Towards View-point Invariant Person Re-identification via Fusion of Anthropometric and Gait Features from Kinect Measurements

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Abstract: In this work, we present view-point invariant person re-identification (Re-ID) by multi-modal feature fusion of 3D soft biometric cues. We exploit the MS Kinect™ sensor v.2, to collect the skeleton points from the walking subjects and leverage both the anthropometric features and the gait features associated with the person. The key proposals of the paper are two fold: First, we conduct an extensive study of the influence of various features both individually and jointly (by fusion technique), on the person Re-ID. Second, we present an actual demonstration of the view-point invariant Re-ID paradigm, by analysing the subject data collected in different walking directions. Focusing the latter, we further analyse three different categories which we term as *pseudo, quasi* and *full* view-point invariant scenarios, and evaluate our system performance under these various scenarios. Initial pilot studies were conducted on a new set of 20 people, collected at the host laboratory. We illustrate, for the first time, gait-based person re-identification with truly view-point invariant behaviour, i.e. the walking direction of the probe sample being not represented in the gallery samples.

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1 INTRODUCTION

As the technology revolution brought greater access to sophisticated multimedia systems, as well as advances in computer vision and machine learning techniques, an exponential growth of smart surveillance systems is underway. The automatic analysis of data collected in surveillance camera networks serves a significant role in the analysis of people and crowd behaviours in public spaces.

Person re-identification (Re-ID) is one of the most interesting, yet challenging, tasks in video surveillance. It consists in recognizing an individual in different locations over a set of non-overlapping camera views (Barbosa et al., 2012). The classical approaches in Re-ID consist in exploiting the appearance cues, such as colour or texture of apparel, thus assuming that subjects will not change their clothing within the observation period. However, they restrain the system from long term applications, since those features undergo drastic variations over long periods.

Hence, a new trend in Re-ID is to leverage longer term biometric traits, called soft-biometrics. Soft biometrics are physical, behavioral or adhered human characteristics, classifiable in predefined human compliant categories which are established by humans with the aim of differentiating individuals (Dantcheva et al., 2010). Soft biometric features leverage characteristic human traits such as anthropometric measurements, height, body size and gait, which are coherent for a long term analysis (Nixon et al., 2015). Soft-biometric features are more stable over long periods than appearance cues and, hence, could be employed towards long term Re-ID applications. Different from hard biometrics (e.g. fingerprint, iris, etc.), they lack the distinctiveness and time invariance to identify a person with high reliability. However, they have certain advantages over hard biometrics, making them best suited to deploy in surveillance applications e.g. non obtrusiveness, acquisition from distance, non-requirement for the cooperation of the subject, computational and time efficiency, and human interpretability.

In this work, we propose a biometric enabled person re-identification system, using two kinds of soft biometric features i.e. anthropometric features and gait features, extracted from the human body skeleton computed by a Microsoft Kinect™ sensor v.2. Anthropometry involves the systematic measurement of the physical properties of the human body, primarily dimensional descriptors of body size and shape. Human gait includes both the body posture and dynam-

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ics while walking (Lee and Grimson, 2002). The cues are extracted from range data which are computed using an RGBD camera. Hence, the great constraint of appearance constancy hypothesis can be relaxed and facilitated towards long-term person Re-ID. To the best of our knowledge only a very limited number of works have been employed in this regard, furthermore, they employ view-point dependent approaches i.e. data is collected and algorithms are tested with a single walking direction with respect to the camera.(Barbosa et al., 2012), (Gianaria et al., 2014) and (Andersson and Araujo, 2015). In this paper, we propose a view-point invariant person re-identification method tested with subjects walking in different directions, by using multi-modal feature fusion of anthropometric and gait features.
The major contributions of the paper are two fold:

- First, to validate the effect of various anthropometric and gait features in distinguishing a person among the population and facilitate towards person Re-ID from those soft-biometric cues. In order to better understand this, we conduct a thorough study by exploiting individual features or combination of features (via fusion).
- Second, is the actual demonstration of the real impact of view-point on the Re-ID paradigm. Since skeleton coordinates provided by kinect data are, in principle, view-point invariant (can be normalized to a canonical view-point by a roto-translation transformation), many works assume view point invariance from the start and do not validate experimentally this assumption. Despite skeleton coordinates are naturally view point invariant, their computation is not (the skeleton reconstruction process depends on view points and self-occlusions). Most work in the literature do single-view probe and single (same)-view gallery (which is basically the view-point dependent approach), which does not allow assessing the view-point invariant characteristics of the algorithm. In order to perform a benchmark assessment, we experiment in this work explicitly different view-points in the probe and gallery samples. In addition, we conduct several tests of view-point invariance: (i) single-view-point probe with multi-view-point gallery (*pseudo* view-point invariance); (ii) novel-view-point probe with multi-view-point gallery (*quasi* view-point invariance) and (iii) novel-view-point probe with single-view-point gallery (*full* view-point invariance). The former two require a large effort in the gallery creation. The latter, is the easiest and most flexible form since only a single camera is required and the person enrollment stage is very simple (one pass only).

The rest of the paper is organized as follows. We review the related works in Section 2. In Section 3, we explain the proposed methodology. In particular, we present the data acquisition set up, feature extraction, signature matching and evaluation methodology. In Section 4, we detail the various experiments conducted and the results achieved. We summarize our work and enumerate some future work plans in Section 5.

