GOA COLLEGE OF ENGINEERING
FARMAGUDI, GOA

DEPARTMENT OF ELECTRONICS & TELECOMMUNICATION ENGINEERING

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HUMAN IDENTIFICATION USING GAIT RECOGNITION

by

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A project submitted
in partial fulfilment of the requirements
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in
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GOA UNIVERSITY

under the guidance of

Prof. MILIND FERNANDES
Assistant Professor,
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CERTIFICATE

This is to certify that the project entitled

"HUMAN IDENTIFICATION USING GAIT RECOGNITION"

submitted by

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has been successfully completed in the academic year 2016-2017 as a partial fulfilment of the requirement for the degree of BACHELOR OF ENGINEERING in Electronics and Telecommunication Department, at Goa College of Engineering, Farmagudi.

(Internal Examiner) (External Examiner)

Place: Farmagudi, Ponda, Goa
Date:

PROJECT APPROVAL SHEET

The project entitled

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completed in the year 2016-2017 is approved as a partial fulfilment of the requirements for the degree of **BACHELOR OF ENGINEERING in Electronics and Telecommunication Engineering** and is a record of bonafide work carried out successfully under our guidance.

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Place: Farmagudi, Ponda, Goa
Date:

Dedication

This thesis is dedicated to our parents, teachers, friends and other acquaintances, who have been there for us in the thick and thin of the implementation of this project.

Acknowledgement

Apart from the combined effort of us four, this project wouldn't have been possible without the guidance and support of our Project Guide Prof. Milind Fernandes. We are grateful to you Sir.

We take this opportunity to thank Mr Valindo Godinho, CTO of Wafer OÜ, a start-up currently situated in Panaji.He helped us with the initial design and working of our Windows App 'TRACE'. He always made himself available to solve any queries and bugs in the code that we encountered.

We would also like to express our sincere gratitude to Dr. H. G. Virani, The Head of Department and the entire staff of Electronics and Telecommunication Department for providing all the required help and facilities needed for the completion of the project. One of the Senior Faculty Members always stayed back late to lock up the Department when we needed to work afterhours and we are really grateful for that.

Lastly, we would like to thank all our classmates who voluntarily helped us build the gait database

Contents

List of Figures

List of Tables

Abstract

In recent years, biometric recognition and authentication has attracted a significant attention due to its potential applicability in social security, surveillance systems, forensics, law enforcement, and access control. A biometric system can be defined as a pattern-recognition system that can recognize individuals based on the characteristics of their physiology or behaviour. One biometric technique for unintrusive identification is gait recognition which basically identifies people by the way they walk. In former work, gait recognition is mainly achieved with camera systems. In this study, we present an approach for gait recognition using Microsoft Kinect V2, a peripheral for the gaming console XBOX One, which provides us with marker less tracking of human motion in real time. We extract and evaluate a number of static and kinematic features and present the results of various classification algorithms for person identification.

Chapter 1

Introduction

Compared to other biometric features such as the iris and fingerprint. Gait has some inherent advantages 1) Perceivable at a distance, on-contact, non-invasive 2) Doesn't require user cooperation 3) Gives fairly accurate readings under low light conditions. Also disguising, hiding one's gait or imitating some other person's gait is practically impossible. As a result it has fascinated several security-sensitive environments such as classified research and nuclear labs, military, banks etc. Gait recognition is particularly useful in crime scenes where other biometric traits (such as face or fingerprint) might be obscured intentionally.

Two common categories of gait recognition are appearance-based and model-based approaches. Among the two, the appearance-based approaches suffer from changes in the appearance owing to the change of the viewing or walking directions. Model based ones are view and scale invariant and reflect in the kinematic characteristics of walking manner. In this study we present a model based approach using the Microsoft Kinect sensor which offers us a 3D model of the human skeleton with capability to track up to 25 joints of the human body.

1.1 Motivation

The initial motivation to build a gait recognition system developed after watching the Gait Analysis scene in the movie Mission Impossible – Rogue Nation (2015) where it was used for authentication for security purposes. Although at that time it felt as a futuristic technology, through research we realised that existing gait recognition approaches mostly use standard video cameras for capturing and recording the movement of walking persons. Here, the main difficulty lies in the extraction of characteristic features that can be used for identification. The challenges of existing gait recognition system and the possibilities Kinect offers lead to the assumption that the problem of gait recognition could be simplified using the Kinect sensor.

