Sign Align – A System to Track and Translate Sign Language

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Acknowledgements

Abstract

This project explores a novel way to combine Hidden Markov Models to build a sign classifier capable of distinguishing between a dictionary of 20 signs of British Sign Language. This classifier can be used to detect signs made in real time with high accuracy and constitutes an important first step towards a full translation system for BSL. In this report we introduce the theory of Hidden Markov Models and show how we implemented and combined these models to build a trainable classifier. We go on to show how we used a Microsoft Kinect sensor to collect sets of training and test data which were used to determine optimal parameterisations of the classifier. The result is a sign classifier which is able to detect signs performed in real-time and which has an accuracy of over 90%. Such an accuracy measure is on par with other sign recognition systems despite the fact that the classifier developed here uses no information about the shape of the signer's hand.

Contents

Chapter 1

Introduction

British Sign Language is the preferred first language of over 125,000 adults in the United Kingdom, in addition to an estimated 20,000 children and thousands of hearing friends, relatives and interpreters. There are many more people worldwide communicating in an estimated 200 different signed languages, with a huge variation in grammar and pronunciation. As such, a system which can recognise signed languages and convert them into text in real time would be a valuable tool for many people.

The aim of this project is to implement a system to recognise gestures of a signed language from a data stream provided by the Microsoft Kinect camera. The problem of continuous gesture recognition has been studied for over 20 years and has seen solutions which often involve specific gloves or expensive hardware and which have been particularly sensitive to lighting conditions and camera placement. Using the Kinect sensor, which is available for purchase off the shelf and is designed to be used without gloves and in a range of conditions, we aim to build a robust sign recognition system which does not suffer from these limitations.

1.1 Sign Language

Signed languages are natural languages which have evolved independently of the spoken languages of the areas in which they are used and often independently

of one another. For example, British Sign Language (BSL) is not simply oral English transcribed but rather a distinct language with its own sentence structure which differs significantly from English. Furthermore, despite the regions sharing a common language, American Sign Language (ASL) is a completely separate language from BSL.

Despite the large variation between regional sign languages the means of communication remain the same. The main component of the sign is the movement of the body and each sign is determined by the movement and location of the hands and arms as well as the hand shape and palm direction. In addition to the manual component of the signs the signer will often use posture, facial expressions, mouth shape or eye movements to convey meaning.

The non-manual components of sign language will be ignored for the purposes of this project. It should be noted that eye tracking and facial expression are essentially independent problems from that of gesture recognition and hence if solutions to the facial expression problem exist they may be combined with the work of this project to produce a more substantial sign recognition system.

We can further break the manual part of a sign in to two components. The first is the movement of the hand, arms and body over time and the second is the orientation of the hand throughout this movement. This is a sensible distinction to make as the same hand shape might be used with different arm movements to produce different signs and so we can reduce the number of distinct gestures we wish to detect by detecting hand movement gestures and hand shapes and then combining the two.

In the next section we will see there is a limitation in our choice of hardware that makes hand shape detection a problem, the solution to which lies outside the scope of this project. However the work in this project to detect arm and body gestures can be combined with future work to produce a system which will more accurately detect a signed language.

1.2 Hardware

The Kinect is a motion sensing camera designed by Microsoft and released in November 2010. The Kinect combines an RGB camera and an infrared depth sen-

sor to detect objects in 3D space. The raw images of these sensors are combined using proprietary software to detect a human body as a skeleton, in particular the Kinect is capable of detecting the positions of the hands, elbows, shoulders and head as points in 3D space.

Microsoft released the Kinect software development kit (SDK) for public use on January 16, 2011. This SDK allows developers build applications which interact with the proprietary skeleton tracking software using C#, C++ or Visual Basic. In this project we will use this SDK to build a gesture recognition framework.

The Kinect camera was originially designed with the ability to detect hand and finger positions. In fact the original patent claims the device would be able to detect American Sign Language (LATTA et al., 2010), however this functionality was removed from the original release of the Kinect sensor. The SDK was updated to recognise open and closed hands on March 18th, 2013 (Microsoft, 2013b) and it is believed that the next iteration of the Kinect hardware will be able to fully detect hand gestures. Third party hand gesture recognition frameworks do exist, however the most successful of these do not make use of the Kinect SDK (I. Oikonomidis, 2013). We aim to build a framework that will be easily extended when the capabilities of the Kinect are improved and for this reason we choose to only use the tools compatible the Kinect SDK.

