CHAPTER 2

Literature review

2.1 Gait assessment

Assessment of spatiotemporal gait parameters is commonly used by rehabilitation professionals to identify gait deviations, and to provides essential information relating to overall health (1), falls status (2), cognitive performance (3), quality of life (4), and mortality rate (5). Lord et al. (1) studied the associations between gait parameters and motor, cognitive, and behavioral characteristics in 189 older adults. Sixteen spatiotemporal gait variables (i.e. gait velocity, step length, step width, step time, swing time, stance time, and their variability, as well as step time asymmetry, swing time asymmetry, stance asymmetry, and step length asymmetry) were assessed using a 7-m instrumented walkway (GAITRite). Motor characteristics were measured using the one leg stance test and the timed chair stand test. Cognitive performance test consisted of a spatial recognition memory test and a pattern recognition memory test. Behavioral characteristics were assessed using the Activities-specific Confidence Scale (ABC), the Geriatric Depression Scale, and the physical fatigue scale. The results showed that step time was associated with scores on the fatigue test, while gait velocity and swing time asymmetry were associated with the ABC score.

Maki (2) examined the association between spatiotemporal measures and the likelihood of future falls and fear of falling. Seventy-five older adults were asked to walk on an 8-m walkway wearing comfortable walking shoes. Footprints and footswitches were used to measure the spatial and temporal gait parameters, respectively. Fall events were monitored prospectively on a weekly basis for one year. In addition, all participants were asked whether they were afraid of falling. The results showed that increased stride width was associated with both falls history and fear of falling. Increased stride-to-stride variability in stride length, gait speed, and double-support time contributed to the history of falls. Alternatively, decreased gait speed, reduced stride length, and increased double-support time were associated with fear of falling.

Verghese et al. (3) investigated whether spatiotemporal gait parameters could predict future risk of cognitive decline and dementia in older adults. Five hundred and ten older adults were asked to walk along a 7-m walkway at their self-selected comfortable walking speed. Two markers placed on the ground were used to indicate the start and end of the 7-m path, with the GAITRite walkway placed on a 5-m section in the middle of this path. An extensive neuropsychological test battery was used to assess general cognition, memory, executive function, and attention. Dementia was diagnosed using established criteria for Alzheimer's disease, vascular dementia, and other dementias. Neuroimaging and blood tests were also used to confirm the diagnosis. A neuropsychological test battery was administered at the first visit and five years follow-up. However, only older adults with suspected dementia received the neuroimaging and blood tests during the follow-up visit. The result showed that gait velocity and stride length were associated with both global cognitive decline and executive function. In addition, cadence, swing time, stride time, and double support time were associated with memory decline. Furthermore, it was found that gait variability, cadence, and temporal variables can predict future risk of dementia. Thus, spatiotemporal gait parameters can be used as an indicator for preclinical stages of dementia.

The association between gait parameters and mortality rate have also been studied. Hardy et al. (5) determined the relationship between 1-year improvement in measures of health, physical function, and 8-year mortality rate in older adults. Four hundred and thirty-nine older adults were assessed for their physical performance, health status, and functional status at baseline, 3, 6, 9, and 12 months in their homes. Physical performance was performed using the Short Physical Performance Battery and 4-m gait speed test. Health status was assessed using the ordinal global health item from the 36-item Short Form Health Survey (SF-36). Functional status was measured using the 32-point basic and instrumental activity of daily living scale from the National Health Interview Survey and the physical function index of the SF-36. Based on their score using the prior definitions of meaningful change on each test, all participants were categorized into three groups: 1-year improver (improved at 1 year), transient improvers (improved at 3, 6, or 9 months, but not at 1 year) and never improvers (never improved) group. Lastly, the date of death was determined using the Social Security National Death Index. The results showed that of all measures, only gait speed was able to predict survival. An improvement in gait speed at 1 year was significantly associated with a reduction in subsequent mortality. The mortality rate at the 8-year follow-up was 31.6% in 1-year improvers, 41.2% in transient improvers, and 49.3% in never improvers. Thus, gait parameters are useful outcome measures to identifying high-risk individuals and evaluating preventive interventions.

2.2 Tri-axial accelerometer

Since gait performance is a marker of health status and a predictor for survival, the ability to correctly quantify gait is of great importance. Gait analyses are commonly performed by using sophisticated measurement tools such as optoelectronic motion capture systems, force plates, and instrumented walkways. However, these systems are time consuming, expensive, require training, and dependent on assessment being performed indoors or in laboratory settings. Recently, accelerometers have been increasingly used as a possible alternative to measuring gait due to its cost-effectiveness and portability.

