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LOW COST GAIT CAPTURE DURING TURNING MOTION

Master's thesis

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ODAV MEETOD KÕNNAKU REGISTREERIMISEKS PÖÖRAMIS LIIGUTUSE JOOKSUL

Magistritöö

Juhendaja: PhD Sven Nõmm

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Author’s declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

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Abstract

The objective of this thesis is to construct an alternative low cost solution for gait capture and analysis for a human subject performing a turning motion.

Main goal is to be develop a simple system, that is reliable, inexpensive, easy to install and operate that can be used for research purposes, mainly medical doctors and researchers dealing with diseases that affect a person’s motor functions.

The methodology applied makes use of commercial general purpose cameras with motion capture capabilities (Kinect v2) and computer software to construct such system.

Main results of experimenting with this prototype shows the advantages of such system and the wide range of applications it can be used for, it shows also how this system tackles the problems with existing solutions (cost, inconvenience, complexity, etc.).

This thesis is written in English and is 44 pages long, including 8 chapters, 7 figures and 2 tables.

Annotatsioon

ODAV MEETOD KÕNNAKU REGISTREERIMISEKS PÖÖRAMIS LIIGUTUSE JOOKSUL

Lõputöö eesmärgiks on välja pakkuda alternatiivne odav lahendus liikumise salvestamiseks ja analüüsimiseks jälgides katsealuse inimese liikumist pöörde momendil.

Põhieesmärgiks on välja töötada lihtne ja usaldusväärne süsteem, mida oleks lihtne paigaldada ja kasutada. Programmi peamiseks eesmärgiks on hõlbustada teaduslikke meditsiinilisi uuringuid. Põhiliseks süsteemi kasutajate sihtgrupiks on teadlased ja meditsiinilise taustaga inimesed, kes uurivad igapäevaselt inimese haiguslikku seisundit, mis mõjutab nende motoorseid funktsioone.

Uurimistöö metoodikaks on kasutatud kaubanduslikuks üldotstarbeks mõeldud kaameraid, mis suudavad tabada liikumise eripärasid (Kinect v2) ning arvutitarkvara, mille konfiguratsioon on üles ehitatud antud informatsiooni vastu võtmiseks ja analüüsimiseks.

Eksperimendi peamiseks tulemuseks on näidata, kuidas antud prototüübi kasutamine annab eelise ning võimaldab laiendada sarnaste süsteemide kasutamist laiemas kontekstis. Süsteemi eesmärgiks on lisaks olemasolevatele lahendustele pakkuda alternatiivset võimalust uurimustööks vähendades võimalikke takistusi nagu kulukus, keerukus, süsteemi kasutamise ebamugavus jne.

Lõputöö on kirjutatud inglise keeles ning sisaldab teksti 44 leheküljel, 8 peatükki, 7 joonist, 2 tabelit.

List of abbreviations and terms

PD	Patient diagnosed with Parkinson’s disease
HC	Healthy Control
PC	Personal Computer
RF	Radio Frequency
IR	Infrared
TTU	Tallinn University of Technology

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1 Introduction

Gait analysis is the study of human motion (walking or running) with the intent of extracting features that describe the motion characteristics of a subject. The goal of such analysis is to provide objective measurements that can be used in numerous applications that include medical diagnostics, enhancing athletes' performance, biometric identification and many other applications.

Human locomotion involves complex interaction between the nervous system and the skeletal system, it also involves a great deal of coordination and synchronization between different body parts and joints in order to maintain balance and maximize efficiency. Gait analysis enables us to abstract these very complex interactions and motions into a set of relatively simple and objective features that uniquely describe the biomechanics of the subject and that serve the purpose of the analysis.

Different features are obtained based on the goal from the analysis and the technique used to obtain these features, these features may include but not limited to:

- Step length
- Stride length
- Speed
- Angular velocity in turning motion
- Foot Angle
- Hip Angle
- Maximum foot height
- Ground reaction force

The applications for gait analysis cover many areas of research, such as medical diagnosis in case of diseases and ailments that affect motor functions as such analysis can provide an objective indicator on the subject's health, gait analysis also can be used as a form of biometric identification since gait characteristics are uniquely associated to each individual, this provides some advantages over other forms of biometric identification as it can be used at a distance using simple equipment and it doesn't require high resolution data such as those needed for other biometric identification methods such as face recognition and iris scanning.

Other applications include sports to help athletes track and enhance their performance, biomechanical studies where the mechanics of locomotion for different species is studied, and many other applications.

Turning motion in humans is quite complex when compared to walking in a straight line as humans are required to perform very complex maneuverers to deal with the centrifugal forces that tend to keep the body moving in a straight trajectory and to maintain balance with the shifting in centre of mass accompanied with such motions.

This makes studying turning motion of special importance due to the numerous applications for such studies and more importantly since there isn't much research in this area compared to studies that have been conducted on simpler forms of locomotion, and the existing solutions either depend on human subjective experience as in the case where a doctor or a researcher would just observe the subject and try to come up with a conclusion, or they rely on expensive equipment that are usually complex to setup and operate.

2 Literature Overview

The study of human gait has the potential to explain much of the human behaviour related to locomotion and provide solutions to many of the problems in different fields of research related such as medicine and biology. The advancement of techniques and sensors has led to gait analysis being used for numerous applications.

Examples of these applications, medical diagnosis of diseases with symptoms related to motor functions and neuromuscular system (e.g. Parkinson's disease) [1] [2], as gait analysis can provide objective quantitative measurements that can be compared against older data collected about the patient or data collected from other individuals which then can be used as an indicator for the progression of such diseases. Automated diagnostics can done as well using machine learning techniques for classification where the gait features extracted for individuals positively diagnosed with such diseases and gait features for healthy individuals are used as training data for supervised learning [3].

Gait analysis has been also used in monitoring rehabilitation processes for patients undergoing therapeutic intervention [4] [5] [6] to track if such rehabilitation techniques are helping the patient regain motor functions as opposed to classical techniques which rely heavily on subjective observations which can be inaccurate for such purpose.

Sports is another field that can make use of gait analysis for different purposes, for instance gait features can be used in the analysis of athletes performance [7] [8] [9], tracking different exercises and activities to monitor what effects they have on the performance and fitness of athletes [10], or even testing sports equipment and surfaces and their impact on performance [11] which can help with designing performance enhancing sports gear.

In the field of neuroscience, gait analysis has been used to study interactions between the brain and the skeletal system [12]. Gait characteristics are also unique to each individual, thus minor variations in gait style can be used as a biometric identifier to provide a way for user authentication and access authorization [13] [14]. Gait analysis has even been performed on animals [15] for different research purposes such as studying animal biomechanics, and comparing styles of locomotion in different species.

There exist many techniques that are used for gait capture, these techniques can be classified into wearable and non-wearable systems, wearable systems include gyroscopic (inertial sensors) [16] [17] which measure acceleration forces at different points of interest, wearable radar transceiver [18] where RF transmitters and receivers placed on the subject body, electromyography sensing devices that record electrical activity of muscle tissue [19], force sensing devices placed inside the shoes worn by the subject [20] [21], ultrasonic sensors [22], optical analysis systems using single or multiple cameras with passive [23] [24] or active markers [25].

On the other hand, non-wearable systems don’t require any active or passive markers or sensors to be worn by subjects, these systems include the use of normal cameras [26] [27] where regular optical cameras record motion then features are extract with the help of image processing and pattern recognition techniques, or depth sensing cameras such as Kinect sensor [28] [29] where the sensor itself has the ability to create a 3D model of the space monitored. A deeper study of different gait analysis techniques is presented in [30].