2 RELATED WORK

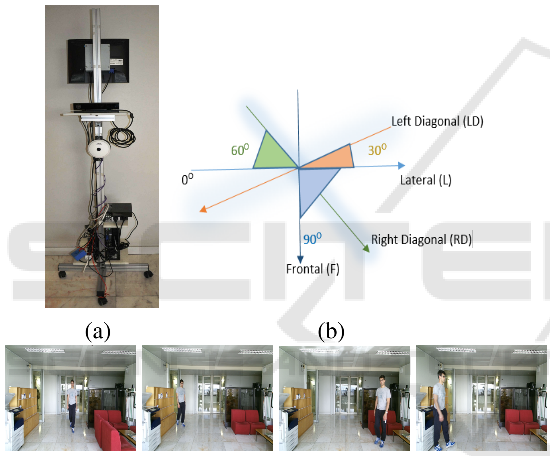
Many of the classical Re-ID systems found in the literature were built on appearance based features (Doretto et al., 2011), (Riccio et al., 2014), exploiting the colour/ texture of the clothing. However, this prevents the Re-ID application when the apparel is changed. In recent years, a new trend employing biometric information has blossomed, owing to the precise and advanced data capturing machines (e.g. HD cameras, motion capture, kinect sensor), especially in analysing the 3D body information that enables view-point invariance.

Many works have been proposed towards view-point invariant Re-ID. In (Zhao et al., 2006), (Iwashita et al., 2010) multiple 2D cameras were used to reconstruct the 3D volumes and thus achieve view-point invariance. Other works use multiple 2D cameras to fit 3D models in the volumetric data e.g. 3D ellipsoids (Sivapalan et al., 2011), articulated cylinders (Ariyanto and Nixon, 2011) and 3D volume shape by the intersection of projected silhouettes (Seely et al., 2008). Current state-of-the-art view-point invariant techniques are presented in (Iwashita et al., 2014), (Fernandez et al., 2016). In (Iwashita et al., 2014), a method using a 4D gait database was proposed. At each frame of a gait sequence, the observation angle is estimated from the walking direction by fitting a 2D polynomial curve to the foot points. Then, a virtual image corresponding to the estimated direction is synthesized from the 4D gait database. (Fernandez et al., 2016) presents a multi-view-point gait recognition technique based on a rotation invariant gait descriptor derived from the 3D angular analysis of the movement of the subject.

Some works exploiting view-point invariant RGBD sensors (e.g. kinect) have also been proposed in the literature. In the work by (Barbosa et al., 2012), they leveraged the soft-biometric cues of a body for person Re-ID. However they used only the static body information i.e. skeleton based features and surface based features, in the frontal view.

Later, some works employed the gait features as well, e.g. stride and arm kinematics (Gabel et al., 2012), knee angles (Aarai and Andrie, 2013), anthropometric and dynamic statistics (Gianaria et al., 2014), anthropometric and angles of lower joints (Andersson and Araujo, 2015).

In this work, we build on the aforementioned state-of-the-art works by proposing some novel ways of improving the Re-ID algorithm, in terms of feature extraction, feature fusion and impact of view angles. In particular, we examine the Re-ID accuracy of various anthropometric and gait features via both individual as well as joint schemes. In addition, we explicitly conduct a view-point invariant Re-ID scenario by collecting video sequences of people walking in different directions, whereas previous related works collect data in a much controlled predefined single direction say, frontal or lateral.



(a) (b)

(c) (d) (e) (f)

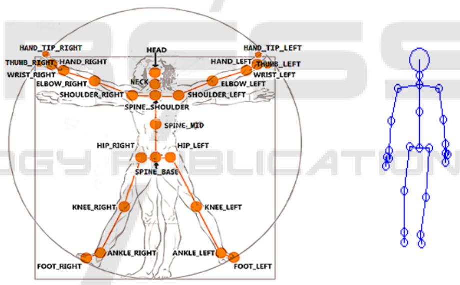
Figure 1: Data acquisition: (a) System set up (b) Subject walking directions in front of the acquisition system (c) Sample frames from our data acquisition, in four different directions- frontal(∼90°), right diagonal(∼60°), left diagonal(∼30°) and lateral(∼0°) respectively.

3 PROPOSED METHOD

In this section, we explain the data acquisition and proposed methodology. More specifically, we detail the set up and the data collection procedure conducted in the host laboratory. Then, we describe various stages of data analysis including pre-processing, feature extraction, signature matching and experimental evaluation strategies.

3.1 Data Acquisition Set Up

For the data acquisition, we used a mobile platform, in which the kinect sensor was fixed at a height of an average human (See Fig. 1(a) for the data acquisition system). This mimics normal surveillance scenarios as well as changes in the position of camera over time, as in a long term person Re-ID scenario. The kinect device is composed of a set of sensors, which is accompanied with a Software Development Kit (SDK), that is able to track movements from users by using a skeleton mapping algorithm, and is able to provide the 3D information related to the movements of body joints. We acquired all the three available data i.e. skeleton, colour and depth. Since the proposed gait algorithm employs the skeleton information, it necessitates to be of multiple frames with high frame rate, and hence captured at the full frame rate of the sensor @ 30fps. In this second version of the device, it is able to track 25 joints at 30 frames per second. Colour and depth information are employed for appearance based features, which generally require single frame, and hence was captured at 1fps. However, these were not used in the current work.



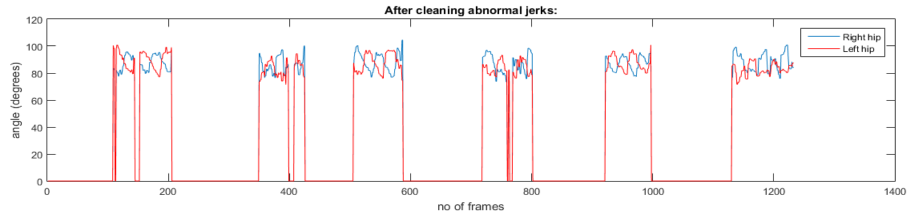
(a) (b)

Figure 2: (a) Skeleton positions relative to the human body[1] (b) A sample skeleton body visualization from our collection.