An accelerometer is a device used for measuring accelerations of a body, often in terms of gravity (g) (1g or 9.81 m/s^2) (24). Sensors record the magnitude and direction of the acceleration in different axes of movement. These accelerometer sensors are described as uni-axial, bi-axial, or tri-axial depending on the axis or axes (e.g. vertical, antero-posterior, and medio-lateral) in which the monitor is most sensitive at detecting accelerations. In human movement studies, the accelerometer is most commonly used to quantify the human body's accelerations, as these accelerations can be used to explain the control of movement, associated with the change in velocity and direction of movement.

The feasibility of body mounted tri-axial accelerometers in quantifying spatiotemporal gait parameters of step time, step length and gait velocity from the assessment of the antero-posterior, medio-lateral and vertical accelerations during ambulation have been demonstrated (25, 26). Examples of the raw acceleration values across all three axes during overground walking are shown in Figure 2.1 & 2.2. In order to quantify gait spatiotemporal parameters from the raw accelerations, all data were filtered using a Butterworth 4^{th} order low-pass filter with a 20Hz cutoff frequency (27, 28). Antero-posterior accelerations were further filtered using a Butterworth 4^{th} order low-pass filter with a cutoff frequency of 2Hz. All positive peaks in the filtered antero-posterior data were identified as heel strikes, with the time difference between heel strikes characterized as the step times. The direction of the acceleration in the medio-lateral direction at the instant of heel strike (positive or negative), was used to identify right versus left steps. Step length was calculated from the change in height of the vertical position across each step cycle and the participant's leg length. Vertical position was computed by double integrating the vertical acceleration data, and high pass filtering the result using a Butterworth 4^{th} order filter with a 0.1 Hz cutoff frequency to remove integration drift (29). Step length was then computed by using the relationship:

$$SL = 2 * \sqrt{2 * h * l - h^2} \qquad \text{(Eq1)}$$

where *SL* was the step length, *h* was the change in vertical position and *l* was the leg length. Gait velocity was calculated as the ratio of step length to step time (27).

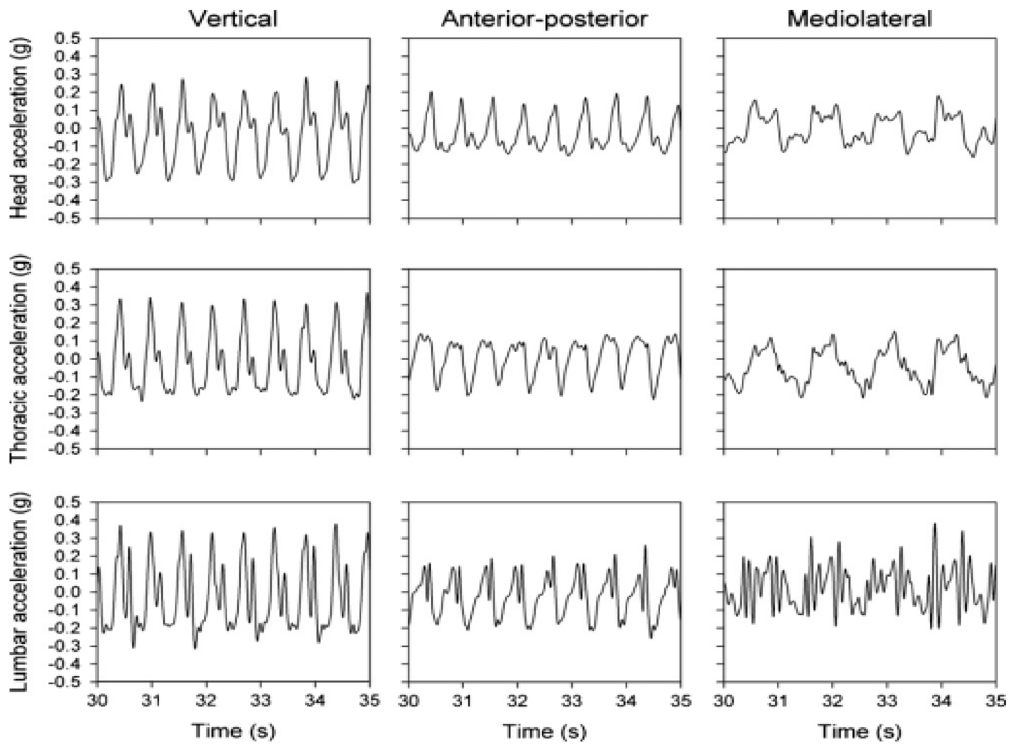

Figure 2.1 Examples of the raw accelerations measured at the level of the head, thoracic, and lumbar spine during walking at a preferred speed of 1.20 m/s (24).