One specific subset of motion capture, is motion capture during a turning gait, in this case the goal is the capture and analysis of the motion of a subject walking along a curved trajectory as opposed to walking in a straight line, this specific category of gait analysis can be used for the study of the mechanical behaviour of human motion during turning in general [31] [32] and for specific purposes such as testing the effectiveness of prosthetics and how can the design of such prosthetics be improved [33], providing a different set of gait characteristics that cannot be obtained by gait analysis of motion in a straight line that can be used for medical diagnosis and rehabilitation for individuals with locomotion impediments due diseases or injuries and test the efficacy of therapy and medication on the mechanical behaviour of the subjects during these kinds of motion [34] [35] [36], or even to help with designing robots capable of performing complex manoeuvres while keeping their balance [37].

The work done in [38] is of specific interest as it provided a solution for motion capture while performing a turning motion using multiple Kinect devices, this makes it very related to the topic of this thesis and the solution presented . The solution uses 4 Kinect devices positioned at a 90º angle of each other, it takes advantage of the fact that Kinect is optimized to work best when the subject is facing the camera, so during a recording session, the software decides which device to use to capture the motion by detecting which direction the subject is facing and which of the four devices has the best orientation relative to the subject. The main difference between that solution and the one presented in this thesis is that the data for each frame comes from only one of the four Kinect devices as opposed to merging the data from different devices.

3 Problem Statement

Microsoft Kinect and other similar commercial motion sensing devices though they started as a mere add-on peripheral to entertainment systems such as a game controller for gaming consoles, they have proved to have the potential to be a very powerful and affordable tool that can be used in many fields of research.

Being a relatively cheap device that contains a collection of sensors such as a high resolution RGB camera, depth sensor and multi-array microphone coupled with an easy to use programming interface that provide full-body 3D motion capture in addition to face and voice recognition capabilities, has led many members of the development and research community to consider using Kinect as a reliable and a low cost tool replacing other expensive special purpose devices and tools.

There has been many research papers that tackled the issue of capturing motion of a subject walking in a straight line where the orientation doesn’t changes. However, for this thesis, the main point of interest is to accurately capture the motion of a subject in a turning motion where the direction the subject faces relative to the sensor changes and use this collected data to extract features of interest.

The idea of the subject moving in a curved trajectory poses the issue of deterioration in the quality of the data collected in case the capturing process is done using a single stationary optical camera or depth sensing device, this is due to the fact that these sensors by nature are optimized to work best when it is able to see all the joints of the subject, yet in the case of a turning motion it’s inevitable that some of the subject body parts will be blocked from view by other body parts.

Kinect software tries to infer the coordinates of body joints that are not directly visible to it, yet the process of inferring the location of these joints is not perfect and by experimenting it was found that the data yielded from this inferring process is usually not in a shape good enough to be used in applications that require high quality and accuracy of the data such as the case here where we try to extract delicate features that depend on the exact locations of these joints and where small errors may have a great negative impact on the end result.

There already exist solutions that focus on this type of application, yet as demonstrated in the literature overview, they either rely on techniques that use sensors that don't depend on line of sight measurements such as inertial sensors or IR transceivers worn by the subject which can be very inconvenient such in applications related to medical diagnosis where these wearables can be uncomfortable for the patients or in sports applications where such wearable devices may interfere with the performance of the athletes wearing these markers or sensors which would defeat the purpose of trying to evaluate the performance of the subject under normal circumstances and conditions.

Other solutions rely on the usage of an array of special cameras that work with passive markers which have a quite complex setup process that would require the operator to construct complex mapping for skeleton data and requires a very specific calibration process that is both lengthy and require special expertise, that makes such solution not suitable for regular users who don't possess high technical knowledge nor for usage in environments that are not specifically dedicated for such experiments, and also since they require the subject to wear these passive markers they again pose the same concerns with wearables in general.

One other solution mentioned earlier doesn't rely on wearables, utilises more than one Kinect device, and it does so by switching on and off these Kinect sensors based on the direction the subject is facing, it does so to make sure that the sensor that is capturing the motion at any moment is the device that has the best view and tracking of the subject motion. Though such solution would yield good results in case the user change orientation, it does not take full advantage of all devices as only one device can be used at a time while the other devices that does not face the subject would be idle and their observations will be discarded in spite of the fact that such data may contain useful information that are not captured by the active device.

4 Methodology

In this section, we demonstrate the technologies used and how and why they have been chosen over other technologies and equipment.

4.1 Hardware

a) Kinect for Windows version 2

Two sensors are used in the system, one is labelled as the master sensor and it will be positioned so as that the subject will be facing it at the starting position of the experiment, the other sensor will be referred to as the slave sensor.

Kinect for Windows version 2 was chosen over version 1 for its advantages such as:

- Improved body, hand and joint orientation
- Higher resolution color and depth cameras
- Bigger horizontal field of view (70 degrees as opposed to 57)
- Bigger vertical field of view (60 degrees as opposed to 43)
- Uses USB 3.0 standard which allows for higher bandwidth which translates to more detailed skeleton data capture at a lower latency which affects the overall quality of data collected

b) Ethernet network Switch

The advantage of using a wired Ethernet communication is higher reliability and faster communication but the system still supports using a wireless network with minimal configuration change without sacrificing much of the system reliability

4.2 Software

a) C# programming language Windows Presentation Foundation (WPF)

C# was chosen over C++ as C++ is more complex to develop with and the performance improvements associated with using C++ are trivial in the scope of this application.

Windows Presentation Foundation (WPF) application was used to provide a graphical user interface for the system.

b) **Kinect for Windows SDK version 2.0**

c) **.Net framework Socket communication**

Since communication is needed between the applications running on the two machines connected to the Kinect devices, there were multiple options considered for the communication.

1. TCP socket communication
2. RESTful API where one PC will provide HTTP services and the other PC can consume them
3. WebSocket where a communication can be established between the two machines over full-duplex channel over a TCP connection

TCP socket communication was chosen for its simplicity and low overhead, TCP sockets provide very basic duplex communication which is sufficient for this application.

4.3 Experiment description

As mentioned before, the main objective of this system is to provide a means for gait capture and analysis of a subject performing a turning motion, so, the experiment used to verify and test the system consisted of the subject walking in a trajectory that can be split into 4 segments:

i. Forward phase: Subject starts facing the master Kinect device at a maximum distance marking the start of the first segment and that is bounded only by the device field of view and the space provided for the experiment, subject then starts walking towards the master Kinect.

ii. First turning phase: When subject reaches a point marking the end of the first segment, he/she start walking in a semi-circular trajectory until he reaches the same distance that marked the end of last segment. At this point the subject should be facing away from the Kinect device.

iii. Backward phase: The subject starts walking away from the Kinect device until he reaches the distance that marked the beginning of the first segment.

iv. Second turning phase: In the 4th segment the subject walks again in a semi-circular trajectory until he gets back to the starting point marking the end of the cycle.

The distance thresholds marking the end of the forward phase and the backward phase can be chosen arbitrarily (default values used in experiments are 1.5 m and 4 m respectively), and they are only bound by the limits on distance posed by the sensor tracking capabilities (0.5 m to 4.5 m)

This cycle maybe repeated any number of times, with a larger number of repetitions allowing for better results.