In order to ensure view-point invariance in our acquisition set up, we collected multiple views of 20 subjects in four different directions, along both ways, as shown in Fig. 1(b). We define the direction angle with respect to the image plane. Lateral walk (L) is at ∼0° and frontal walk (F) is at ∼90°. And there are two diagonal walks at different view angles. Right diagonal (RD) begins at one of the corners of the hall, which has ∼60°, whereas Left diagonal (LD) begins somewhere in the half way, thus defining ∼30°. In each of these four directions, a minimum of three

[1]For body joint types and enumeration, refer to the link: https://msdn.microsoft.com/en-us/library/microsoft.kinect.jointtype.aspx

(a)



(b)

Figure 3: (a) The abnormal shifts towards the ending of each sequence are due to the jerks of skeleton occurring at its respective frames. (b) Abnormal frames are filtered out. Now we have the cleaned frames selected.

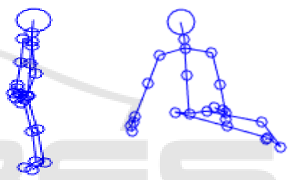
walking sequences were collected both in the front and rear views (refer Fig. 1(c)-(f)). During the walking, the people are assumed to walk with their natural gait. Altogether we have 240 video sequences comprising 20 subjects (12 video sequences per person) in the aforementioned directions. Since kinect gets the joint information of the skeleton data, it is in principle, view-point and scale invariant. In addition to that, we hypothesize that the subject makes straight walks during a single gait acquisitions, as kinect depth range is limited (80cm to 4 meters) .

Kinect can track in real-time a skeleton model, composed of 25 body joints, as shown in Fig. 2(a). The skeleton joints can be used to describe the body measurements (anthropometrics) as well as the body movements (gait) in real time and in 3D space (Shotton et al., 2013).

3.2 Pre Processing

Prior to the feature extraction, we applied some preprocessing for noise removal. The primary effect of noise are jerks/ abnormalities in the skeleton data, during the sequences (see examples in Fig. 4). In addition, in some frames, the skeleton is not detected. We could observe that, when the person approaches the boundary of the kinect range, these issues occur very often. In order to handle such situations, we propose a semi- automatic approach to select the best frames to retain and further analyse out of a video sequence.

Humans walk in a periodic fashion. It is necessary to estimate the gait feature over each of these periods of walking, known as gait cycle, which acts as the functional unit of gait. A gait cycle comprises of sequence of events/ movements during locomotion since one foot contacts the ground until the same foot again contacts the ground. Prior to getting the gait period, we intend to filter out the unwanted jerks by means of exploiting the evolution of hip angles over time. We noticed that the jerks made these angles to grow abnormally, which also created drastic variations in the corresponding signals. An example of such a situation is depicted in Fig. 3(a). In order to clean/ remove such unwanted frames, we put a threshold on the angular values (usually, the normal expected values of hip angles are in between $70° <$hip angle$<105°$). Only the frames containing the angles in between the upper and lower threshold are selected. This step automatically cleans our noisy data. A cleaned version of the previous signal is depicted in Fig. 3(b).



(a) (b)

Figure 4: (a) Some views confuse the joint positions making the skeleton based approach quite difficult (b) Abnormal jerks occuring at certain frames, during the video sequence.

The next step is gait cycle estimation. In order to have a better overview of how the lower limbs move along the video sequences, we compute the distance between the feet during a gait sequence. The three

Table 1: List of anthropometric and gait features used in our experiments. (L& R correspond to 'left and right' and x& y correspond to 'along x and y axes').

Anthropometric features	Gait features	
Height Arm length Upper torso Lower torso Upper-lower ratio Chestsize Hipsize	Hip angle(L&R) Knee angle(L& R) Foot distance Knee distance Hand distance Elbow distance Head position(x& y) Spine position(x& y)	Hip position(L&R)(x& y) Knee position(L&R)(x& y) Ankle position(L&R)(x& y) Hand position(L&R)(x& y) Shoulder position(L&R)(x& y) Stride Stride length Speed

consecutive peaks in such a signal provides a gait cycle. Referring to Fig. 5, we can see that in each video sequence, the frames between adjacent markers (stars in same colour) make a gait cycle[2]. At this point, we make this step manually. Albeit we provide the method to automatically select the adjacent peaks defining a gait cycle, we carry out a manual verification by checking the real video sequence and the signal peaks to verify that they are aligned. Also, the phase is verified at this point by checking which leg is in movement. From the peak signal alone, this information is not easy to extract.

After selecting the frames defining gait cycle, we extract the features.

3.3 Feature Extraction

After data acquisition and filtering, attributes were extracted for each walk, both static physical features defining the anthropometric measurements and dynamic gait features defining the kinematics in walking. To each subject, an identifier was provided for re-identification. The extracted feature attributes are explained in detail, next.

Anthropometric features: Under the anthropometric feature set, we collected many body measurements defining the holistic body proportions of the subject. This includes height, arm length, upper torso length, lower torso length, upper to lower ratio, chest size, hip size. These seven features constitute the body features.

The length of a body part is defined as the sum of the lengths of the links between the delimiting joints. For example, the arm length is the sum of Euclidean distances from shoulder to elbow (joint 4-joint 5), elbow to wrist (joint 5- joint 6) and wrist to hand (joint 6- joint 7). We calculate these static features across each frame, and then compute the mean value of each feature over a gait cycle. The mean value of the anthropometrics over gait periods, are used as the static feature descriptors in our experiments.

Gait features: Under the gait features, we collect behavioural features, deriving from the continuous monitoring of joints during the gait. The key advantage of using the kinect is to collect a rich set of view-point invariant[3] dynamic spatio-temporal features derived from the body movements.