1.2 Proposed Idea

In this paper we propose a skeleton model based approach (provided by Microsoft Kinect Sensor) for gait recognition and person identification. Our system consists of three components: The first component records the skeletal data offered by Kinect using the SDK provided by Microsoft. The second component processes on this data using MATLAB for feature extraction. Finally we use different classification algorithms available in MATLAB classification toolbox to identify a person using previously recorded training data and compare their performance and accuracy. This is a prototypic implementation of a gait recognition system, where we evaluate the possibilities of gait recognition using the Microsoft Kinect.

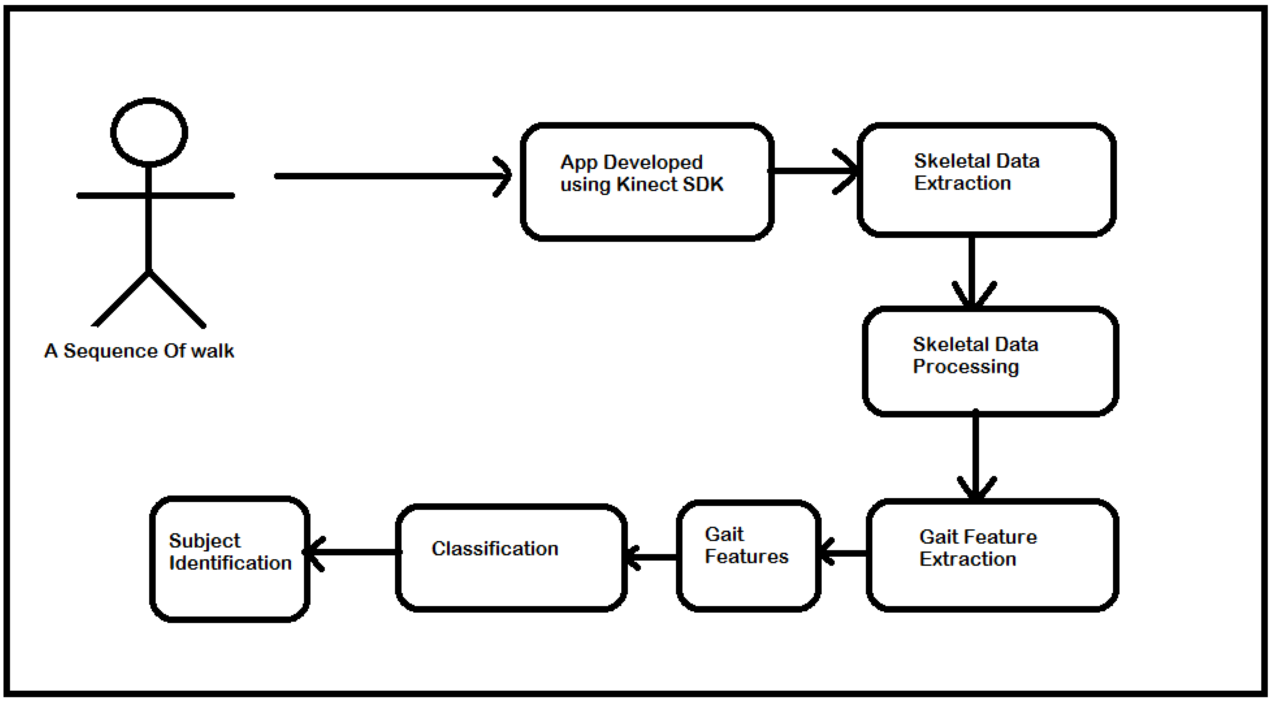

Figure 1.1: Process flow Diagram

Chapter 2

Literature Review

2.1 Full Body Gait Analysis with Kinect

1. Authors: Moshe Gabel, Ran Gilad-Bachrach, Erin Renshaw and Assaf Schuster

2. Abstract: Human gait is an important indicator of health, with applications ranging from diagnosis, monitoring, and rehabilitation. In practice, the use of gait analysis has been limited. Existing gait analysis systems are either expensive, intrusive, or require well-controlled environments such as a clinic or a laboratory. We present an accurate gait analysis system that is economical and non-intrusive. Our system is based on the Kinect sensor and thus can extract comprehensive gait information from all parts of the body. Beyond standard stride information, we also measure arm kinematics, demonstrating the wide range of parameters that can be extracted. We further improve over existing work by using information from the entire body to more accurately measure stride intervals. Our system requires no markers or battery-powered sensors, and instead relies on a single, inexpensive commodity 3D sensor with a large preexisting install base. We suggest that the proposed technique can be used for continuous gait tracking at home.