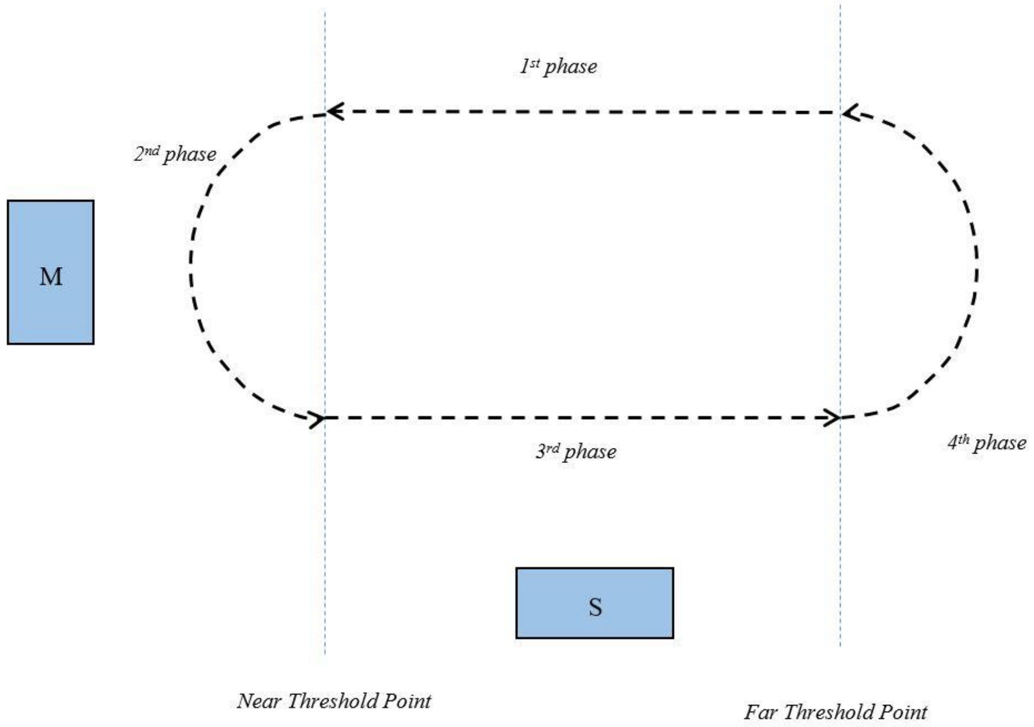

Figure 1 Experiment Description

5 Solution

In order to be able to maintain the quality of data captured during a turning motion, two Kinect sensors are used simultaneously to record the subject's motion. With this approach we have a redundancy in the captured information that enables us to discard less accurate observations made by one sensor in favour of the more accurate data collected by the sensor that has a better view of the subject at each frame.

To do that, we construct a new skeleton by merging the data collected by both sensors, then this new skeleton is what is used to extract the features.

The requirements for the system include:

- The system should be user friendly and can be used by non-technical individuals
- The system should be easy to calibrate
- The system should be portable, meaning it doesn't require specific environment in order to work properly
- The system should perform analysis automatically at the end of an experiment
- The system should output the analysis results in a format that can be interpreted by humans and machines

5.1 Preparation

5.1.1 System setup and calibration

The experiment requires that the two Kinect sensors to be positioned 90 degrees relative to each other where the slave resides on the master device's right side and both sensors at the same height from the ground.

Figure 2 Kinect Coordinate System

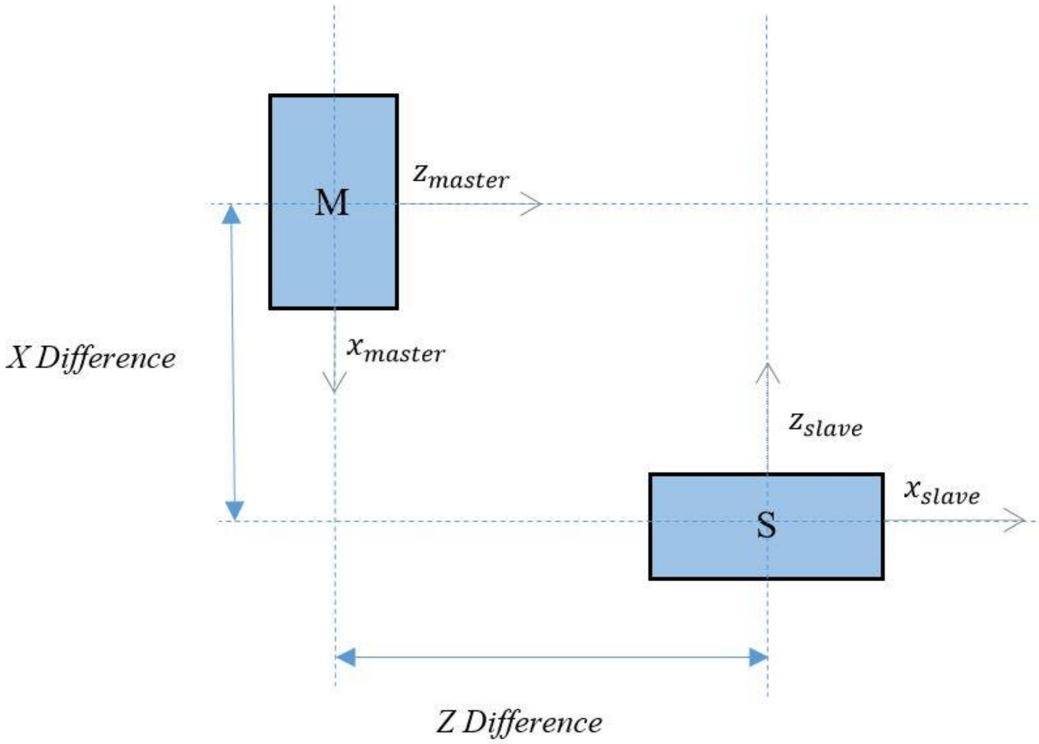

Figure 3 Top View of Setup

The 2 values needed for calibration are the distance between the two devices in X-axis and Z-axis with respect to the master sensor, the 2 distance values are measured as accurately as possible relative to the master sensor.

X Difference value is distance of slave sensor from the origin point for master sensor in the X-axis of the master device.
Z Difference value is distance of slave device from the origin point for master device in the Z-axis of the master device.

Other than these two values we need to only provide the IP address of the slave PC, this can be obtained from the slave UI where the IP address is shown in the status bar, or the user may run a command on the slave PC to get the IP address (i.e. ipconfig).

5.1.2 Auto calibration

Currently the system does not provide an automatic way for calibration, however, the system can run in calibration mode, in this mode the recording will be done in the same way, the difference is that instead of using the provided calibration values from the application properties to merge the body frames from the two devices, the system instead tries to interpolate these values using the same technique used for rotation and merging, but instead of having the rotated value as the result of the equation, we assume that the rotated skeleton matches perfectly with the skeleton recorded by the master sensor (ideal case) and calculate the X and Z differences that would achieve such result using the below equations.

$$d_x = x_{master} + z_{slave}$$

$$d_z = z_{master} - x_{slave}$$

Where:

d_x: distance between devices in x axis with respect to master
d_z: distance between devices in z axis with respect to master
x_{master}: coordinate of joint in x axis relative to master
z_{master}: coordinate of joint in z axis relative to master
x_{slave}: coordinate of joint in x axis relative to slave
z_{slave}: coordinate of joint in z axis relative to slave

For using such technique we may only work with tracked joints (joints that are visible to the sensor and whose value is measured and not inferred), inferred values are discarded as they are not accurate enough and can be detrimental for the end result. For each frame recorded these two equations are computed for every tracked joint, and the calculated value would be the average of all these computed values.

$$\overline{d_x} = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} d_{x_{ij}}}{n \times m}$$

$$\overline{d_z} = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} d_{z_{ij}}}{n \times m}$$

Where:

n: number of frames in calibration session
m: number of tracked joints in the i^{th} frame

The number of frames collected during a recording session (*n*) in calibration mode affects the accuracy of the results, with higher number resulting in higher accuracy, this is because with higher number of values, the effect of erroneous readings will be minimized due to the averaging.

At the end of the calibration session, results are presented to the user so that they can be used as a reference to allow for better calibration.

5.2 Steps for gait capture and analysis

In this section, a breakdown of the gait capture and analysis process is presented.