1.3 Project Outline

Figure 1.1 shows a basic outline of the system built during in this project. The SignAlign system takes an input stream from the Kinect sensor, converts it to an appropriate format and uses a trained classifier to determine the sign that was performed to generate the input stream. The majority of this project is dedicated to building and parameterising the sign classifier and implementing a means to collect training data. In chapter 2 we introduce the theory of Hidden Markov Models and explore their strengths and limitations with regard to the problem of gesture recognition. In chapter 3 we show how we implemented and combined these models to create models of signs and how these were then combined to build the classifier. In chapter 4 we show how we built an interface to the Kinect Sensor

and collected skeletal stream data. In chapter 5 we explore how the parameters chosen in building the classifier affect the overall accuracy of the system and use a hold-out set to determine parameter values which optimise performance. Finally in chapter 6 we evaluate the success of our system and explore possible extensions to SignAlign.

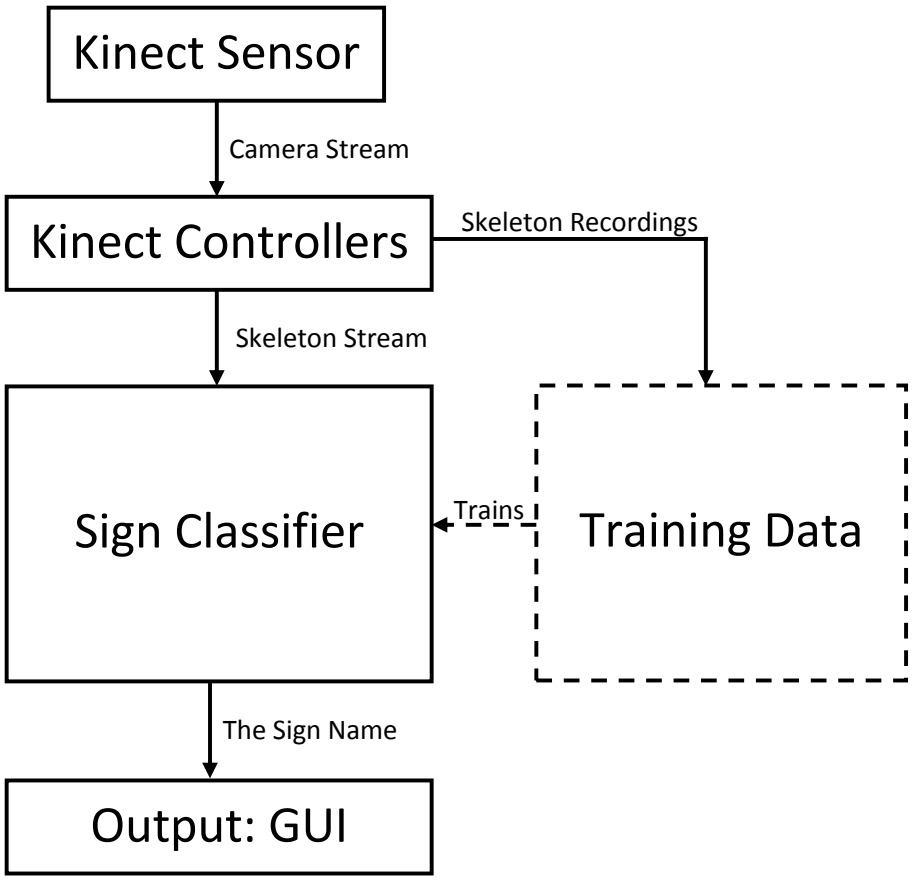


Figure 1.1: A basic outline of the SignAlign system

Chapter 2

Background and Model Selection

2.1 Model Selection

Our first task in implementing a sign recognition system was to determine a model suitable for the task of gesture recognition. We required a model which could be trained on a moderate sized training set and which is computationally efficient enough to be run in real time. Our research determined that Hidden Markov Models, Neural Networks or a Finite State Machine approach would be suitable for gesture recognition and that these models had been used for similar applications before (Mitra and Acharya, 2007). We decided that Hidden Markov Models would be the most suitable for the task of sign language recognition because they are approximately *scale invariant*, meaning that they perform well even with minor scaling of their input, and hence resilient to the changes in input occurring when the signer changes.