3. Hardware used : Microsoft's Kinect Xbox 360 console.

4. Methodology : Our technique uses a "virtual skeleton" produced by the Kinect sensor

and software. The skeleton information is converted into a large set of features which are fed to a model that predicts the values of interest. For example, inorder to measure stride duration, the model detects whether the foot is touching the ground. The outcome of this model is fed to a state machine that detects the current state from which the measurements are derived.

5. Conclusion In this work we have presented a novel method for full body gait analysis using the Kinect sensor. Using the virtual skeleton as the input to a learned model, we demonstrated accurate and robust measurements of a rich set of gait features. We showed that our method improves on prior art both in terms of having smaller bias and in having smaller variance. Moreover, our method can be extended to measuring other properties, including lower limb angular velocities and core posture. The sensor used is affordable and small, thus allowing installation in domestic environments. Since the sensor does not require maintenance, it allows for continuous and long term tracking of gait and its trends. These properties enable many applications for diagnosis, monitoring and adjustments of treatment. However measuring the utility of the methods presented here for medical applications is a subject for further research.

2.2 Motion Analysis using Kinect sensor

1. Authors: Richa D'Costa, Manpreet Kaur, Nishtha D. Wanchoo. Under the guidance of PROF. MILIND FERNANDES, Asst. Professor at Goa College of Engineering

2. Abstract: With the advent of Microsoft Kinect sensor, a flexible low cost tool has been made available that enables marker less tracking of human motion in real time. The study explores the possibility of utilizing Microsoft's Kinect sensor to analyse the biomechanics of the shot put throw. It presents a software prototype capable of capturing, recording, analyzing and comparing movement patterns using three-dimensional vector angles. The goal of the present work is to ease the analysis of a shot put game for overcoming the difficulty of visual error detection in shotput game using a software prototype which compares an amateur's game to that of a professional to yield results, which is implemented by using the Kinect sensor. It combines both the biomechanics analysis and Kinect motion capturing and develops a shot put game improvement solution with coaching evaluation.

3. Tools used : Microsoft Kinectv2 sensor, Visual studio 2013, Excel 2013

4. Methodology : Shotput is a game involving many complex motions simultaneously which includes rotational, translational and lateral motions. For any beginner, it gets very difficult to detect the stage of the throw which needs an improvement. Existing methods involve a coach trying to evaluate the stage of flaw in the game by observation. This has 2 major drawbacks: 1)The presence of a skilled trainer is inevitable for every throw of the beginners practice session. 2)The accuracy level would be lower than desired, since the correction of flaw in the game is manual method. To overcome the above difficulties ,we have developed a software prototype for which could detect the flaw in the beginners game without constant physical presence for the busy trainer. Our prototype software takes care of mainly 3 important parameters in the game: 1. The time duration at each phase: It must be well within the range of our reference for maximum release velocity. 2. The following angles at the start of the initial phase: Right knee, Left Knee, Right hip, Right elbow If these angles are well within our reference angles, it results in higher build up energy to have an increased release velocity 3. The release angle of the player: When release angle is within the range of 38°-42°, maximum range is attained.

5. Conclusion : The Kinect system being a marker-less system, is able to capture the human motion with a reduction in time, whereas in a marker-based system attaching markers on the skin of the subject is a time consuming process (which can take 15 to 20 minutes). Although our software prototype could be used in a shot put game to provide coaching evaluation, the results cannot be completely relied upon, as the accuracy was limited due to decreased resolution of Kinect sensor. A few drawbacks of this sensing technology were the fixed location of the sensor with a range of capture of only roughly ten meters, a difficulty in fine movement capture, and shoulder joint biomechanical accuracy. The better reliable results refer to the hip flexion and knee angles and the results of hip adduction and ankle angles are not accurate enough to be relied on. This suggests that Kinect is better for capturing the rotation pattern of the joints with a large range of motion. In conclusion, Kinect system is a reliable system which permits to obtain acceptable kinematics results.