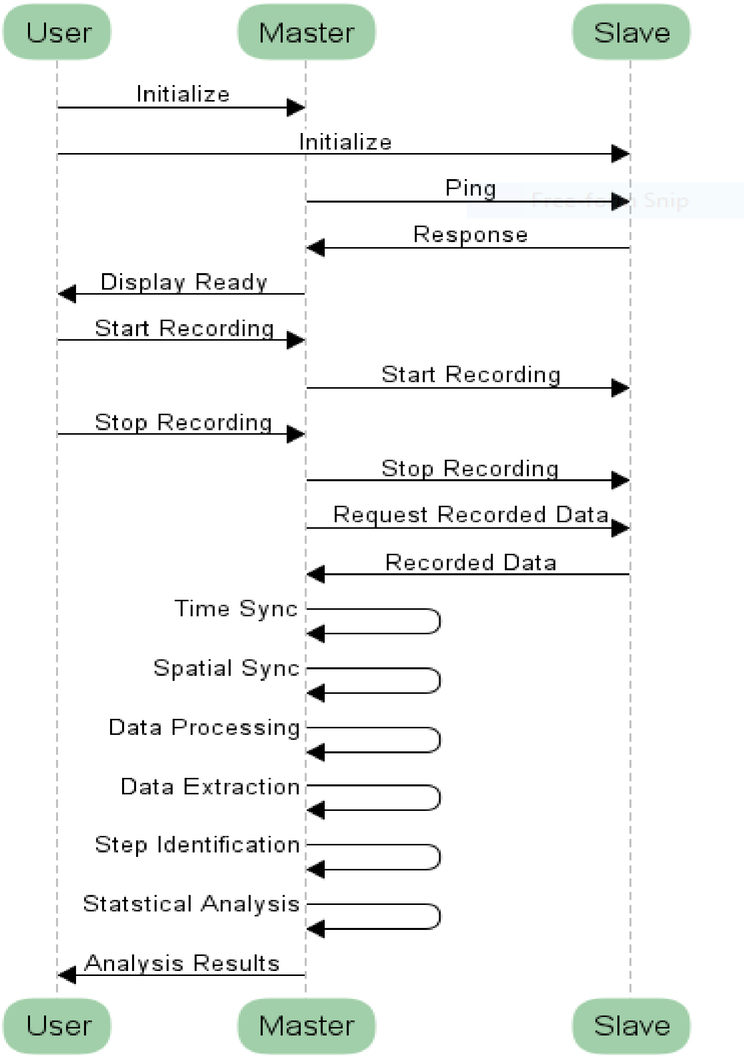

Figure 4 Solution Sequence Diagram

The below steps occur sequentially at the time the operator initiates the recording session on the master application.

→ *Operator initiates recording session*

5.2.1 Recording

- Master PC start recording body frames received from the master Kinect sensor as well as the timestamp associated with each frame.

- Master PC stores the time the operator initiated the recording.
- Master PC signals the slave PC to start recording.
- Slave PC stores the time it received the signal to start recording.
- Slave PC start recording frames received from the slave Kinect sensor as well as the timestamp associated with each frame.

→ *Operator ends recording session*

5.2.2 Data Gathering

When the recording session is complete, the master PC makes a request to the slave PC to send the data recorded by its side, the slave computer then constructs an object that contains all the recorded data, serialize this object to JSON format, then sends it over the network to the master.

5.2.3 Time Synchronization

Before we can merge the data, we need to figure out which master and slave frames should be merged. Since each sensor is connected to a separate PC, that means that timestamps will be relative to the machine's clock, and although the two machines are on the same network so the Network Time Protocol (NTM) will make sure that the clocks are relatively synchronized, there's still difference between the two machines clocks big enough to make it hard to sync the frames.
So solution had to be implemented to account for this difference in clocks.
The slave data object also contains the time at which the slave received the signal to start recording, by having this piece of information in addition to the time when the master sent the start recording signal and calculating the network average delay, the clock differences between the master and slave machines can be calculated and used to correct the slave body frames timestamps.

$$\Delta t = t_{master} + \frac{t_{latency}}{2} - t_{slave}$$

Where:

Δt: time difference between master and slave machine clocks
t_{master}: timestamp of recording start relative to master machine clock
t_{slave}: timestamp of recording start relative to slave machine clock
$t_{latency}$: latency of the network

The difference between the machines clocks is then used to correct the timestamps from the slave machine to be relative to the master machine clock.

$$t_{corrected} = t_{original} + \Delta t$$

After that the frames from the two sensors that have the smallest difference in time are mapped to each other.

5.2.4 Spatial synchronization

The body coordinates recorded by each Kinect device are relative to the position of that device camera as it is used as the origin point for the coordinate system, so before we can merge the data from both Kinect sensors, we need to have the values from both sensors relative to a single origin point which is the master Kinect sensor camera.

The slave frames are rotated by 90º and translated to use the master Kinect device as the origin point instead of the slave Kinect device.

The below simple equations are used to get the new coordinates for the slave body frames relative to the master sensor's origin point (assuming the above mentioned configuration is used):

$$x_{rotated} = z_{slave} - d_x$$

$$z_{rotated} = d_z - x_{slave}$$

$$y_{rotated} = y_{slave}$$

$$(assuming\ both\ devices\ are\ the\ same\ height\ from\ the\ ground)$$

The coordinates from each frame for both Kinects are now merged into a single body frame. The merging process follows these rules to calculate the coordinates for each body joint in the new skeleton.

- If both sensors were able to track the joint, the coordinates will be the averaging of the two sets of coordinates.
- If only one of the sensors was able to track the joint and the value from the other sensor was only inferred, then we discard the inferred value in favor of the tracked value.
- If both sensors were unable to track the joint, then we again the average value of the two is taken to try to minimize the error.

5.2.5 Noise reduction and data post processing

Raw data is analyzed and then necessary processing is applied in order to remove data irregularities so as to furtherly improve the quality of the statistical features to be derived from this data.

The processing is done basically by having a set of simple rules that are used to filter out the frames and frames that do not fulfill these filtering criteria are discarded. These rules include real life assumptions such as that only one foot maybe moving at a time and if two frames show that one foot is ahead of the other, all frames in between should show the same.

5.2.6 Relevant data extraction

Ankle data are extracted from the resultant merged body frames, as the ankle point are the best body joints that can be used to identify the steps from the data.

5.2.7 Step Identification

Steps are identified based on the ankle coordinates for both feet.

This is done by checking which foot at each frame is the one moving, a step is marked as the frames between the start of motion of one foot until it stops moving and the other foot starts moving instead.

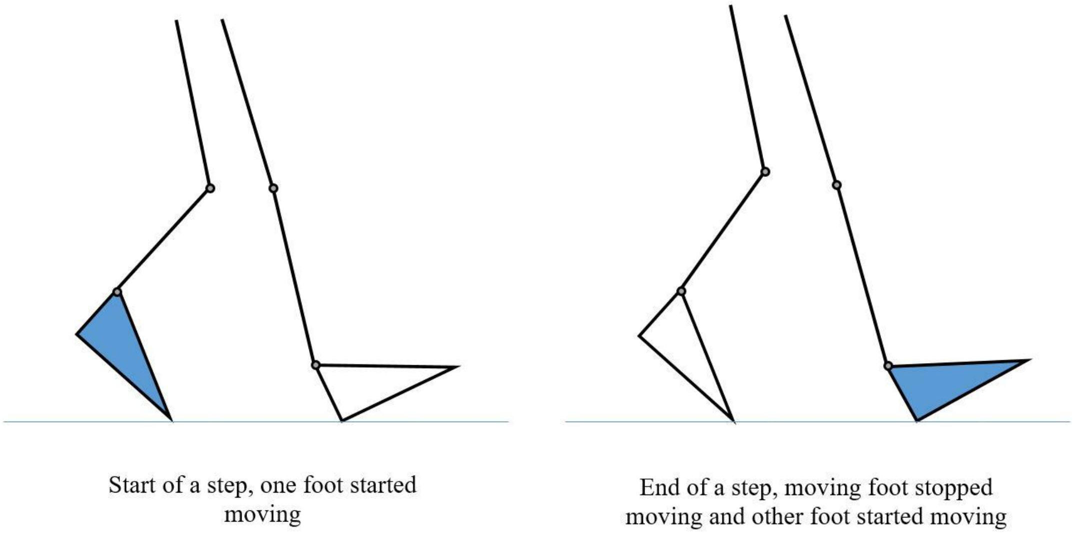

Figure 5 Illustration of Step

The output from this step is an object that contains attributes describing each step such as the number of frames marking the start and end of the step, the length of the step in meters, and the time that took the subject to perform this step in seconds.