First we computed three scalar features related to walking, viz., stride length, stride time and the speed of walking. The stride length is the distance between two stationary positions of the same foot while walking (Equation (1)). It comprises the left step length and right step length[4]. The duration to complete a stride is called stride time (Equation (2)). It is obtained by calculating the number of video frames in a gait cycle divided by the frame rate of acquisition (30 fps). From these two, we can obtain the speed of walking as the ratio between stride length and stride time (Equation (3)).

$$\text{Stride length} = \text{Left Step length} + \text{Right Step length} \tag{1}$$

$$\text{Stride time} = \frac{\text{Number of frames in gaitcycle}}{30} \tag{2}$$

$$\text{Speed} = \frac{\text{Stride length}}{\text{Stride time}} \tag{3}$$

[2]Note that, we collect three sequences of walking per person in each direction. Since the person makes a walk in a direction, and then a return walk to the initial point, apparently we have 6 sequences, as we can see in Fig. 5. However, we do not consider the return walks in this work, and hence, we have altogether 3 video sequences under consideration, as marked.

[3]As mentioned before, despite the joint coordinates can be easily transformed to a canonical reference frame, the process to estimate the joints positions suffers from self-occlusions due to view-point.

[4]Step length is the distance between the heel contact point of one foot and that of the other foot.

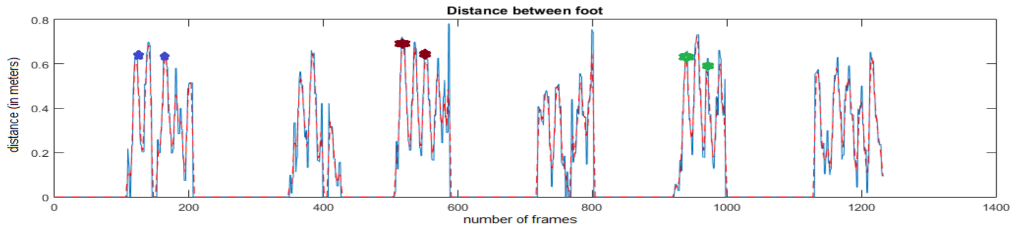


Figure 5: Gait cycle estimation. The two adjacent markers (3 consecutive peak) within a sequence, represent a gait cycle.

In addition, we also computed a set of 32 features, related to the temporal evolution of the angles (at various body joints), distance (between various right-left limbs during the gait) as well as the position (evolution of body joint along the gait). From these spatio-temporal gait signals, we extract the mean and variance of the signal. Altogether, we have a feature set containing 35 gait features (3 scalar and 32 dynamic) and 7 anthropometric features. Table 1 presents a detailed list of the feature set.

3.4 Signature Matching

This section explains how the features can be employed either individually or jointly towards the Re-ID problem. A classical Re-ID problem is usually evaluated by considering two sets of signatures (feature descriptors) collected from people: a gallery set and a probe set. Then, the Re-ID evaluation is carried out via associating each of the signature of the probe set to a corresponding signature in the gallery set. To evaluate the performance of Re-ID algorithms in closed-set scenarios, the cumulative matching characteristic (CMC) curve (Grother and Phillips, 2004) is the most acclaimed and popular method of choice. The CMC curve shows how often, on average, the correct person ID is included in the best K matches against the training set, for each test image. In other words, it represents the expectation of finding the correct match in the top K matches.

Nearest Neighbor (NN) is among the most popular as well as most performing classifier, which is commonly used in similar full body biometrics realm (Andersson and Araujo, 2015), (Barbosa et al., 2012). Hence, in this work, we exploit NN approach for the classification, using the Euclidean distance as metric. Suppose, we have signatures representing each individual feature vectors, the Euclidean distance between the signature in the probe is compared against the rest in the gallery. Then, the most similar signature in the gallery is selected as the correct Re-ID class.

Concerning anthropometric features in our work, the feature vector is composed of multiple body features, where each of the features has a numerical value associated with an individual trait e.g. height, arm length. In the case of gait features, these individual features are vectors representing mean and variance. Hence, while computing the Euclidean distance, we calculate the distance for each individual feature in the probe, against their corresponding feature peers in the gallery. Thus, we get the Euclidean distance of each probe feature against the gallery, as a distance matrix.

Let us define a probe descriptor **P**, which is a concatenation of n individual features.

$$\mathbf{P} = [p_1, p_2, \cdots, p_i, \cdots p_n] \in \mathbb{R}^{1\times n} \tag{4}$$

The gallery contains a set of similar feature descriptors, which we represent as a matrix G. Each row of G represents an n-dimensional feature vector corresponding to an individual. Likewise, k feature descriptors from multiple subjects are arranged to make a gallery matrix of dimension $k \times n$, as follows.

$$\mathbf{G} = \begin{bmatrix} g_{1,1} & g_{1,2} & \cdots & g_{1,i} & \cdots & g_{1,n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ g_{j,1} & g_{j,2} & \cdots & g_{j,i} & \cdots & g_{j,n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ g_{k,1} & g_{k,2} & \cdots & g_{k,i} & \cdots & g_{k,n} \end{bmatrix} \in \mathbb{R}^{k\times n} \tag{5}$$

Then, for the Euclidean distance computation, we calculate the distance of each individual probe feature element, say, $p_i, (i = 1, \ldots, n)$ against its counterpart feature samples in gallery i.e. $g_{j,i}, (j = 1, \ldots, k)$, as a distance vector viz., $D(p_i, g_{j,i})$.

$$\begin{aligned} D(p_i, g_{j,i}) &= |p_i - g_{j,i}|\,, \\ \forall\, i = 1,..,n\ \&\ j &= 1,..,k. \end{aligned} \tag{6}$$

This results in a distance matrix $\mathbf{D} \in \mathbb{R}^{k\times n}$, as follows in Equation 7. Each element in the matrix D is given by $d_{j,i} = D(p_i, g_{j,i})$.