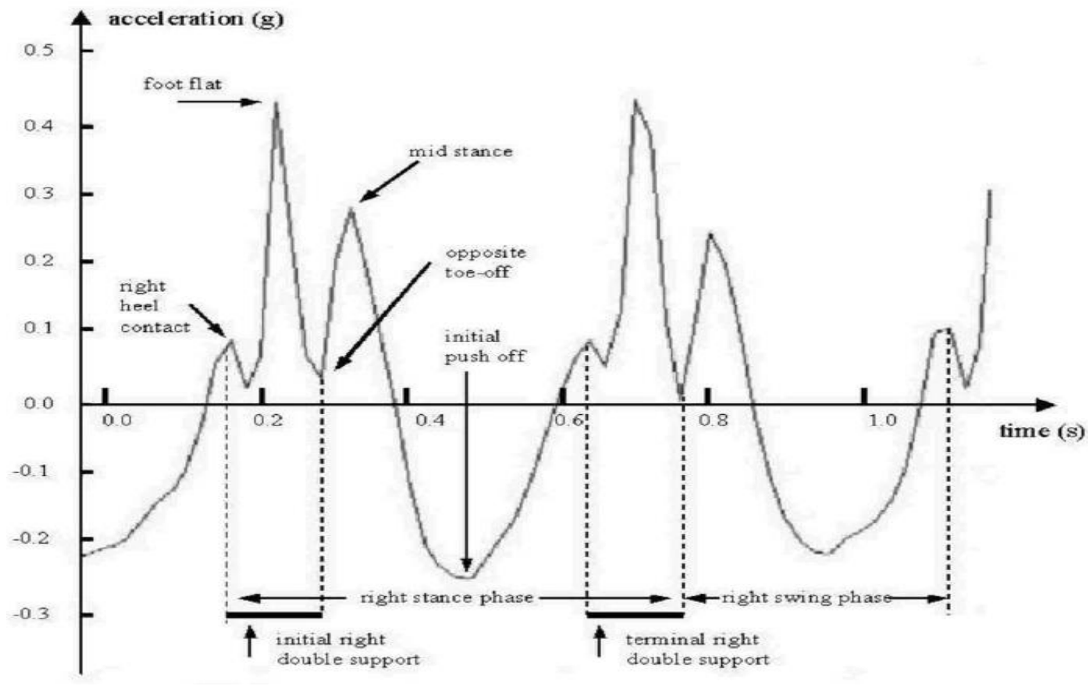

Figure 2.2 Vertical acceleration over one stride. The vertical acceleration pattern is repeated twice for each gait cycle with a similarity of specific events (indicated by arrows) between right and left steps (30).

Previous studies have demonstrated that using a tri-axial accelerometer was valid for assessing spatiotemporal gait parameters. For example, Hartmann et al. (14) examined the concurrent validity of a trunk tri-axial accelerometer system (DynaPort$^{®MiniMod}$) with the GAITRite system for assessing spatiotemporal gait parameters at preferred, slow, and fast self-selected walking speed in an older adult population. Twenty-three older adults were asked to walk along the 13-m walkway, with only the data from the central 7.32 m active sensor area of GAITRite used. The tri-axial accelerometer was placed at the level of the second sacral vertebrae with sports tape. Gait data was collected simultaneously between the two systems. The older adults were first instructed to walk at their comfortable speed. Then, the order of the fast and slow walking speeds were randomized. The results showed that the levels of agreement was excellent between the tri-axial accelerometer and GAITRite system for walking speed, cadence, step duration, and step length (intraclass correlation coefficients (ICCs) between 0.99 and 1.00, ratios limits of agreement (RLOA) between 0.7% and 3.3%) (Figure 2.3). In addition, the levels of agreement between the two systems was moderate for variability of step duration (ICCs between 0.88 and 0.98 with RLOAs between 19% and 34%), and low for variability of step length (ICCs between 0.24 and 0.33 with RLOAs between 73% and 87%). Overall, temporal gait parameters (i.e. step duration and variability of step duration) showed higher levels of agreement compared to spatial gait parameters (i.e. step length and variability of step length).

