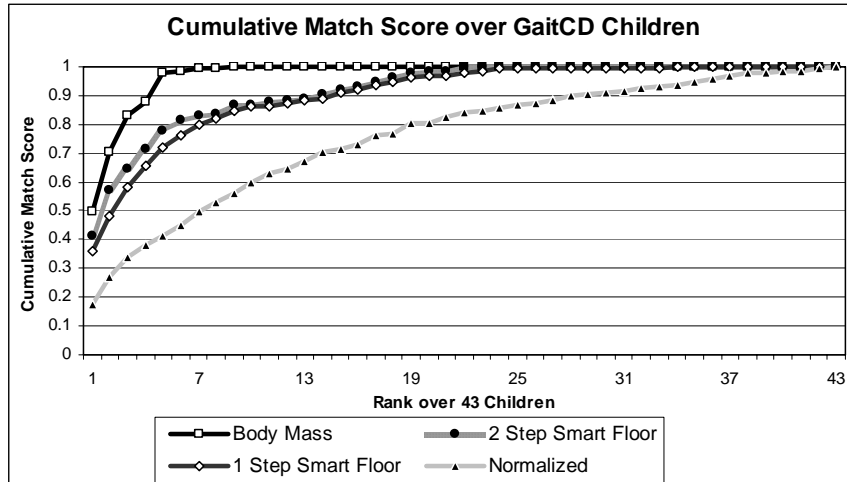


Fig 8. The figure shows the identification rank of the 43 children when identified by body mass or the features used in the Smart Floor. The normalized curve is the 1-Step Smart Floor algorithm applied to forces scaled by the inverse of the average standing force of the children.

7 Future Work

While this study does establish the accuracy with which body mass can be measured using ground reaction forces on a population of children in a clinical setting, it is unclear exactly what precision and accuracy can be obtained on a population of adults in a normal environment. While the results from the study on children seem to indicate this precision and accuracy will be well within the range necessary to retain identification power, the degree of the identification power will remain uncertain until tested on a population of adults using a more economically designed force plate. Researchers at the Duke University Home Depot Smart Home have constructed a custom force plate and are designing studies to determine how effectively the adult body masses can be measured.

Beyond indicating a person's body mass, the pattern of ground reaction forces may contain other information that can be used to classify and identify individuals. This identifying information could be combined with body mass information to improve identification accuracy. Simply scaling the forces experienced by the inverse of the standing force should be sufficient for removing part of the influence of body mass on the ground reaction force patterns. The Active Floor indicated that this was done and the identification rates fell below 50%, but exactly how much identification power remained was not described in detail. Future work on identifying using ground reaction forces should separate out the influence of body mass before identifying further patterns. If the identification algorithms for using ground reaction forces

include a feature distance measure between individuals, one simple measure which could quantify the influence of body mass in the identification algorithm is the correlation between the feature distances and the differences in body mass. The closer this correlation is to 1, the more likely the body mass may be exerting a greater influence in the identification algorithm.

Extracting these patterns from the footstep ground reaction forces requires the segmentation of footsteps from the forces recorded. Previous studies have either required users to step directly onto separate force plates or have selected from a larger pool of footsteps those which are easily segmented from each other. Moreover, previous studies have tended to test only one person at a time. When multiple people are present, the ground reaction forces must be assigned to a particular individual. These segmentation tasks are non-trivial and depend on the granularity of measurement. The larger the force plates are, the more likely ground reaction forces will come from different individuals, but the smaller the plates, the less likely a single footstep will fall on a single force plate. Designs and methods need to be developed for assigning the ground reaction force to a particular person with a group.

Finally, the inclusion of body mass into biometric fusion systems based at least partially on anthropometric measures should be explored. Large anthropometric databases exist for both children and adults. These body measures may be combined in such a way as to provide a relatively strong level of identification. Once the methods for measuring these body parameters have been developed and the measurement error has been characterized, the databases can be used to predict the possible identification power of the system on large populations.

8 Conclusion

The results from this study indicate that ground reaction forces during normal walking are sufficient for measuring body mass in a fraction of a second and with a standard deviation of less than 1 kg. This result is based upon the analysis of data obtained during clinical gait trials on children. If this level of accuracy can be obtained within the general population, then body mass has sufficient discriminating power to be included in biometric fusion systems. The difference in body mass has been shown to be highly correlated with the feature distance of another gait recognition system. Improved performance was achieved by measuring body mass directly and using that feature alone for recognition. Because both the application domain and the selection of force plate hardware impact on the degree of accuracy and precision realized in a given system, this study quantifies the level of recognition possible under more generalized error models.

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