5.3 Statistical Analysis

Statistical analysis is performed on the body joints data that resulted from the merging of the body frames captured by both devices in order to construct a number of defining features of the subject's gait during a recording session.

These features can then be used to compare the subject's gait from different recording sessions or to compare the subject's gait features with other subjects who are in a different conditions which can give the medical doctors or researchers a reference that can be used to make conclusions about the progression of a disease affecting the subject's motor capabilities, test the viability of a specific therapeutic method, or even predict a the possibility of a healthy person of getting such disease which can help the doctors take a preventive actions that may have a dramatic outcome on the subject health.

The analysis results are exported to file in a format that is both human readable and machine readable, this allows other researchers to perform further analysis on the data that the system generated.

The features that are identified are classified as the following:

1. Simple spatial and temporal features:
   i. Length of each step taken during the session, this is calculated using the absolute difference in coordinates in the X and Z axis (**Euclidean distance**) between first and last frame in the step.

$$l = \sqrt{\left(x_{last} - x_{first}\right)^2 + (z_{last} - z_{first})^2}$$

   ii. Time taken between the start and end of each step, time difference between the last and first frame in the step.

$$t = t_{last} - t_{first}$$

   Where:

   t_{first}: timestamp of first frame in the step
   t_{last}: timestamp of last frame in the step

2. Average features:

   i. Average length of steps in a session

$$\bar{l} = \frac{\sum_{i=0}^{n-1} l_i}{n}$$

   ii. Average time for step taken

$$\bar{t} = \frac{\sum_{i=0}^{n-1} t_i}{n}$$

   iii. Average number of steps per second in the session

$$\bar{s} = {}^{1}\!/_{\bar{t}}$$

   iv. Gait speed in meters per second during the session

$$v = {}^{\bar{l}}\!/_{\bar{t}}$$

Where:

n : number of steps
$\bar{l}$: average step length
$\bar{t}$: average duration of a step
$\bar{s}$: average number of steps per secod
v : average speed in meteres per second

3. Angles of main body joints

The last class of features extracted is the minimum and maximum angles experienced by the subject during a step, this angle is defined by three body joints forming this angle, and these angles are chosen for their significance for medical research.

Each joint is represented as a vector of the coordinates in 3 dimensions, below are the steps taken to calculate the angle given the 3 joints forming this angle.

   i. The vectors representing the two bones connecting the start and end joints with the mid joint are calculated.

$$b_1 = j_{start} - j_{mid}$$

$$b_2 = j_{end} - j_{mid}$$

ii. The vectors of the bones are normalized.

$$A = \frac{b_1}{\sqrt{b_{1_x}^2 + b_{1_y}^2 + b_{1_z}^2}}$$

$$B = \frac{b_1}{\sqrt{b_{2_x}^2 + b_{2_y}^2 + b_{2_z}^2}}$$

Where:

A : normalized vector of b_1
B : normalized vector of b_2

iii. The angle is calculated using the Euclidean norm of the cross product and the dot product of the bones vectors.

$$angle = \tan^{-1} \frac{\|A \times B\|}{A \, . \, B}$$

The angles calculated are shown in the table below:

Start Joint	Mid Joint	End Joint
Right Hip	Right Knee	Right Ankle
Left Hip	Left Knee	Left Ankle
Head	Spine Base	Right Knee
Head	Spine Base	Left Knee
Right Knee	Spine Base	Left Knee
Head	Neck	Spine Mid
Neck	Spine Mid	Spine Base
Head	Neck	Spine Base

Table 1 List of angles in analysis

The output result from the recording session is exported to CSV files containing:

- Coordinates: each row represents a single frame and includes the coordinates for each joint, the timestamp for the frame relative to the master machine clock, and a number indicating the path segment this frame belongs to.
- Analysis: each row represents a single step and includes the length of the step, duration taken to complete the step, and the minimum and maximum value for each of the angles mentioned above. The file also contains the average values mentioned before.

After the files are generated, the application plays back the recorded session showing the skeletons from the master and slave machines as well as the skeleton that resulted from merging the 2 skeletons.

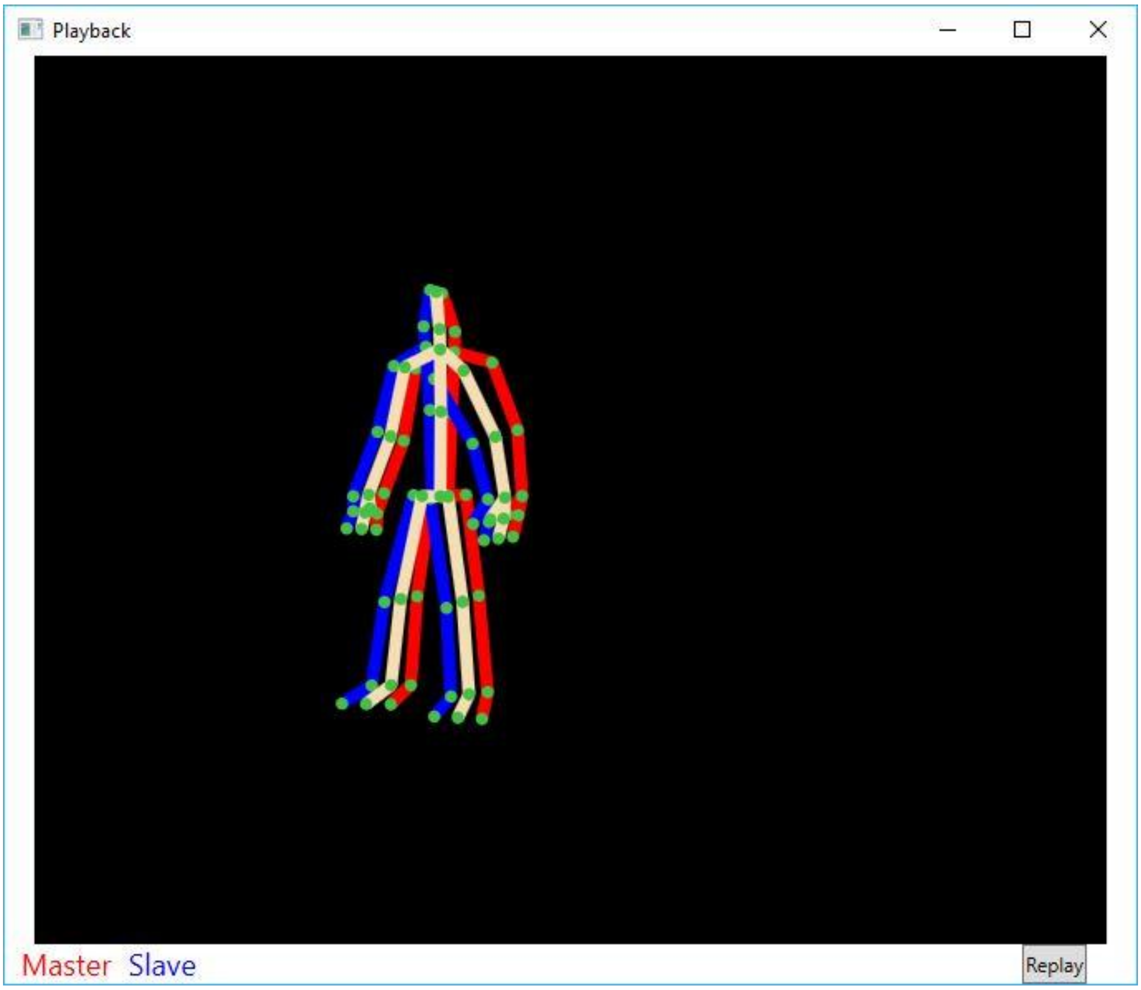

Figure 6 Playback View of Recording

6 Main Results

In order to test the solution, we needed to verify that the results presented by the system reflect actual real-life values and it should show also that there is an advantage for using 2 Kinect sensors simultaneously as opposed to using either of the sensors at a time.