$$\mathbf{D} = \begin{bmatrix} d_{1,1} & d_{1,2} & \dots & d_{1,i} & \dots & d_{1,n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{j,1} & d_{j,2} & \dots & d_{j,i} & \dots & d_{j,n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ d_{k,1} & d_{k,2} & \dots & d_{k,i} & \dots & d_{k,n} \end{bmatrix} \in \mathbb{R}^{k\times n}$$
$$= \begin{bmatrix} \mathbf{d_1} & \mathbf{d_2} & \dots & \mathbf{d_i} & \dots & \mathbf{d_n} \end{bmatrix} \in \mathbb{R}^{k\times n} \tag{7}$$

Our idea is to get a single distance score, corresponding to the overall feature set. We accomplish this via a score level fusion strategy. Since different features have different magnitude ranges, the distance scores also will have its impact. Hence, while doing the fusion, the score will be biased towards the higher measured distance, leading to the problem of heterogeneity of measures. In order to avoid this, we carry out a min-max normalization strategy, which normalize each of the feature distance score within the [0,1] range. More specifically, we normalise each column corresponding to a particular feature, separately, i.e. considering the distance vector corresponding to a particular feature as in Equation 7, $\mathbf{d_i} = [d_{1,i}, \cdots, d_{j,i}, \cdots, d_{k,i}]^T$, the normalized distance vector $\mathbf{z_i} = [z_{1,i}, \cdots, z_{j,i}, \cdots, z_{k,i}]^T$ is computed as follows:

$$\mathbf{z_i} = \frac{\mathbf{d_i} - \min(\mathbf{d_i})}{\max(\mathbf{d_i}) - \min(\mathbf{d_i})} \tag{8}$$

Afterwards, we generate the fused feature score $\mathbf{Z}$, by summing the individual normalised distance vectors, $\mathbf{z_i}$ with $i = 1, ..., n$.

$$\mathbf{Z} = \begin{bmatrix} \mathbf{z_1} + \mathbf{z_2} + \cdots + \mathbf{z_i} + \cdots + \mathbf{z_n} \end{bmatrix} \in \mathbb{R}^{k\times 1} \tag{9}$$

Then, we sort the fused score $\mathbf{Z}$ in the ascending order and calculate the final CMC curve based on the ranked list of matches.

3.5 Evaluation Methodology

In order to evaluate our proposal, we conduct multiple extensive experiments to verify the impact of each feature individually and jointly, as well as the influence of various view-points on the Re-ID paradigm. Basically, we conduct two major experiments in this regard. 1) view-point dependent and 2) view-point independent.

In the view-point dependent Re-ID experiment, the walking direction is pre-defined. Hence, the gallery and probe contains the samples from the subjects with the same walking direction. Apparently, this is a much simpler problem of person recognition[5]. In this view-point dependent experiment, further detailed analysis is carried out in order to understand the impact of various features (individual vs fusion) on the overall Re-ID.

In the view-point independent Re-ID experiment, the key idea is to corroborate the effect of different walking directions in the Re-ID scenario. We categorize three major view-point invariant scenarios in this regard -a) Pseudo view-point invariance, b) Quasi view-point invariance and c) Full view-point invariance- based on the samples available in the gallery and probe sets (See Table 2). The Re-ID becomes more challenging while moving from pseudo towards full view-point invariant, due to the limited availability of samples in the training set as well as the challenging view angles in the probe set.

Table 2: Chart showing the Re-ID accuracy rates for Experiment 4.2.2.

Index	View-point invariance	Gallery	Probe
a	Pseudo	Multi views	Single view
b	Quasi	Multi views	Novel view
c	Full	Single view	Novel view

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4 EXPERIMENTAL RESULTS

Since a standard gait dataset with different views acquired with kinect sensor was unavailable, we created a new one consisting of 20 people walking in four different directions i.e. frontal (F), left diagonal (LD), right diagonal (RD) and lateral (L). We have asked each person to walk naturally along a hall in four directions, and three times in each direction. Thus, altogether we have 12 sequences per person in different directions i.e. a total of 240 sequences in the dataset.

In this work, we conduct multiple experiments, as explained in Section 3.5. In the first experiment, we conduct Re-ID in individual directions, and in the second experiment, we employ view-point invariant Re-ID. In each of these experiments, we evaluate the performance of our system via CMC curve analysis. More specifically, each sequence in the probe is tested against the training set and the ranked list of Re-ID is obtained via signature matching. (The rank is computed by person i.e. best of the three sequences.) The process is repeated for all probe sequences. Then the

[5]Recognition is a special case of Re-ID, in which the operator has much control on the conditions (same camera, no change in view-point/ illumination/ background etc.)

average over all probe sequences Re-ID is computed and represented as CMC result.

4.1 Experiment 1: View-point Dependent Re-ID

In this experiment, we test Re-ID in individual directions. This is done to verify the performance of the proposed method along specific directions. Or in other words, we test how well the system can act when both the probe and gallery contain the features extracted in a particular direction. We carry out a leave-one-out evaluation strategy, in which any of the gait sequences will be selected as a probe and tested against the remaining 59 sequences. This is then repeated 60 times, with each of the gait sequence used exactly once as the test data, and the average Re-ID result is computed.

We exploit both the anthropometric and gait features. Regarding the anthropometric features, we select seven body measurements: *height, arm length, upper torso, lower torso, upper-lower ratio, chest and hip* (see Table 1 for the list of features). An example for the estimation of 'height' feature is shown in Fig. 6, by calculating the mean information within a gait period.

