# On Including Quality in Applied Automatic Gait Recognition

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## Abstract

*Many gait recognition approaches use silhouette data. Imperfections in silhouette extraction have a negative effect on the performance of a gait recognition system. In this paper we extend quality metrics for gait recognition and evaluate new ways of using quality to improve a recognition system. We demonstrate use of quality to improve silhouette data and select gait cycles of best quality. The potential of the new approaches has been demonstrated experimentally on a challenging dataset, showing how recognition capability can be dramatically improved. Our practical study also shows that acquiring samples of adequate quality in arbitrary environments is difficult and that including quality analysis can improve performance markedly.*

## 1. Introduction

Quality is key to deployment of automated biometric recognition in real-world environments. Gait recognition analyses the way we walk, combined with our posture. Major advantages of gait include: it is non-invasive, hard to conceal and capable of being acquired at a distance. Many studies have demonstrated that gait has the potential to become a powerful biometric for surveillance applications [1].

There are number of factors that affect gait recognition performance. Covariate factors can be related to the subject (e.g. different clothing) or to the environment (e.g. different background or lighting). There are studies that quantify the effect of various covariates [2]. View angle, clothing, footwear and walking surface have been most commonly quoted to affect recognition.

In addition, these factors are confounded by errors in the silhouette segmentation process common to many recognition approaches. The silhouette extraction process separates the subject from the background and eliminates the color and texture of the clothes. Background subtraction is not a perfect process and poor segmentation can result even when the video is of good quality. Some of the factors influencing the process are: subject clothing, change in illumination and background, distance from camera, and occlusion. These factors can result in silhouette imperfections such as shadows, holes in the silhouettes, noisy contours, and undetected body parts.

Many approaches rely on clean silhouette data. However, a number of studies have established the negative effect of poor silhouette quality on recognition performance [3, 4]. Approaches such as [5] propose a robust gait representation that works better with partial silhouettes. A study [6] has proposed a way of reducing the noise around the contours. We are not aware of any work in the literature that uses quality metrics to improve a pre-processing step, although all approaches could benefit from improvement in silhouette quality.

This paper extends the existing quality metrics and proposes novel ways of using the metrics to improve recognition in real-world environments. The potential of the techniques is demonstrated using a new database specifically captured for this study. The database has been recorded at two realistic locations. We show that recognition can be improved by using quality metrics to improve background subtraction which is an important step in most gait recognition approaches. The results also show the benefit of using quality metrics to select the best quality gait cycle.

## 2. Dataset

There is no publically available gait dataset that contains samples of the same subject taken at two different locations, without introducing additional covariates such as clothing or view point. Our new database enables investigation of the effect of different environment-dependent covariates in a principled manner. It also provides a challenging environment for development and evaluation of quality metrics.

The NPL-SOTON gait database has been recorded at two indoor locations – a corridor (with large windows at each end) and a large room as shown in Figure 1. Both locations are realistic environments for indoor surveillance with significant and uneven change in illumination.

**Figure 1 – Locations for the experiments**

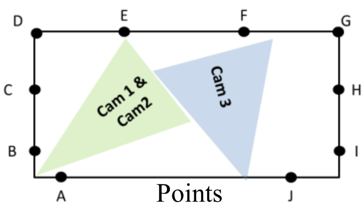


**Figure 2 – Walking directions**

The setup (Figure 2) was replicated at both locations using three cameras for data collection. The fields of view of the cameras are shown in Figure 2. Camera 2 is elevated above camera 1 and shares its field of view. The instructions given to the 23 subjects were to "walk normally in a straight line between two points'. Nearly 2000 sequences were collected at different view angles to the camera. Calibration data is available for all cameras at both locations.

## 3. Quality metrics

Changes in the operational environment of a system can result in different quality of biometric samples. As such, analyzing quality can be key to improving performance.

### 3.1 Quality metric 1 – Exploiting periodicity

Human gait is a periodic motion. If there is little noise associated with binary silhouettes (e.g. in the form of shadows, reflections etc.) then the total number of white pixels forms a periodic signal. Models have been developed to represent this signal. An example is shown in Eq. 1 [3].

$$y(t) = a + b\cos(\omega t) + c\cos(2\omega t) + z(t) \qquad (1)$$

where $\omega = 2\pi/T$ and $T$ is the gait period, $a$ is the average area of a silhouette, $b$ and $c$ reflect the periodic variation in silhouette size, and $z(t)$ is noise.

This model is good at detecting noise when it varies over the gait sequence. Distorted silhouettes are likely to produce noisy foreground-sum signals. However, there are situations in which a signature of poor quality exists and the model is not able to detect it. For example, if the top part of the silhouette is missing for all frames the resulting foreground-sum signal is likely to still fit the model in Eq. 1 very closely. Figure 3 shows an example of this which occurred in testing a fully automated system. The fit would have been even better if the subject was walking at 90 degrees to the camera.