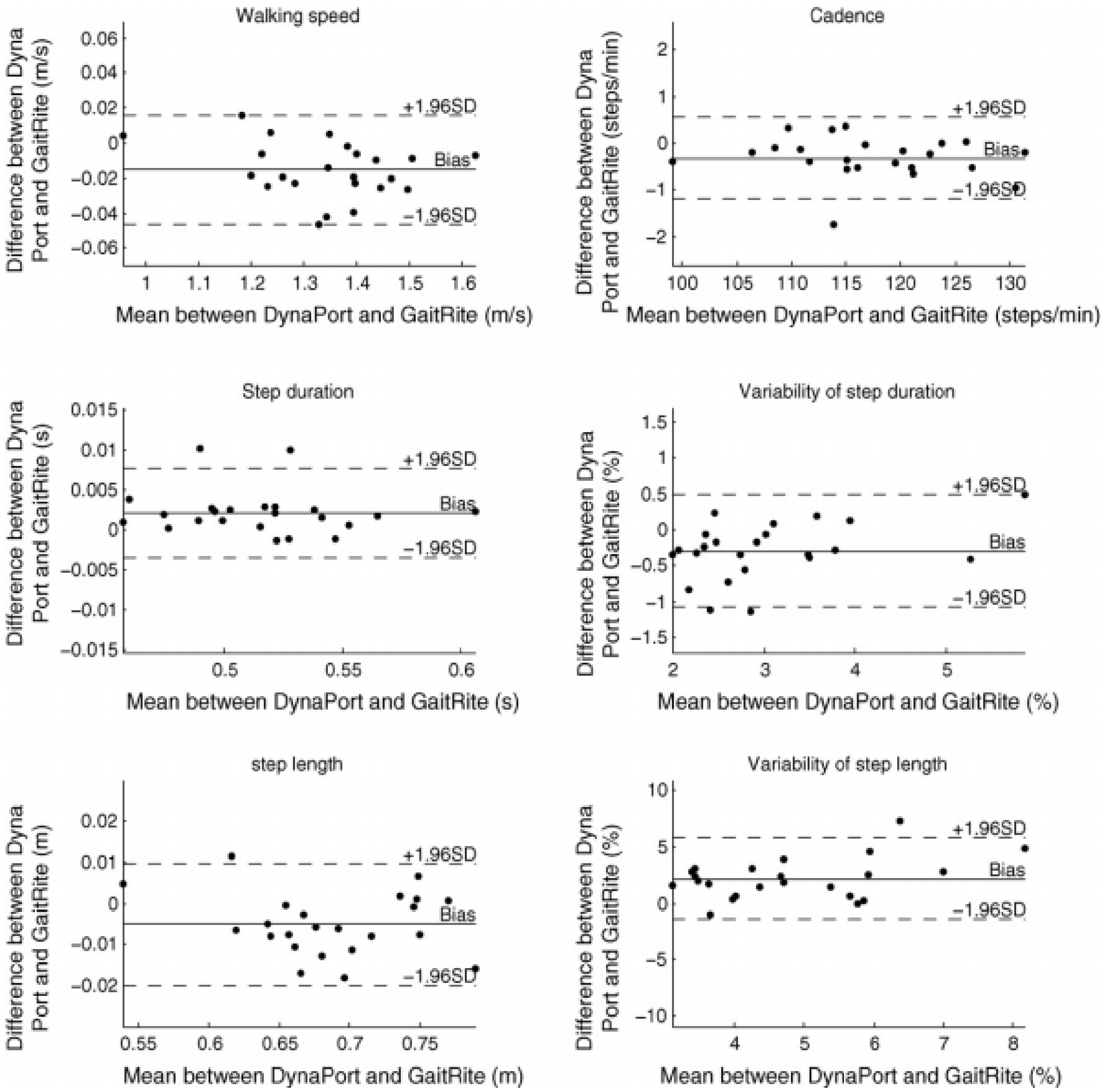

Figure 2.3 Bland–Altman plots of all averaged gait parameters across four walking trials at preferred walking speed. Solid line systematic bias; dashed lines limits of agreements (14).