A number of experiments have been devised where the experiment area floor area was covered with markers that shows the path for the subject and where exactly the subject should start and end each step, any by knowing the distance between these markers we can verify the results.

In these experiments we focused on the step length as the feature to compare different approaches as this is the gait feature whose actual value can be measured with highest accuracy.

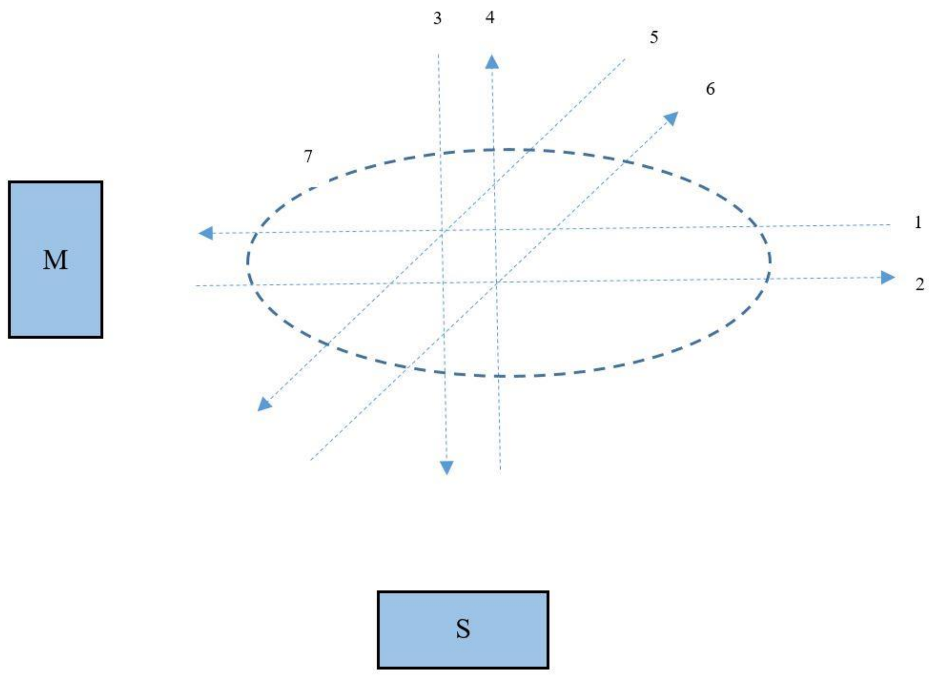

Figure 7 Illustration of Testing Experiments

The figure above shows the 7 experiments conducted, in the first two experiments, in the subject walks towards and away from the master camera, in the second two, the subject walks towards and away from the slave camera, in the 5th and 6th experiments the subject walks diagonally on a 45º path relative to the Z-axis of either Kinect devices, for the last experiment the subject walks in elliptical path.

For experiments 1 to 6, the subject takes 3 steps in each recording session, and for experiment 7 the total number of steps per session is 12. Each step was marked to have the exact length of 0.5 meters. Experiments 1 to 6 were repeated 5 times each, and experiment 7 was repeated 20 times for a total of 50 recorded sessions.

Table below show the actual value of the average step length, and results calculated from using the data collected by each Kinect by itself, and the results from the combined data over all the sessions recorded.

Exp.	Master Avg.	Master Error	Slave Avg.	Slave Error	Merged Avg.	Merged Error
1	0.520933	**4.1866%**	0.419622	16.0756%	0.56292	12.584%
2	0.510597	**2.0119%**	0.416064	16.7872%	0.334915	33.0169%
3	0.4266	14.6798%	0.535034	**7.0068%**	0.536138	7.2276%
4	0.458239	8.352%	0.504538	**0.90779%**	0.493546	1.2906%
5	0.528244	**5.6489%**	0.626241	25.2482%	0.531878	6.3756%
6	0.56298	12.596%	0.546824	9.3648%	0.539675	**7.935%**
7	0.558474	11.6948%	0.540933	8.1866%	0.493471	**1.3058%**

Table 2 Results of experiments of testing solution

From this table, we can see that:

- Experiment 1 & 2: The subject is facing towards or away from the master Kinect, this resulted in the error in measurements from the master data alone was smaller than the error resulting from the slave data alone and the merged data.

- Experiment 3 & 4: The subject is facing towards or away from the slave Kinect, so we can see similar results to experiment 1 & 2 where the accuracy of measurements are better in case of the slave data rather than the master data or the merged data.

- Experiment 5 & 6: Here the subject is walking diagonally, so there is no advantage in visibility for neither cameras, but we can also see that the merged data gives results similar to the data with the best results or better than both.

- Experiment 7: Here we can see clearly that the merged data is providing more accurate results than either Kinect did on its own.

7 Discussion

Experiments have been conducted to verify that the system addresses the purpose of this thesis and the problems pointed out earlier with existing solutions, these experiments have shown how the system would behave under different conditions.

We can see that since Kinect was designed with the purpose of monitoring and capturing the motion of people directly facing it, a single Kinect proved to be best at capturing motion in case the subject is either facing towards or away from the camera, in case the subject is facing the Kinect with angle, the quality of the data deteriorates.

The results have displayed that using two Kinect devices with the setup mentioned before, does in fact make a positive impact on the quality of the data collected while monitoring a subject performing a turning motion, as opposed to using a single device which was the main objective from this solution.

Also the system has addressed the other issues with the existing solutions. The system is easy to setup, it requires no special equipment other than the two Kinect devices themselves, it is also easy to calibrate with few configuration parameters needed to be provided before the system is ready for recording. Also the system provides a way for automatic calibration, which can help the operator of the system with the calibration process.

The system does not involve the use of any wearables of any kind, making it convenient for using with senior patients, people with disabilities, or children.

The system does not require a special environment to work properly, as it only needs an experimentation floor area that is equivalent to that of a medium sized room, this coupled with the fact that it is easy and quick to setup and calibrate, make the system portable.

7.1 Future Work

The system can be extended in order to make it capable of performing analysis of other types of motion other than the main purpose here which was turning motion. As shown from the results the quality of the analysis of merged data is slightly lower than the analysis of data from a single Kinect in the case of the motion is in a straight path towards or away from this single Kinect. There's a room of improvement in that case where there can be an option in the system to have the analysis based only on one of the devices without merging the data, or have the system generating analysis for each device by itself in addition to the analysis from the merged data (this is already supported by the system with minor modifications). In the same sense, other features maybe added to the system in order to provide high quality gait analysis for other types of motion, giving the system the potential to be a generic tool for gait analysis.

One other area of improvement would be to integrate a module that can interpret the analysis generated by the system automatically, and then provide some conclusions based on these gait characteristics of the subject such as the probability of the subject developing some motor function disorders.

Such module would make use of machine learning techniques such as artificial neural networks or deep learning, where gait features coupled with medical conditions of test subjects can be used as training data to create a model that can be used later to classify a subject condition based on his/her gait characteristics.