2.3 Gait Recognition with Kinect

1. Authors: Johannes Preis, Moritz Kessel, Martin Werner and Claudia Linnhoff-Popien from Ludwig Maximilians University, Munich, Germany

2. Abstract: The prominence of systems for automatic person identifcation has risen increasingly during the past years. One biometric technique for unintrusive identifcation is gait recognition which ofers the possibility to recognize and identify movement patterns of persons from some distance away. In former work, gait recognition is mainly achieved with camera systems. In this paper, we present an approach for gait recognition based on Microsoft Kinect, a peripheral for the gaming console XBOX 360, with an integrated depth sensor alowing for skeleton detection and tracking in realtime. We evaluate a number of body features together with steplength and speed, their relevance for person identifcation, and present the results of an empirical evaluation of our system, where we were able to accomplish a success rate of more than 90% with nine test persons.

3. Tools used : KinectV1,WEKA

4. Methodology : We propose a model-based approach for gait recognition based on the skeleton provided by Mircosoft Kinect. As said before, Kinect provides a high quality skeletal model of up to two users in front of the Kinect sensor in a Cartesian coordinate system. We decided to use this skeletal data for recognition and did not use the depth and color images directly. Our system consists of three components: The first component records the skeletal information offered by Kinect which is then processed by the second component for feature extraction. Finally, we use the machine learning framework WEKA to identify a person on the basis of previously recorded training data.

5. Conclusion : In this paper, we presented a model based approach to gait recognition based on Microsoft Kinect. We use 13 biometric features such as the height, the length of limbs, and the steplength which are computed from the skeleton frames generated by Kinect. Based on testdata from 9 different persons, the three basic classifers Naive Bayes, 1R, and C4.5 were trained and evaluated concerning the success rate of their classifcation. Based on the features used of the decision tree C4.5, we found out that only four features, namely

height, length of legs, length of torso, and length of the left upper arm, were suffcient to correctly identify a person in 91% of all cases using the complete video from the specific experiment and the Naive Bayes classifer. Classification based solely on steplength and speed still yielded 55.2% success rate using either Naive Bayes or the decision tree.

Chapter 3

INTRODUCTION TO KINECT SENSOR

3.1 Kinect v2 Sensor Specifications

Microsoft Kinect Sensor was initially marketed to add motion control to games and is used as a peripheral for Xbox 360. Based around a webcam-style add-on peripheral, it enabled users to control and interact with their console/computer without the need for a game controller, through a natural user interface using gestures and spoken commands.

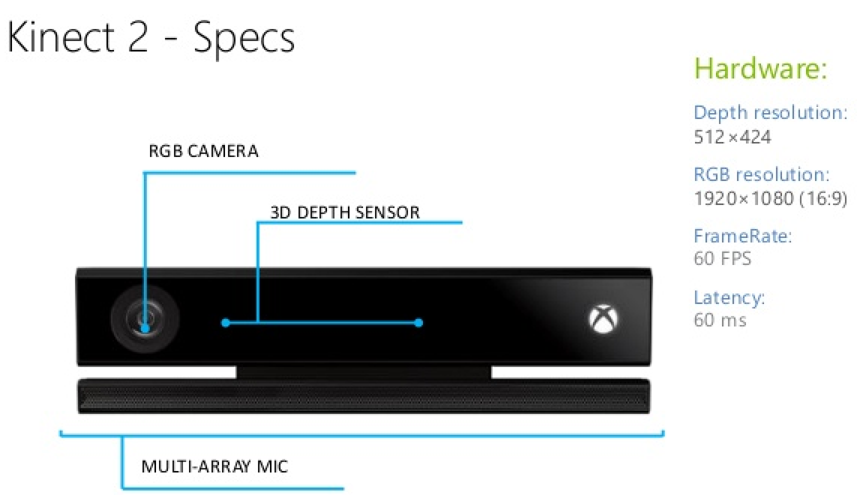

Figure 3.1: Microsoft Kinect V2 Sensor

The second version of the Kinect that is used in this study was released with Xbox One on November 22, 2013. This new hardware and software provided many improvements, including:

1. Improved body tracking - The enhanced fidelity of the depth camera, combined with improvements in the software, have led to a number of body tracking developments. The latest sensor tracks as many as six complete skeletons (compared to two with the V1), and 25 joints per person (compared to 20 with the V1). The tracked positions are more anatomically correct and stable and the range of tracking is broader.

2. Improved depth sensing - With higher depth fidelity and a significantly improved noise floor, the sensor gives you improved 3D visualization, improved ability to see smaller objects and all objects more clearly, and improves the stability of body tracking.