2.2 Hidden Markov Models

A *Hidden Markov Model* (HMM) is (following the definitions in Rabiner (1989)) a doubly stochastic process which consists of an underlying discrete Markov chain with state set $S = \{S_1, \ldots, S_n\}$ and stochastic matrix $A = [a_{i,j}]_{N \times N}$ where

$$a_{i,j} = \mathbb{P}(q_{t+1} = S_i | q_t = S_j) \text{ for each } 1 \leq i, j \leq N$$

which is hidden from an observer in the sense that one cannot directly observe the current state of the Markov chain. Instead we have a collection of M observable symbols, say $V = \{v_1, \ldots, v_M\}$, which may be observed with probability dependent on the state of the underlying Markov chain (Figure: 2.1). We encode these so-called *emission probabilities* in a matrix $B = [b_j(k)]_{N \times M}$ where

$$b_j(k) = \mathbb{P}[v_k \text{ occurs at time } t | q_t = S_j]$$

Now if we take an initial state distribution $\boldsymbol{\pi} = [\pi_1, \ldots, \pi_N]$ for our Markov chain with

$$\pi_i = \mathbb{P}[q_1 = S_i]$$

then the HMM generates a sequence of observations

$$\boldsymbol{O} = O_1, O_2, \ldots, O_T$$

by the following process:

1. Choose an initial state $q_1 = S_i$ stochastically from the initial state distribution $\boldsymbol{\pi}$
2. For $t = 1$ to T
    i. Choose $O_t = v_k$ according to the distribution $b_i(k)$ of the current state S_i
    ii. Stochastically transition to a new state S_j from S_i according to A

Note now that a hidden Markov Model is entirely determined by the transition matrix A, the emissions matrix B and the initial distribution $\boldsymbol{\pi}$ (the dimensions N and M are encoded in the dimensions of the matrices) hence for convenience we may denote a HMM by

$$\lambda = (A, B, \boldsymbol{\pi})$$

Hidden Markov Models were first introduced by in a series of papers by L.E Baum and others in the late 1960s (Baum and Petrie, 1966; Baum et al., 1970) and have been since used to study handwriting recognition (Bunke et al., 1995),

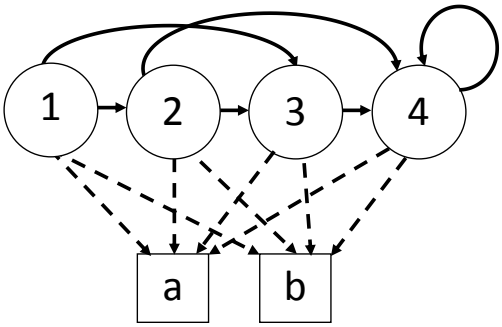


Figure 2.1: A Hidden Markov Model. The underlying Markov Chain contains 4 states (depicted as circles) which emit two possible observations (a or b).

speech recognition (Jelinek, 1998; Juang and Rabiner, 1991), natural language modelling (Jurafsky et al., 2002; Manning and Schütze, 1999) and biological processes (Durbin et al., 1998; Krogh et al., 1994; Liò and Goldman, 1998).

Given these definitions there exist three basic problems which form the basis of using HMMs as a tool for machine learning

1. Given an observation sequence $\boldsymbol{O} = O_1, O_2, \ldots, O_T$ and a HMM λ, what is $\mathbb{P}(\boldsymbol{O}|\lambda)$ - the probability that the observation sequence $\boldsymbol{O}$ was produced by λ?

2. Given a HMM λ and an observation sequence $\boldsymbol{O} = O_1, O_2, \ldots, O_T$ what is the state sequence of the underlying Markov chain in λ which is most likely to have generated $\boldsymbol{O}$?

3. Given an observation sequence $\boldsymbol{O}$, how to do we choose the parameters of $\lambda = (A, B, \boldsymbol{\pi})$ which best optimise $\mathbb{P}[\boldsymbol{O}|\lambda]$?

In fact the problem of sign language gesture recognition can be seen as an instance of problems 3 and 1. First we take for each gesture g a set of training

data which are recordings of the joints in 3D space. This training data forms a collection of observation sequences $\boldsymbol{O}_1, \ldots, \boldsymbol{O}_n$ which are used in a solution to problem 3 to parameterise a Hidden Markov Model λ_g to model the gesture.