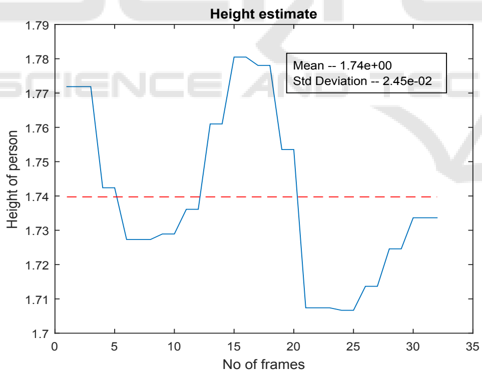
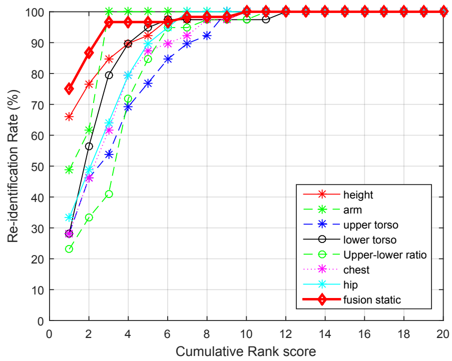


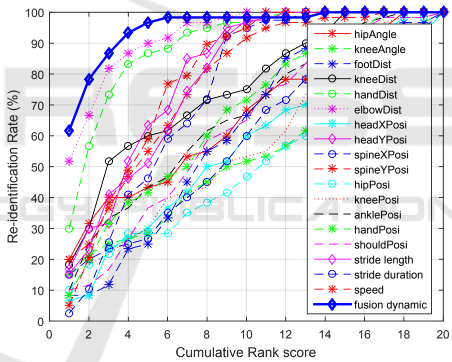
Figure 6: Height estimation from the sequence of frames within a gait cycle.

First, we analysed the Re-ID ability of our framework exploiting individual features. An example of CMC curve produced from each anthropometric features in frontal view is shown in Fig. 7(a). Among them, the most informative features are the height and arm length information with Rank-1 CMC accuracy of 65.9% and 48.7% respectively.

Similarly, we also analysed the impact of other individual gait features separately. Please refer to Fig. 7(b). It includes various body angles, distances and evolution of certain joints, along the time. The mean and variance information are extracted to generate the feature vector. We noticed that, all of those gait features are less informative and distinguishable in comparison with the anthropometric features. Referring to Fig. 7(b), the important gait features are the elbow distance and hand distance achieving Rank-1 CMC rates 51.67% and 30%, respectively whereas the least informative features were speed and stride length which achieved 5.12% and 2.5% accuracy respectively.



(a)



(b)

Figure 7: Individual feature performance towards Re-ID: (a) Static anthropometric features and scalar gait features (stride length, stride time and speed). The bold red curve with diamond markers corresponds to the fusion CMC result obtained by exploiting all the anthropometric features. (b) Dynamic gait features. The result by fusing all the gait features is shown in bold blue curve with diamond markers.

Next, we conducted fusion of the multiple features aka multi-modal fusion. Initially, various anthropometric features were fused together which resulted in the bold red CMC curve in Fig. 7(a), which achieved 75% Re-ID rate at Rank-1. Similarly, the fusion of gait features were also conducted. The result is shown with the bold blue CMC curve in Fig. 7 (b), which achieved 61.67% Rank-1 Re-ID rate. We could observe that, fusion of body related measurements produced higher Re-ID performance in comparison with the fusion of the gait features. It was quite noteworthy

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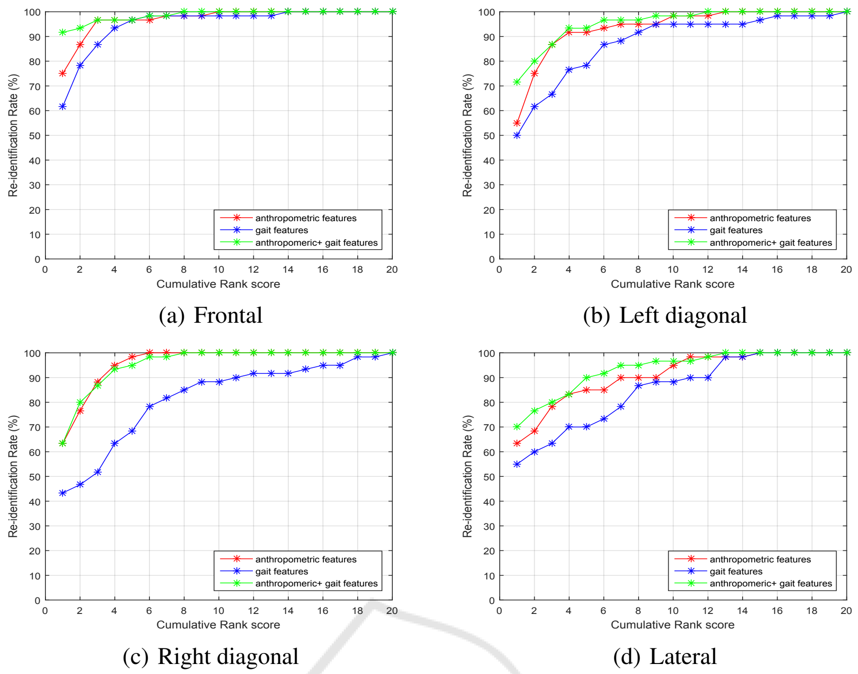

(a) Frontal (b) Left diagonal

(c) Right diagonal (d) Lateral

Figure 8: Multimodal fusion of anthropometric features, gait features (using mean-variance) and the fusion of both, in various directions. (a) Frontal (b) Left diagonal (c) Right diagonal (d) Lateral.

that even by combining 35 gait features, it couldn't achieve similar Re-ID accuracy as obtained by the anthropometric fusion by seven features. This gives the intuition that in frontal view, anthropometrics features are more significant than the gait features in discriminating the population.