3. 1080p colour camera (30 Hz, 15 Hz in low light) - The colour camera captures full, beautiful 1080p video that can be displayed in the same resolution as the viewing screen, allowing for a broad range of powerful scenarios. In addition to improving video communications and video analytics applications, this provides a stable input on which to build high quality, interactive applications.

4. New active infrared (IR) capabilities (512 x 424 30 Hz) - In addition to allowing the sensor to see in the dark, the new IR capabilities produce a lighting-independent view—and you can now use IR and colour at the same time

5. The Kinect V2 has a range of 0.5 to 4.5m

	Version 1	Version 2
Depth range	0.4m → 4.0m	0.5m → 4.5m
Color stream	640×480@30fps	1920×1080@30fps
Depth stream	320×240	512×424
Infrared stream	None	512×424
Type of Light	Light coding	ToF
Audio stream	4-mic array 16 kHz	4-mic array 48 kHz
USB	2.0	3.0
# Bodies Traked	2 (+4)	6
# Joints	20	25
Hand Traking	External tools	Yes
Face Traking	Yes	Yes+Expressions
FOV	57° H 43° V	70° H 60° V
Tilt	Motorized	Manual

Figure 3.2: Table specifying differences between Kinect v1 and v2

3.2 Skeleton Tracking

By using the depth stream, the Kinect SDK is able to detect the presence of the person in front of the sensor. Kinect is capable of simultaneously tracking up to six people, including two active individuals for gait analysis with a feature extraction of 25 joints per person. The number of people the device can "see" (but not process as individuals) is only limited by how many will fit in the field-of-view of the camera. For each tracked person, Kinect SDK API provides a "skeleton" as a set of motion data. A skeleton contains 25 position sets, one for each "joint" of the body.

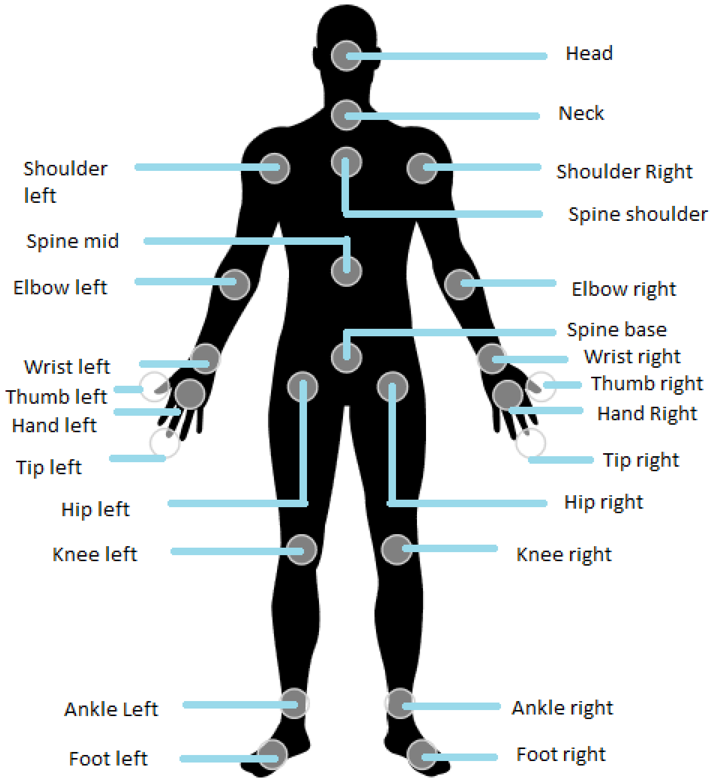

Figure 3.3: Joints Represented by Skeleton Tracking

3.3 Measuring Distances Using Kinect

Kinect integrates an infrared sensor, along with a depth processor. The visible area is called "field of view". The depth processor produces depth frames. Each depth frame is a grid of points. The Kinect SDK is then feeding the depth frames to a powerful body-detection algorithm. The algorithm identifies 25 human body joints and calculates their coordinates in the 3D space. Every single joint has 3 values: X, Y, and Z. It is projected in a Cartesian coordinate system. The point is the position of the sensor. Every other point is measured in terms of the position of the sensor! Check the graphic below. It's viewing the sensor and the scene from above.

- X is the position in the horizontal axis.
- Y is the position in the vertical axis.
- Z is the position in the depth axis.