Nevertheless, the periodic model gives a useful quality metric if combined with additional ones. A number of new possible metrics were evaluated and the most effective ones in combination with metric 1 are presented in the next two sections.

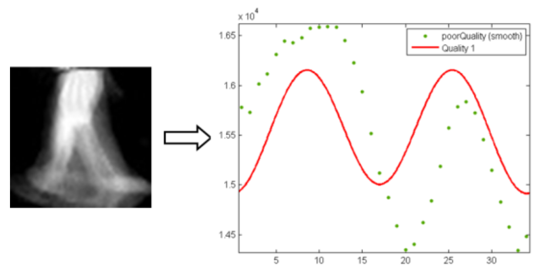


**Figure 3 – Model fitting quality metric 1**

### 3.2 Quality metric 2 – Signature structure

This quality metric focuses on analyzing the structure of a gait signature. The Gait Entropy Image [1] highlights the dynamic areas of the Gait Energy Image by calculating the Shannon entropy at each pixel:

$$H(x,y) = -\sum_{k=1}^{K} p_k(x,y) \log_2 p_k(x,y) \qquad (2)$$

$p_k(x,y)$ is the probability that a pixel takes on the $k$th value. A binary image corresponds to $K = 2$.

The Gait Entropy Image contains pixels of high intensity values in the areas of the human body that are moving and low intensity values in the areas that are static. If silhouettes have been poorly segmented there will be entropy in areas that there should not be. There are a number of areas on the human body that can be tested for presence or absence of entropy. For example, there should be a small number of bright pixels in the head and torso region and large number of high intensity value pixels round the arms and the legs. Average anthropometric measurements of the human body [7] have been used to locate different parts of the body. Examples are shown in Figure 4. Equation 3 shows an example of the thorax region.

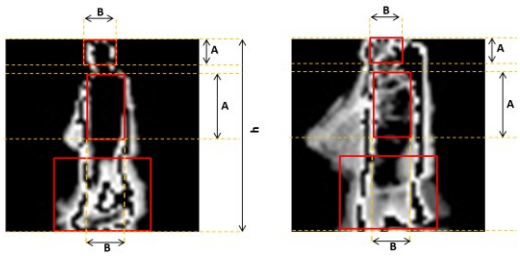

**Figure 4 – Example for quality metric 2**

$$m_2 = \sum_{x \in A} \sum_{y \in B} H(x, y) \qquad (3)$$

where for height $h$ and centre $c$, the thorax is between $A=[c - 0.174h/2,\ c + 0.174h/2]$ and at height between $B=[0.182h,\ 0.53h]$.

### 3.3 Quality metric 3 – Use of height

To establish temporal correspondence, the height of the bounding box formed around the subject's silhouette can be analyzed over a gait cycle or walking sequence to reveal any anomalies in the process of subject-background separation. If calibration data is available the actual height of the subject can be used.

A model can be fitted to the height signal and the error of fit can reveal poor quality signatures. Similar models as Eq. 1 can be used, as in

$$h(t) = a + b\cos(\omega t) + c\cos(2\omega t) + z(t) \qquad (4)$$

Examples are shown below in Figure 5. The left side of the figure represents a sample of good quality and the right shows a sample of poor quality. The red line represents the line of best fit.

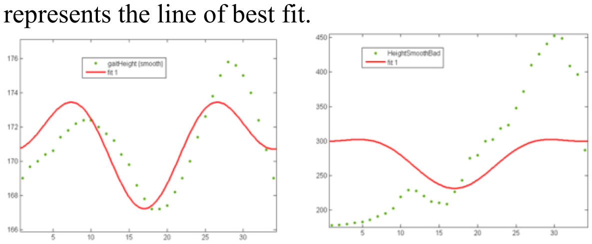

**Figure 5 – Model fitting for metric 3**

## 4 Deploying quality metrics

In the case of metrics 1 and 3, quality is evaluated by measuring the root mean square error. In the case of metric 2, the actual value is an indicator of quality. For the thorax region, low values for $m_2$ indicate a signature of good quality. Simple normalization by scaling between 0 and 1 was performed for each metric in order to combine the results.

Quality metrics can be used at various stages in a biometric system. The ways in which we use quality are vital if a sample is acquired in real world conditions where re-capturing is not possible. Our experience of using an automated system in realistic environment shows that acquiring a signature of good quality is very difficult. Conditions such as lighting constantly change in unpredictable manner. The changes are even more significant in the case of matching across different locations and across time. The following two sections show the result obtained by analyzing our database.