After conducting the fusion among the anthropometric features and gait features separately, we further conducted the multimodal fusion of all the biometric features (i.e. both anthropometric and gait features), altogether. The results obtained in these multi-modal fusion technique in frontal sequence is presented together in Fig. 8(a). Red and blue curves denote anthropometric fusion (75% Rank-1 score) and gait fusion (61.67% Rank-1 score) result respectively. The combined anthropometric+ gait fusion result is represented via green curve with a Rank-1 Re-ID accuracy of 91.67%. We could observe that the naïve integration could improve the overall performance while fusing both anthropometrics and gait features together.

Similar experiments are also conducted in the other three views as well, i.e. left diagonal, right diagonal and lateral. We show the fusion results of all the three experiments in Fig. 8(b), (c) and (d) with an overall Rank-1 scores of 71.67%, 63.33% and 70%, respectively. In all these scenarios also, we could observe that the anthropometric features outperform the gait features. Also, while fusing both the anthropometric and gait features together, the overall performance improved.

A similar human classification strategy based on gait features has been reported in (Gianaria et al., 2014), by employing 20 people. In contrast to our methodology, they have conducted the experiments only in a single view (i.e. frontal) as well as an exhaustive selection of the set of different features along with a SVM classification scheme. However, our experiments were explicitly made in different views, and via naive score-level fusion of multi-modalities. Hence, an approximate comparative analysis is made at this point, particularly Fig. 8(a) referring to the frontal Re-ID experiment. The highest classification accuracy observed in their case is 96.25% (19.25 times the chance level[6]) under fine tuned parameter set (elbow distance, knee distance, mean of head, mean of knee). Nevertheless, our direct approach of naive fusion also could achieve quite similar result 91.67% (18.34 times the chance level) without the exhaustive feature search or the fine tuning of the parameter set.

[6]Chance level is Re-ID of 1 subject out of 20 subjects, i.e. 0.05.

4.2 Experiment 2: View-point Independent Re-ID

In Section 4.1, we have conducted experiments along various view angles at ∼0°, ∼30°, ∼60° and ∼90°, separately. Albeit we could analyse the impact of various features in each of these directions, we did not so far experiment how feasible and robust is our system in order to perform in view-point invariant scenario i.e. irrespective of any particular direction. Hence, we conduct a thorough analysis of various view-point independent Re-ID schemes i.e. pseudo view-point invariant, quasi view-point invariant and full view-point invariant.

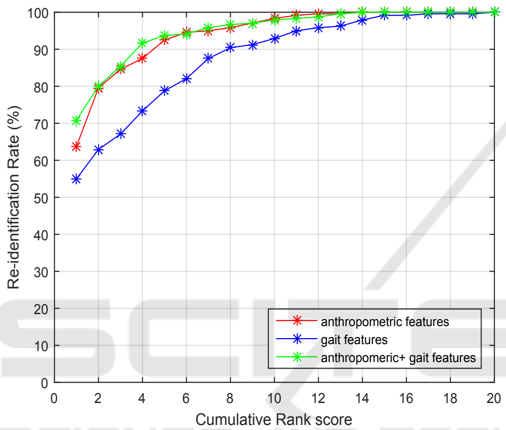

Figure 9: Pseudo view-point invariant Re-ID results using anthropometrics+ gait.

4.2.1 Pseudo View-point Invariant Re-ID Experiment

In pseudo view-point invariant case, we consider that the gallery contains samples from multiple views. And, the probe will be a new sample taken from any of these views. This kind of set up requires either a large number of cameras with different camera views (in the case of normal surveillance case), or the persons different views acquired in the enrollment phase (authentication phase). The nomenclature 'pseudo' is attributed to the fact that the probe view is already encountered among the gallery views and hence its a pseudo view-point invariant Re-ID.

Since we have used 20 people's gait in four different directions, each with three sequences, altogether we have 240 gait sequences. We conduct a leave-one-out evaluation strategy, in which any of these sequences will be selected as a probe and tested against the remaining 239 sequences in different views. Altogether 240 runs were conducted and the averaged result was computed. The achieved performance of the system is depicted in Fig. 9.

We could observe that, the fusion of anthropometric features achieved 63.75% (red curve in Fig. 9) and the fusion of gait features achieved 55% with (blue curve in Fig. 9) respectively. While combining both of them, we could obtain improvements in their performance i.e. ∼71% Rank-1 Re-ID rate. This is a promising result highlighting the performance and robustness of our system towards handling various direction of gait, which is a big challenge in the Re-ID task. Our intuition is that the increased number of samples per person (12 sequences) compared to a single direction (three sequences) could enhance the Re-ID rate.

4.2.2 Quasi View-point Invariant Re-ID Experiment

Here, in the quasi-view-point invariant scenario, the gallery contains multiview samples of the subjects. However, the probe sample is taken from a new view angle which has not been introduced in the training phase. This is a realistic scenario, where a new camera view is encountered in which the person has to be re-identified, provided that many other training samples in different views are available in the gallery. This is a more challenging case than the pseudo view-point invariant case, since the probe direction is encountered in the system for the first time.

In order to test this case, we keep all the samples in a particular direction in the test set, whereas all the other three directions are made available in the training phase. In particular, we have 180 gait sequences of 20 people corresponding to three directions being kept in the training set. The 60 gait sequences from the fourth walking direction (which was not introduced in the training phase) are used for testing. Hence, 60 runs per view are carried out and the average result is estimated. We conduct the experiment for all the frontal, left diagonal, right diagonal and lateral views as the test direction.