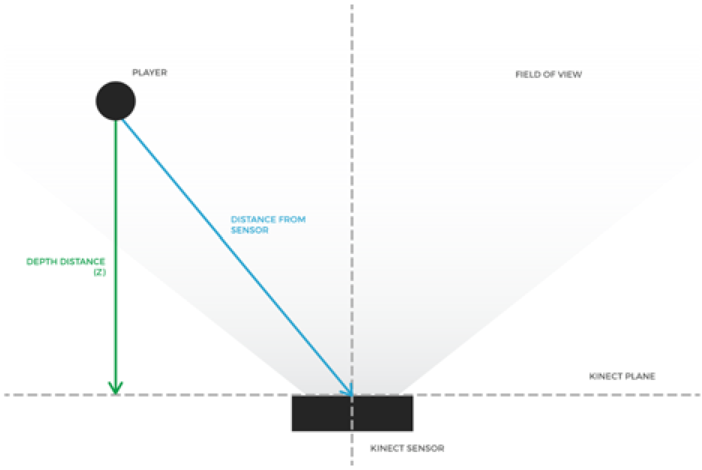

Figure 3.4: How Kinect Measures Distances

As seen from the figure Z value is not the linear distance between the point and the sensor. Instead, it's the distance between the point and the plane of the sensor

Chapter 4

Study of Classification Algorithms

We would briefly like to discuss the classification algorithms we have used in our study

4.1 Support Vector Machine (SVM)

SVMs are supervised learning algorithms used for classification and regression analysis. A support vector machine constructs a hyperplane or set of hyperplanes in a high or infinite dimensional space, which is then used to separate out and classify the data. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class, since in general the larger the margin the lower the generalization error of the classifier. SVM is able to discriminate data that is not linearly separable by using the kernel trick. The trick stipulates the original finite-dimensional space to be mapped into a much higher-dimensional space, presumably making the separation easier in that space. This is done by selecting a kernel function to suit the problem. The hyperplanes in the higher-dimensional space are defined as the set of points whose dot product with a vector in that space is constant.

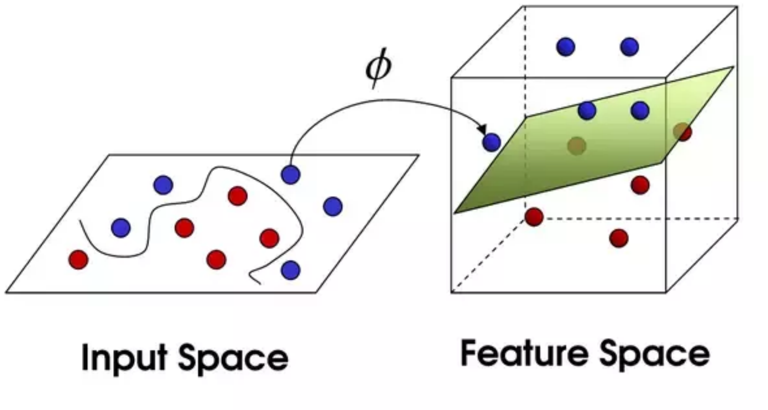

Figure 4.1: Kernel trick representation

4.1.1 Pros and Cons associated with SVM

The advantages of SVM are it is effective in high dimensional spaces and in cases where number of dimensions is greater than the number of samples. It uses a subset of training points in the decision function (called support vectors), so it is also memory efficient. It is versatile means different Kernel functions can be specified for the decision function. Common kernels are provided, but it is also possible to specify custom kernels.

Despite this it doesn't perform well when we have large data set because the required training time is higher. It also doesn't perform very well, when the data set has more noise i.e. target classes are overlapping and SVM doesn't directly provide probability estimates, these are calculated using an expensive five-fold cross-validation.

4.2 k-Nearest Neighbors algorithm (k-NN)

The k-nearest neighbors algorithm (k-NN) is a non-parametric method used for classification and regression. The closest neighbor (NN) rule distinguishes the classification of unknown data point on the basis of its closest neighbor whose class is already known. The value 'k' indicates how many nearest neighbors are to be considered to characterize class of a sample data point. It makes utilization of the more than one closest neighbor to determine the class in which the given data point belongs to and consequently it is called as KNN. If k = 1, then the object is simply assigned to the class of that single nearest neighbor.