**Table 1 – Combinations of gallery and probe**

| Probe Loc. (Dir.) | Gallery Loc. ( Dir. ) | Cam No | Quality used | CCR (%) |
|---|---|---|---|---|
| Corridor (IB) | Corridor (IB) | 1 | No | **74** |
| Room (IB) | Room (IB) | 1 | No | **91** |
| Corridor (IB) | Room (IB) | 1 | No | **22** |
| Room (IB) | Corridor (IB) | 1 | No | **21** |
| Corridor (IB) | Room (IB) | 1 | Yes | **40** |
| Corridor (HC) | Room (IHC) | 3 | No | **0** |
| Corridor (HC) | Room (IHC) | 3 | Yes | **30** |
| Corridor (HC) | Corridor (HC) | 3 | No | **65** |
| Corridor (HC) | Corridor (HC) | 3 | Yes | **95** |


**Figure 6 - Signature quality improvement**

### 4.1 Improvement in background subtraction

Matching signatures of inconsistent qualities can result in poor recognition performance. The aim is to perform the background subtraction process with the parameters that produce the best quality signature. This is achieved by dynamically changing some of the key parameters. If a signature is below a pre-defined quality threshold, then a new signature is produced by varying the background subtraction parameters. In theory it is possible to find parameters that will produce an optimal gait signature.

An experiment was performed to understand the impact of quality on performance. Twenty-three subjects (2 samples per subject) were used. All samples were captured in the same day and no additional subject dependent covariates were introduced.

The combination of gallery and probe is shown in Table 1. The experiments shown in the first and last two rows of Table 1 have been performed to understand the effects of using quality when matching samples acquired at the same location. The rest of the experiments focus on samples acquired at different locations. The system operated in recognition mode and all three quality metrics are used.

Figure 6 shows example signatures (of the same subject) before and after quality metrics were applied. The figure demonstrated the benefit of using quality metrics in a fully automated gait recognition system for matching across locations.

The results reveal improvement in performance, both in the case of samples acquired at the same location and at different locations when quality metrics are used. The CCR rate increases on average by 20-30%. A ROC curve for the last two entries of Table 1 is shown in Figure 7. The equal error rate decreased from 20% to 5% for matching across locations if quality is used. A further improvement in signature quality would be achieved by optimizing a larger number of background subtraction parameters.

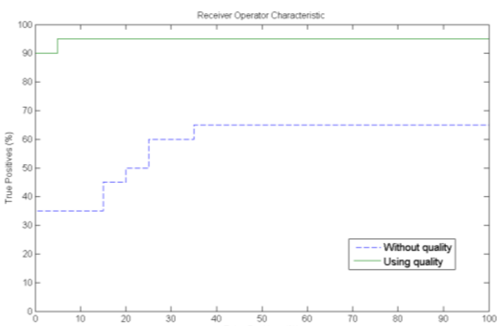


**Figure 7-ROC analysis of quality improvement**

### 4.2 Selection of the best gait cycle

Selection of a gait cycle is an important step in gait recognition for a large number of approaches. There can be many possible gait cycles available for a given video sequence. More specifically, there are $L_c$-$t$ potentially valid cycles, where $L_c$ is the length of the clean signal i.e. number of frames where the subject is fully visible and $t$ is the gait period. A gait cycle selection algorithm that utilizes quality metrics can lead to the best quality cycle being chosen. The cycle that produces the best value for the combination of all quality metrics can be used.

An experiment has been performed to show the potential benefits of deploying quality metrics for selecting the most appropriate gait cycle. The combination of gallery and probe is shown in Table 2. Samples from twenty-three subjects captured by ‘Camera 1’ were used. The results reveal an improvement in performance.

**Table 2 – Combinations of gallery and probe**

| Probe | | Gallery | | Quality | CCR (%) |
|---|---|---|---|---|---|
| Loc. | Dir | Loc. | Dir | | |
| Corridor | IB | Corridor | IB | No | 60 |
| Corridor | IB | Corridor | IB | Yes | 75 |

## 5. Conclusions

We have extended the quality metrics and proposed a novel way of using quality metrics to improve an important pre-processing step. Segmentation is the first processing step of most gait recognition algorithms and the success of further processing depends on this process. The approach is generic and can be applied in other domains that employ background subtraction as a pre-processing step. We have also used quality metrics to select the best gait cycle.

The benefits of using quality have been demonstrated on a new and challenging dataset specifically collected for this study. In addition, the advantages have been validated in ‘real-life’ use. Experiments have been performed over multiple locations and the results reveal that quality of gait samples is a step in the right direction for deployment of gait recognition in real-world environments.

While it is difficult to acquire samples of good quality in a realistic environment, the techniques presented here show that quality of gait samples is a promising avenue for future research. Improving the quality would allow other techniques that rely on silhouette data to generalize to unknown environments.

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