8 Summary

The main purpose of this thesis was to come up with an alternative low cost solution for motion capture and gait analysis during a turning motion. The system created uses two Kinect devices working in tandem to provide a statistical analysis of a subject's gait characteristics.

The system is relatively cheap compared to other specialized equipment used for motion capture purposes, uses readily available commercial equipment, it is easy to setup and calibrate the system in a matter of few minutes making the system highly portable. The system also relies on non-wearable equipment making it more convenient to use for different applications.

Experiments have been conducted in order to test the viability of the system, the results obtained from the experimentation shows that the problems stated related to other solutions have been addressed and that the system achieves its purpose.

Acknowledgments

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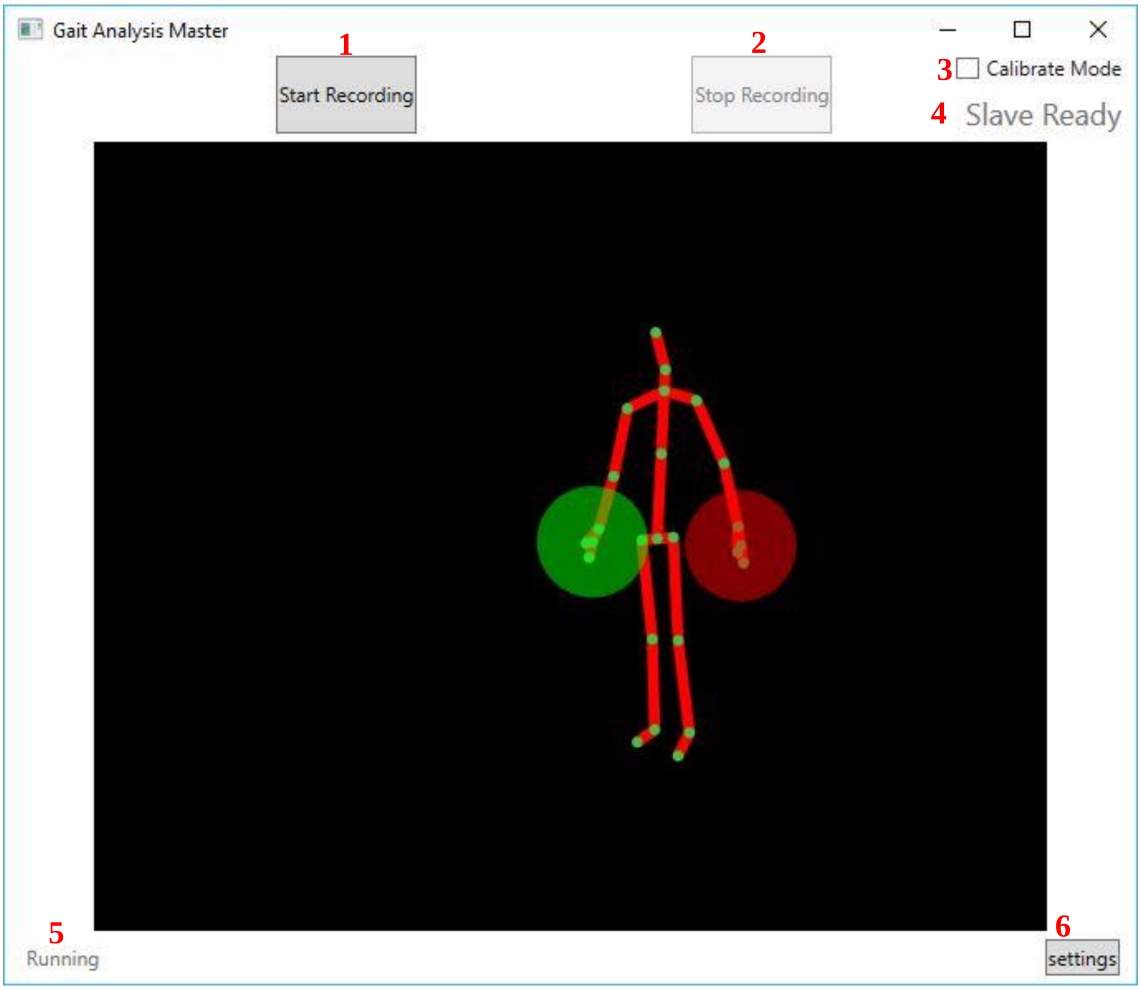
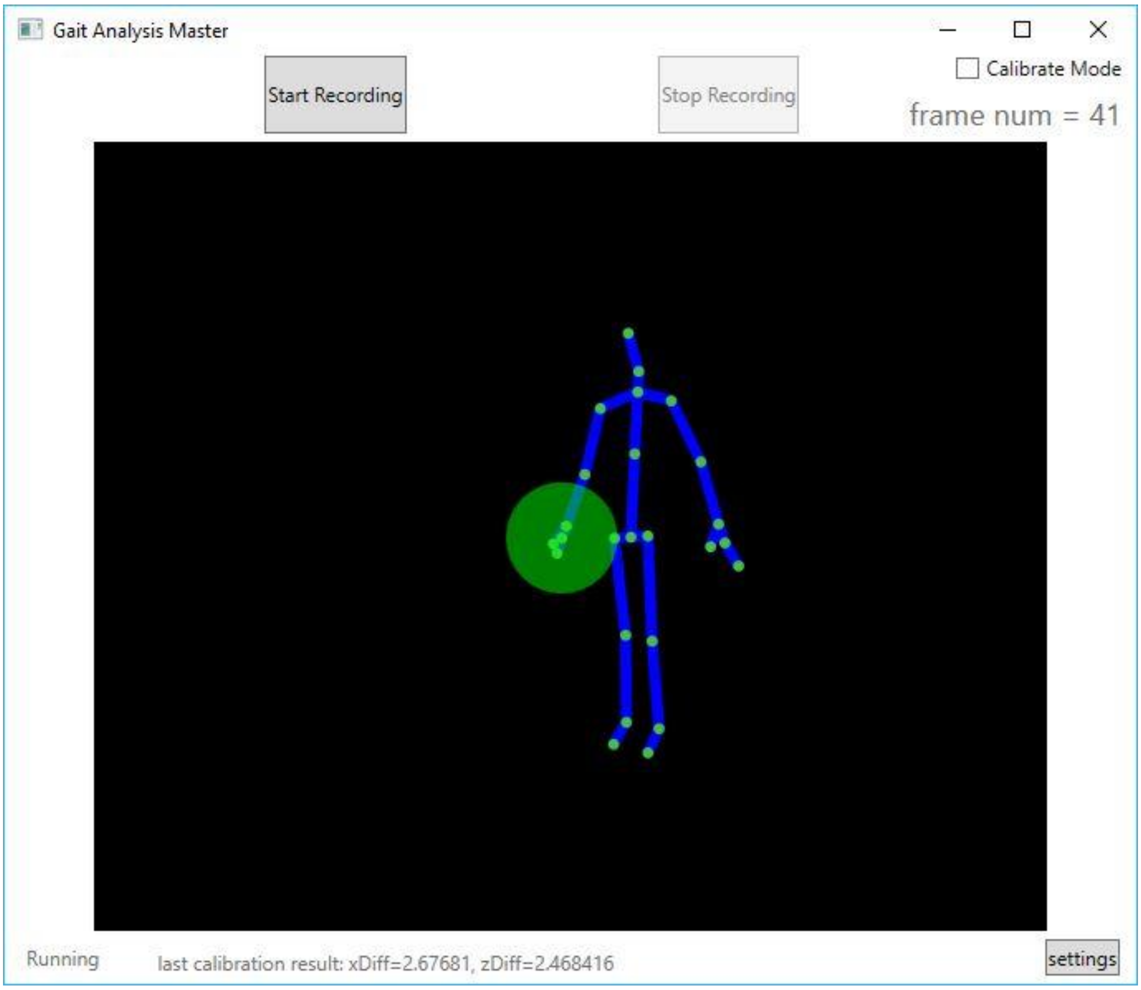
Appendix 1 – Application Manual