The Re-ID rates at Rank-1, Rank-5 and Rank-10 are presented in Table 3. It is observed that the highest Rank-1 CMC rate for the anthropometric fusion is reported in the frontal view case (41.33%) and the counterpart for the gait fusion was reported in lateral view (31.67%). Coherent results were also observed in the fusion of anthropometric+ gait case as well, where frontal samples got re-identified with the highest recognition rate (65%) followed by lateral samples (41.67%) among all the directions, in the Rank-1 scenario. With Rank-5 and Rank-10 rates in CMC curves, the Re-ID accuracy improved drastically >73.33% and >90% respectively, in all the directions. Once again the highest Re-ID rates were reported in frontal case (Rank 5- 86.67% and Rank 10- 98.33%). This means that, given other multiple views in the gallery set, frontal view probes are the best in re-identifying people.

Table 3: Chart showing the Re-ID accuracy rates for Experiment 4.2.2. The accuracy rates shown in each cell represents Rank-1, Rank-5 and Rank-10 CMC rates respectively. The highest Re-ID rate observed is highlighted in bold letters.

Probe direction	**Anthropometric based Re-ID**	**Gait based Re-ID**	**Anthropometric + gait based Re-ID**
Frontal	**41.33%** **90.00%** **98.33%**	26.67% 68.33% 96.67%	**65.00%** **86.67%** **98.33%**
Left Diagonal	33.33% 73.33% 91.67%	21.67% 53.33% 88.33%	28.33% 73.33% 90.00%
Right Diagonal	28.33% 80.00% 93.33%	10.00% 56.67% 90.00%	31.67% 83.33% 93.33%
Lateral	40.00% 68.33% 93.33%	**31.67%** **70.00%** **81.67%**	41.67% 75.00% 96.67%

4.2.3 Full View-point Invariant Re-ID Experiment

Full view-point invariance is the case which has only one walking direction in the gallery and any new arbitrary walking direction for the probe. In terms of creating a training set, this is the easiest way because it requires only one camera and one view of the person to create a gallery. At the same time, it is the most challenging scenario in terms of Re-ID, since it requires to get recordings from merely one view and able to Re-ID in any other arbitrary view.

We conducted 12 various combinations of probe-gallery set based on the walking direction, in order to guarantee a truly view-point invariant Re-ID. The experiments and the results achieved are reported in Table. 4. In each of the test case (e.g. frontal), we keep any of the other three view-point data sequences as the gallery (e.g. left diagonal or right diagonal or lateral). And the same procedure is repeated for all the four directions. In all of these experiments, each of the probe and gallery contains 60 gait sequences from 20 people. Per each combination, 60 runs were carried out and the average Re-ID resut is estimated. In the tabular results (see Table. 4), we report only the overall anthropometric+ gait multimodal fusion results at various ranks (Rank-1, 5 and 10) of CMC curves. It is observed that the highest Re-ID rates (48.33%) are achieved when frontal sequences are kept in the gallery. With the diagonal samples the second best Re-ID results are achieved (∼35%).

Despite most works assume that kinect data is pose invariant, this is not really the case as demonstrated in all the experiments of our work. Re-ID rates are always better in the frontal view that in the other, due to the quality of the data acquired. We show that with an adequate use of pre-processing and soft biometrics we can achieve some level of view-point invariance, but still not perfect.

Table 4: Chart showing the Re-ID accuracy rates for Experiment 4.2.3. The accuracy rates shown in each cell represents Rank-1, Rank-5 and Rank-10 CMC rates respectively. The highest Re-ID rate observed is highlighted in bold letters.

		PROBE			
		Frontal	Left Diagonal	Right Diagonal	Lateral
GALLERY	Frontal	- - -	26.67% 78.33% 91.67%	**48.33%** 88.33% 93.33%	**48.33**% 73.33% 93.33%
	Left Diagonal	33.33% 75.00% 90.00%	- - -	30.00% 70.00% 85.00%	35.00% 78.33% 96.67%
	RightDiagonal	35.00% 85.00% 95.00%	25.00% 68.33% 83.33%	- - -	18.33% 58.33% 85.00%
	Lateral	18.33% 78.33% 90.00%	28.33% 78.33% 93.33%	15.00% 68.33% 86.67%	- - -

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5 CONCLUSIONS & FUTURE WORK

A view-point invariant Re-ID system exploiting the skeleton information provided by the kinect sensor has been proposed. We have used both the static and dynamic features related to the human posture and walking, in order to extract features to classify the people in the population. Extensive study on the impact of various features both individually and jointly, as well as various view angles have been conducted. We have acquired the kinect data in-house from 20 people walking in four different directions, and analysed our proposed methodology.

We could observe that the static anthropometric features are more informative than gait features, when employed individually. However, while fusing many static anthropometric features and dynamic gait features, we noticed that the overall recognition accuracy increases in both cases. Also, by combining the whole set of static and dynamic features, the final overall Re-ID rate improved further. In addition to evaluations in individual directions, we also conducted view-point invariant Re-ID experiments in realistic conditions where people walk in different directions. Three cases studies were conducted in this regard viz. *pseudo, quasi* and *full* view-point invariant. It is found that our system is quite robust and promising with a Rank-1 Re-ID rate of ∼92% in view-point dependent scenarios and ∼71%, ∼65% and ∼48% in pseudo, quasi and full view-point independent scenarios, respectively. Since the direct comparison with other works are not possible due to the novelty of the approach, we carry out comparative analysis against the most similar view-point dependent approach (Gianaria et al., 2014) in the front view, and very similar Re-ID results (19 times and 18 times the chance level, respectively) were reported.

In the future, we envisage to extrapolate this study by collecting more data in more random directions of walk. Also, in terms of the feature fusion, we would like to employ context based fusion or feature selection strategies (eg: quasi-exhaustive learning strategy (Barbosa et al., 2012), correlation-based feature subset selection (Andersson and Araujo, 2015)), in order to fine tune the selection of most informative features and thus improve the Re-ID accuracy.

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