Then given a fresh observation sequence $\boldsymbol{O}$ we can use a solution to problem 1 to compute $\mathbb{P}[\boldsymbol{O}|\lambda_g]$ for each g. We can then take the gesture g for which this probability is maximised and, provided the probability exceeds some threshold, conclude that the gesture g corresponds to the observation sequence $\boldsymbol{O}$.

2.2.1 The Forward and Backward Variables

Suppose we are given an observation sequence $\boldsymbol{O} = O_1, O_2, \ldots, O_T$ and a HMM λ and wish to solve the evaluation problem (problem 1). Rabiner (1989) notes that a direct computation of $\mathbb{P}[\boldsymbol{O}|\lambda]$ will take time order $\mathcal{O}(2TN^T)$ which is infeasible even for moderate values of N and T. Instead we use a dynamic programming approach, *the forward algorithm*, introduced in Baum and Sell (1968) and Baum et al. (1970).

Define the *forward variables* $\alpha_t(i)$ for each $1 \leq t \leq T$ and $1 \leq i \leq N$ by

$$\alpha_t(i) = \mathbb{P}[O_1, \ldots, O_t, q_t = S_i|\lambda]$$

These can be inductively computed by the following procedure

$$\begin{aligned}
&\alpha_1(i) = \pi_i b_i(O_1) \\
&\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(i) a_{ij}\right] b_j(O_{t+1}) \qquad \text{for } 1 \leq t \leq T-1 \text{ and } 1 \leq j \leq N
\end{aligned}$$

and further

$$\mathbb{P}[\boldsymbol{O}|\lambda] = \sum_{i=1}^{N} \mathbb{P}[\boldsymbol{O}, q_T = S_i|\lambda] = \sum_{i=1}^{N} \alpha_T(i)$$

The set of forward variables can be computed by dynamic programming in $\mathcal{O}(N^2T)$ time and hence we can compute $\mathbb{P}[\boldsymbol{O}|\lambda]$ in this time - a significant improvement over direct computation.

Symmetrically to the forward variables we can define a collection of *backward*

variables by

$$\beta_t(i) = \mathbb{P}[O_{t+1}, O_{t+2}, \ldots, O_T | q_t = S_i, \lambda]$$

Which gives the probability of a partial observation sequence from a time t given the state of the HMM λ at time t. These too can be computed iteratively as

$$\beta_T(i) = 1 \qquad \text{for each } 1 \leq i \leq N$$

$$\beta_t(i) = \sum_{j=1}^{N} a_{i,j} b_j(O_{t+1}) \beta_{t+1}(j) \qquad \text{for } t = T-1, T-2, \ldots, 1 \text{ and } 1 \leq i \leq N$$

and these too can be computed by dynamic programming in $\mathcal{O}(N^2 T)$ time. The backward variables are not needed in the solution to the evalutation problem but are used in the following section to re-parameterise hidden Markov Models.

2.2.2 Forward-Backward Algorithm

The problem of parameterising a Hidden Markov Model λ is considerably more difficult than the other two problems of HMMs. In fact it is known that there is no analytic solution which provides a model λ to maximise the probability of some observation sequence $\boldsymbol{O}$ (Rabiner, 1989). Instead we must use local optimisation methods which given an initial parameterisation λ_0 iteratively improve it until $\mathbb{P}[\boldsymbol{O}|\lambda]$ reaches a local maximum.

We will use a modified version of the *Baum-Welch algorithm* introduced by Baum et al. (1970) called the *forward-backward algorithm* (Rabiner, 1989) which is reproduced below. This algorithm is an instance of an expectation-maximization algorithm (Moon, 1996) which is a general technique used to determine maximum likelihood estimators in a number of machine learning models (Bishop et al., 2006).