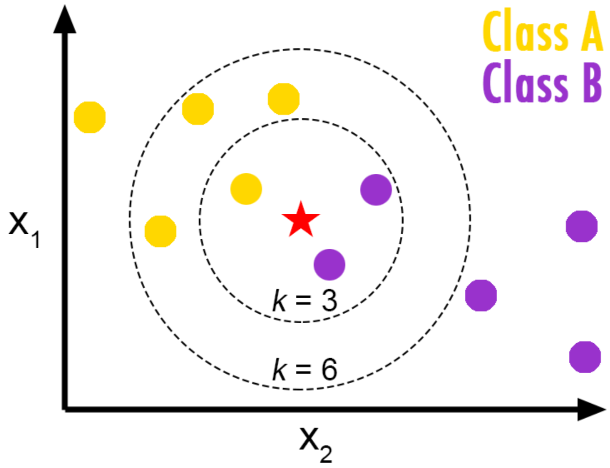

Figure 4.2: Nearest Neighbours for different values of k

4.2.1 Pros and Cons associated with k-NN

The advantages of k-NN are that it is simple to implement. It can quickly respond to changes in input. k-NN employs lazy learning, which generalizes during testing, this allows it to change during real time use. It naturally handles multi-class cases and can do well in practice with enough representative data.

Disadvantages of this method is its computation time. Lazy learning requires that most of k-NN's computation be done during testing, rather than during training. This can be an issue for large datasets. Large search problem to find nearest neighbours is another con. Storage of data and in the case of many dimensions, inputs can commonly be "close" to many data points. This reduces the effectiveness of k-NN, since the algorithm relies on a correlation between closeness and similarity.

4.3 Decision tree learning

Decision tree learning uses a decision tree (as a predictive model) to go from observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves). Tree models where the target variable can take a discrete set of values are called classification trees; in these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. To predict a response, follow the decisions in the tree from the root (beginning) node down to a leaf node. The leaf node contains the response.

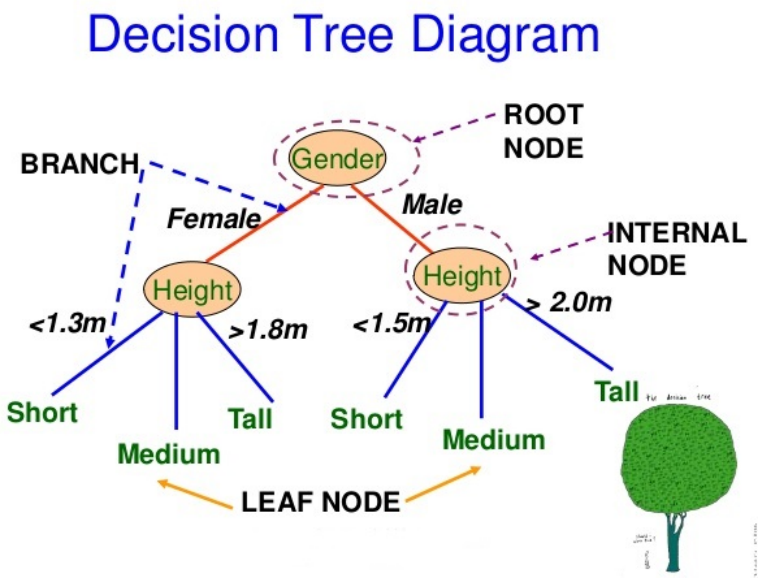

Figure 4.3: Decision tree diagram

4.3.1 Pros and Cons associated with Decision tree

The advantages are that they are very fast to build and test. Building algorithms that work on highly non-linear data. In some use cases, visualizing the tree might be important. This can't be done in complex algorithms addressing non-linear needs. Make minimal assumptions. Nonlinear relationships between parameters do not affect tree performance.

The disadvantages are it is not stable, even a small change in input data can at times, cause large changes in the tree. Changing variables, excluding duplication information, or altering the sequence midway can lead to major changes and might possibly require redrawing the tree. Decision Trees do not work well if you have smooth boundaries. i.e they work best when you have discontinuous piece wise constant model. If you truly have a linear target function decision trees are not the best. They do not work best if you have a lot of uncorrelated variables and a tree with many levels and branches can lead to an over optimized result, or many false positives due to multiple comparison.

Chapter 5

Conclusion

5.1 General Conclusion

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5.2 Challenges

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5.3 Future Work

This is the third section of the fifth chapter.

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Appendices

Appendix A

Appendix

First page of Appendix A

Second page of Appendix A.

Appendix B

Data Sheets

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