Accelerometers have become increasingly popular as instruments for assessing physical activity, energy expenditure, and gait. Additionally, accelerometers show a number of advantages, including a lower cost, portability, a small size, and ease of use. As a consequence, accelerometers can be used in real life environments to support rehabilitation, and continuous physical activity monitoring at home. Thus, user-friendly portable gait analysis systems which are able to collect data from many gait cycles and allow measurements in a more challenging context are potentially important for clinical and research settings.

2.3 The use of smartphones to measure gait

The use of smartphones for medical purposes by health care providers is increasing because of the steadily growing number of downloadable applications that transform the mobile phone into a medical device (31). Modern smartphones have built-in sensors (i.e. accelerometer, gyroscope, compass, and camera) which health applications utilize to quantify minute-by-minute activity of patients (e.g. walk or sit) and to obtain measurements useful for clinical practice. Mobile medical applications are an emerging technology that needs to be appropriately validated, along with the specific mobile platform, to ensure their safe and effective operation.

2.3.1 Smartphone-enabled camera-based system

Kim et al. (21) examined the concurrent validity of the wearable smartphone-enabled camera-based system (SmartGait; Figure 2.4) with a pressure-sensing walkway (GAITRite) for measurement of spatiotemporal gait parameters. Fifteen healthy young adults were asked to walk along an 8-m walkway at three different speeds: slow, preferred, and fast speeds. A GAITRite mat was placed in the middle of the walkway, whereas the SmartGait was attached at the participant's waist. Step length (SL), step width (SW), step time (ST), gait speed, double support time (DS) and their variability were collected concurrently with the two systems. The results found that SmartGait demonstrated modest to excellent concurrent validity with GAITRite (ICCs between 0.731 and 0.982) for all parameters at all speeds in healthy young adults. The absolute difference ranged from 0.3-9.6 cm for SL, 0.1-1.4 cm for SW, 10.9-42.9 ms for ST, and 0.03-0.14 m/s for gait speed. Thus, the results of this study demonstrated that a wearable smartphone camera-based system was a valid tool for the assessment of gait in clinical practice. Furthermore, this application did not require extensive equipment or trained personnel, allowed for home-based evaluations, and provided continuous real-time assessment.