For $t \in \{1, \ldots, T-1\}$ and $i, j \in \{1, \ldots, N\}$ define

$$\gamma_t(i, j) = \mathbb{P}[q_t = S_i, q_{t+1} = S_j | \boldsymbol{O}, \lambda]$$

such that $\gamma_t(i,j)$ is the probability of being in state S_i at time t and transitioning to S_j at the next time step given the HMM λ and the observation sequence $\boldsymbol{O}$. Then by definiton of the foward and backward variables we have

$$\gamma_t(i,j) = \frac{\alpha_t(i)a_{ij}b_j(O_{t+1})\beta(j)}{\mathbb{P}[\boldsymbol{O}|\lambda]}$$

We can define for each $1 \leq t \leq T-1$ and each $1 \leq i \leq N$ the probability of being in state i at time t by

$$\gamma_t(i) = \mathbb{P}[q_t = S_n|\boldsymbol{O}, \lambda] = \frac{\alpha_t(i)\beta_t(i)}{\mathbb{P}[\boldsymbol{O}|\lambda]}$$

and then we have

$$\gamma_t(i) = \sum_{j=1}^{N} \gamma_t(i,j)$$

Now using these equations we can compute

$$\sum_{t=1}^{T-1} \gamma_t(i) = \text{The expected number of transitions from } S_i$$
$$\sum_{t=1}^{T-1} \gamma_t(i,j) = \text{The expected number of transitions from } S_i \text{ to } S_j$$

which can be used to reparameterise the model $\lambda = (A, B, \boldsymbol{\pi})$ as follows. Set

$$\begin{aligned}
\overline{\boldsymbol{\pi}} &= \text{the expected number of times in state } S_i \text{ at time } 1 = \gamma_1(i) \\
\overline{a_{ij}} &= \frac{\text{the expected number if transitions from } S_i \text{ to } S_j}{\text{expected number of transitions from state } S_i} \\
&= \frac{\sum_{t=1}^{T-1} \gamma_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \\
\overline{b}_j(k) &= \frac{\text{the expected number of times in state } S_j \text{ observing symbol } v_k}{\text{the expected number of times in state } S_j} \\
&= \frac{\sum_{\substack{t=1 \\ O_t = v_k}}^{T} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(j)}
\end{aligned}$$

Then if denote $\overline{\lambda} = (\overline{A}, \overline{B}, \overline{\boldsymbol{\pi}})$ it has been proven (Baum and Sell, 1968; Levinson

et al., 1983) that either

1. $\mathbb{P}[\boldsymbol{O}|\overline{\lambda}] > \mathbb{P}[\boldsymbol{O}|\lambda]$ or
2. λ is locally maximized with respect to $\mathbb{P}[\boldsymbol{O}|\lambda]$ and $\overline{\lambda} = \lambda$

It follows that given an initial HMM λ we may improve it to a locally optimal model for some observation sequence $\boldsymbol{O}$ via the following local search:

1. Whilst $\mathbb{P}[\boldsymbol{O}|\lambda]$ increases:
   i. Compute the $\alpha_t(i)$, $\beta_t(i)$, $\gamma_t(i,j)$ and $\gamma_t(i)$
   ii. Compute the new parameters $\overline{A} = [\overline{a}_{ij}]$, $\overline{B} = [\overline{b}_j(k)]$ and $\overline{\boldsymbol{\pi}} = [\overline{\pi_1}, \ldots, \overline{\pi_N}]$
   iii. Set $\lambda := \overline{\lambda}$
2. return λ

Note that this algorithm may not actually terminate. In practice we threshold the increase of $\mathbb{P}[\boldsymbol{O}|\lambda]$ to ensure termination in a reasonable time.

2.2.3 Limitations of HMMs

A significant limitation of Hidden Markov Models is that they can have only a finite set V of possible observations. This prevents us from using a HMM to model a specific gesture exactly. Take for example the problem of detecting the gesture of a circle drawn on a 2D plane. We might create a Hidden Markov Model in which the states of the Markov chain represent some specific points on the plane and want our matrix B to be such that

$$b_j(\boldsymbol{p}) = \mathbb{P}[\text{the pen is at point } \boldsymbol{p} \text{ at time } t \mid q_t = S_j] \qquad \text{for each point } \boldsymbol{p} \in \mathbb{R}^2$$

However as the plane is continuous and V is finite this is not possible. One solution is to discretise the plane and have only a finite (but large) set of observation symbols. This method has been used with some success to distinguish between gestures with large variations, for example different tennis strokes (Yamato et al., 1992), and it is this method that we use for our system. It could be argued that this discretisation of the observation space could cause us to lose some subtlety

in the input and hence prevent us from distinguishing between similar signs. We attempt to compensate for this by taking into account the full torso in determining a sign and using the elbows, shoulders and head to help distinguish signs where the hands are not sufficient alone.