1. Master Application Interface



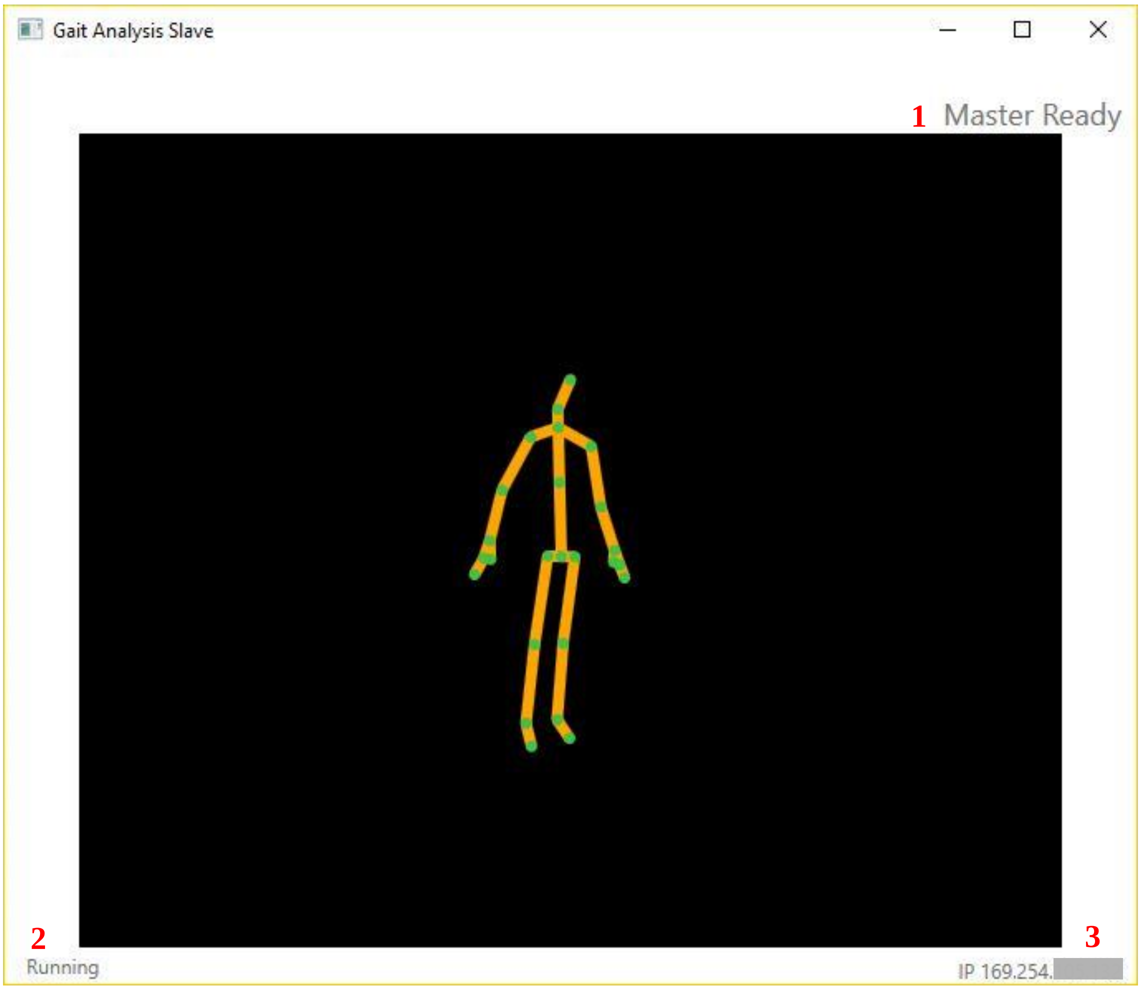
1. Start button: Initiates a recording session, it's only enabled when a Kinect device is connected to the machine and the slave is ready to start.
2. Stop button: Ends a recording session.
3. Calibrate Mode checkbox: if checked before starting a session, that means this session will be only for calibration purpose and no analysis will performed.
4. Slave status: indicates whether the slave machine is reachable and ready to start recording.
5. Kinect status: indicates whether a Kinect device is detected or not.
6. Settings button: Opens the settings menu

The below shows the interface at the end of a calibration session:



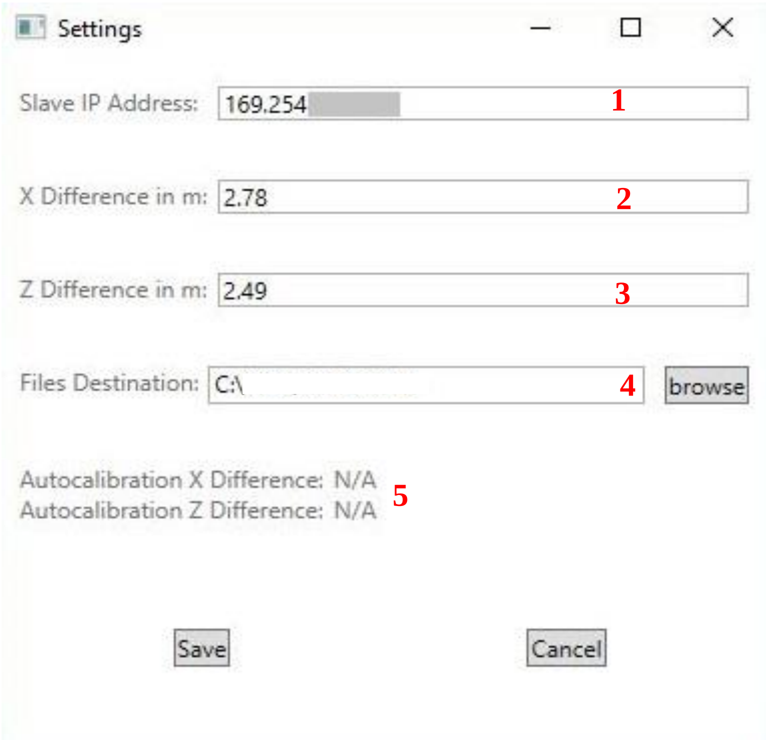
The calibration results can be seen at the bottom, at the top right corner we can see the number of frames recorded in the last session.

2. Slave Application Interface



1. Master status: indicates whether the master machine is reachable.
2. Kinect status: indicates whether a Kinect device is detected or not.
3. IP address: the IP address for the slave machine.

3. Master Application Settings Window



1. The IP address for the slave machine.
2. The X difference value needed for calibration in meters.
3. The Z difference value needed for calibration in meters.
4. The destination for the generated files for recording sessions.
5. The auto calibration values from last calibration session for reference.

4. Operation Manual:

1. Start the applications on both machines (order of which application starts does not matter)

2. In the settings window of the master application, the value for X and Z difference, the slave machine IP address, and the destination for generated files are set.

3. (Optional) perform a calibration session by checking the "Calibrate Mode" checkbox, then pressing "Start Recording" button, record the subject performing any kind of motion (even just standing) and it's better to make sure that the subject is visible for both Kinect devices throughout the recording session, then stop the recording session by pressing the "Stop Recording" button. After that the values from the calibration session can be used to enhance the X and Z difference values.

4. Start a normal recording session by making sure the "Calibrate Mode" checkbox is unchecked then pressing "Start Recording" button, the subject is recorded performing the experiment, then the recording session is finished when the "Stop Recording" button is pressed.

5. A playback of the recorded session is displayed, and the analysis results can be found at the destination specified.