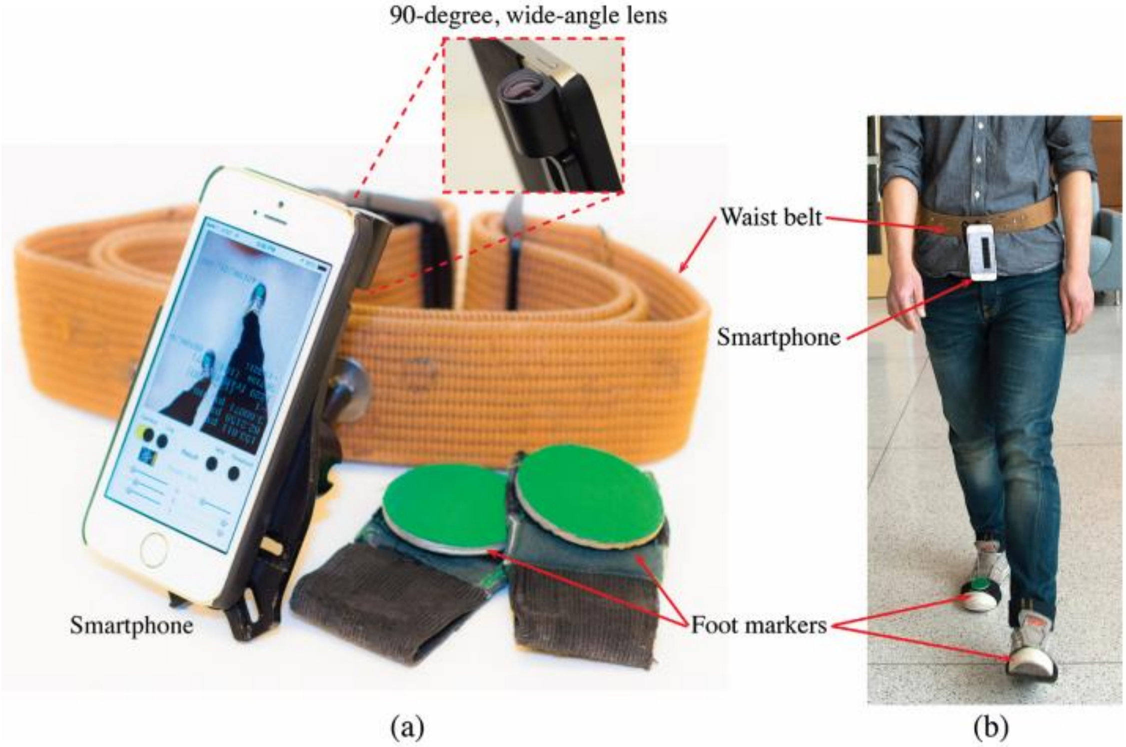

Figure 2.4 (a) SmartGait system and its various hardware components and (b) a participant wearing the SmartGait (21).

2.3.2 Smartphone-based accelerometer system

Furrer et al. (22) determined the intra-session reliability as well as concurrent validity of a smartphone-based accelerometer as compared to a marker-based motion capture system. Twenty-two healthy young adults were asked to walk barefoot at a self-selected speed across a 10-m walkway. Vertical center of mass displacement and step duration were assessed simultaneously between two systems: a smartphone attached over the region of the third lumbar vertebrae and an eight-camera motion capture system with 34 reflective markers placed on bony landmarks of the entire body. The results showed good to excellent reliability (ICCs between 0.71 and 0.80) for spatial parameters and fair to excellent reliability (ICCs ranged from 0.49 to 0.86) for temporal variables. All variables correlated significantly with measurements of the motion capture system with moderate correlation (ranging from 0.61 to 0.68) for spatial parameters and moderate to strong correlations (ranging from 0.62 to 0.92) for temporal variables. Hence, the smartphone application utilizing an accelerometer, a strong alternative wearable system for laboratory and community-based gait assessment, was a reliable and valid tool for the quantification of level walking in healthy young adults.

Since smartphones are normally used for communication and leisure, it will not always be oriented or fixed to the body in the same manner. Based on results from questionnaires provided to over 1500 persons from 11 cities in nine countries, phones are carried upwards of 60% of the time in bags or pant pockets for women and men, respectively (32). The following most common locations are on a belt-clip (13.8% for men, 0.8% for women), on the upper body (8.3% for men, 2.2% for women), and in the hands (3.5% for men, 9.1% for women).

Antos et al. (23) investigated the accuracy of activity tracking using a smartphone-based accelerometer when placed at four locations (i.e. hand, belt, pants pocket, and bag) while performing five activities (i.e. sitting, standing, walking, and transition between sitting and standing), and quantified which phone locations were most suitable for activity tracking (Figure 2.5). The results showed that both the activity and phone location could be accurately predicted using the smartphone built-in accelerometer, with 88% accuracy for activities and 96.4% accuracy for phone locations. The best tracking accuracy was while the phone was in the pocket (94.2%), followed by the belt

(93.1%), the bag (89.1%), and the hand (79.0%). In different location tracking, it was found that walking had the highest tracking accuracy (99.6%), followed by sitting (97.1%), standing (94.5%), sit to stand transitions (89.9%), and then stand to sit transitions (87.3%). Thus, placing the smartphone in the pocket or on a belt (positioned close to the body's center of mass) is recommended because these locations provided the highest accuracy to characterize gross body movements.

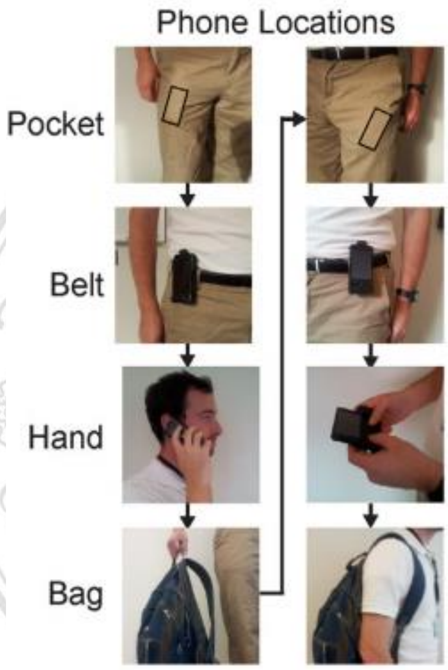

Figure 2.5 Carrying a mobile phone in the pocket, belt, hand, or bag (23).