A second solution is to utilise *Continuous Distribution Hidden Markov Models* which extend HMMs by replacing the emissions matrix B with a probability density function. This method proved to be outside of the scope of this project but is one that has proven fruitful in previous pattern detection systems. As such we have built our sign recognition system to allow the discrete Hidden Markov Models to be replaced by a continuous counterpart provided with relative ease (by implementing a certain interface).

2.3 Previous Work

Motivated by the success of hidden Markov Models for speech in the mid 1970s (Baker, 1975; Jelinek et al., 1975) these models were adopted for gesture detection. Yamato et al. (1992) used discrete HMMs with observations from a 2D camera to detect tennis strokes and later Starner and Pentland (1995) implemented a system to recognise American Sign Language in real-time using by continuous density hidden Markov Models. This system relied on a single camera and required the user to wear a pair of special gloves. By imposing a restricted grammar to only allow sentences of a particular structure they were able to achieve an accuracy of 97.0% on an independent training set.

More recently the SignSpeak project, which aims to use a 2D video camera and an extension of HMM techniques (Dreuw et al., 2009, 2010), has received EU funding. This project aims to solve the problems of image extraction, sign recognition and language translation to provide a complete video-to-text system.

Chapter 3

Implementing a Classifier for Isolated Signs

3.1 Implementing a Hidden Markov Model Class

Our first task in implementing a classifier for signed languages was to implement a general purpose class `DHMM` (figure: 3.1) which can be instantiated to model a Hidden Markov Model $\lambda = (A, B, \pi)$ by providing appropriate parameters. In this class we implemented solutions to the evaluation and training problems and provided methods for saving and loading the trained parameters. Extending the methods described in the previous section we taylored this implementation for use learning from a collection of data recorded from the Kinect Sensor.

3.1.1 Scaling

In the previous section we introduced methods for solving the evaluation and re-estimation problems for Hidden Markov Models. These methods, whilst mathematically sound, introduced certain problems during implementation. In particular these solutions involve the products of a large number of probabilities, especially for long observation sequences, and as a consequence when implemented in C# (which lacks arbitrary precision floats) can cause errors due to underflow. This problem is a common one in the implementation of Hidden Markov Models and to solve it we used the methods used by Rabiner (1989) (and corrected

by Rahimi (2000)) and scaled the intermediate α, β and γ variables to prevent underflow. To do this we normalize the $\alpha_t(i)$ by setting

$$\overline{\alpha}_1(i) = \alpha_1(i) \text{ for each } 1 \leq i \leq N$$

and inductively define for each $1 \leq t < T$

$$\begin{aligned} c_t &= \frac{1}{\sum_{i=1}^{N} \overline{\alpha}_t(i)} \\ \hat{\alpha}_t(i) &= c_t \overline{\alpha}_t(i) \text{ for each } i \\ \overline{\alpha}_{t+1}(i) &= \sum_{j=1}^{N} \hat{\alpha}_t(j) a_{ji} b_i(O_{t+1}) \text{ for each } i \end{aligned}$$

which prevents underflow in the intermediate calculation of the α variables. These scaled variables satisfy for each $1 \leq i \leq N$ and $1 \leq t \leq T$

$$\hat{\alpha}_t(i) = c_1 \dots c_t \alpha_t(i)$$

by induction on t (Stamp, 2004). We then have that

$$\begin{aligned} 1 = \sum_{i=1}^{N} \hat{\alpha}_T(i) &= c_1 \dots c_T \sum_{i=1}^{N} \alpha_T(i) \\ &= c_1 \dots c_T \mathbb{P}[\mathbf{O}|\lambda] \end{aligned}$$

and hence we can compute the log-probability of an observation sequence $\mathbf{O}$ by

$$\log(\mathbb{P}[\mathbf{O}|\lambda]) = -\sum_{t=1}^{T} \log(c_t)$$

which allows us to determine probabilities which might have otherwise been lost due to underflow. We use the same scale factors on the β variables by defining

$$\overline{\beta}_T(i) = \beta_T(i) \text{ for each } 1 \leq i \leq N$$

and then inductively setting, for $1 \leq t < T$ and $1 \leq i \leq N$

$$\hat{\beta}_t(i) = c_t \overline{\beta}_t(i)$$
$$\overline{\beta}_t(i) = \sum_{j=1}^{N} a_{ij} b_j(O_{t+1}) \hat{\beta}_{t+1}(i)$$

We then redefine the γ variables for $1 \leq t < T$ and $1 \leq i, j \leq N$ as

$$\gamma_t(i,j) = \hat{\alpha}(i) a_{ij} b_j(O_{t+1}) \hat{\beta}_{t+1}(j)$$
$$\gamma_t(i) = \hat{\alpha}_t(i) \hat{\beta}_t(i) \frac{1}{c_t}$$

Now if we use these variables in the re-estimation it is still the case that the the probability $\mathbb{P}[\mathbf{O}|\lambda]$ increases with each iteration (Rabiner, 1989) and hence we can perform the iterative reestimation procedure for HMMs without introducing underflow errors.

3.1.2 Training From Multiple Observation Sequences

A second restriction of the training procedure presented in chapter 2 is that it restricts the training data of the HMM to be a single observation sequence. As we are going to train our HMMs on data which is derived from the Kinect Sensor data of a person performing a sign this is too great of a restriction. For example the way in which a person performs a sign will be unique each time and will differ between signers, and so to train a recogniser on a single observation sequence would not fully capture the range of movements which might be interpreted as that sign. Fortunately the reestimation procedure can be extended (Li et al., 2000; Rabiner, 1989; van Oosten, 2010) to allow training from a set of multiple observation sequences $\mathcal{O} = \{\mathbf{O}_1, \ldots, \mathbf{O}_K\}$ to maximise

$$\mathbb{P}[\mathcal{O}|\lambda] = \prod_{i=1}^{K} \mathbb{P}[\mathbf{O}_i|\lambda]$$

by computing for each $1 \leq i \leq K$ the set of scaled $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\gamma}$ variables associated with the observation sequence $\mathbf{O}_i$ and the associated scales. Using these scaled

variables we can reestimate the parameters of our HMM as

$$\overline{\pi_i} = \frac{\sum_{k=1}^{K} \gamma_1^{(k)}(i)}{\sum_{j=1}^{N}\sum_{k=1}^{K} \gamma_1^{(k)}(j)}$$

$$\overline{a}_{ij} = \frac{\sum_{k=1}^{K}\sum_{t=1}^{T_k-1} \hat{\alpha}_t^{(k)}(i) a_{ij} b_j(O_{t+1}^{(k)}) \hat{\beta}_{t+1}^{(k)}(j)}{\sum_{k=1}^{K}\sum_{t=1}^{T_k-1} \hat{\alpha}_t^{(k)}(i) \hat{\beta}_t^{(k)}(i) \frac{1}{c_t^{(k)}}}$$

$$\overline{b}_j(l) = \frac{\sum_{k=1}^{K}\sum_{t\in\{1,\ldots,T_k-1\} \text{ and } O_t = v_l} \hat{\alpha}_t^{(k)}(i) \hat{\beta}_t^{(k)}(i) \frac{1}{c_t^{(k)}}}{\sum_{k=1}^{K}\sum_{t=1}^{T_k} \hat{\alpha}_t^{(k)}(i) \hat{\beta}_t^{(k)}(i) \frac{1}{c_t^{(k)}}}$$

and this will ensure that $\mathbb{P}[\mathcal{O}|\overline{\lambda}] \geq \mathbb{P}[\mathcal{O}|\lambda]$. Using this procedure we implemented the `Reestimate` method of our `DHMM` class.

3.1.3 Observation Vector Quantization

In order to use discrete observation Hidden Markov Models for the problem of gesture recognition we must restrict the continuous observation space to a discrete set of observation symbols. As the ideal number of observation symbols was unknown we implemented a general purpose method for vector quantization.

To quantize the training data for a single discrete HMM instance we merged all of the points of all of the training data into a single 3D point cloud and partitioned this point cloud into k clusters. To do this we implemented Lloyd's algorithm (Lloyd, 1982) to solve the k-means clustering problem (Figure: 3.2). We then defined a translation from the continuous $\mathbb{R}^3$ observation space provided by the Kinect Sensor to a finite set of $k+1$ observations by assigning to each point the number of the cluster with the centroid closest (via Euclidean distance) to it, or $k+1$ if the distance from the point to each of the means exceeds twice the standard deviation of the cluster with the greatest variance. In fact, this quantization method will work just as well to translate arbitrary dimension continuous spaces to a finite observation set and hence offers us the opportunity to extend our

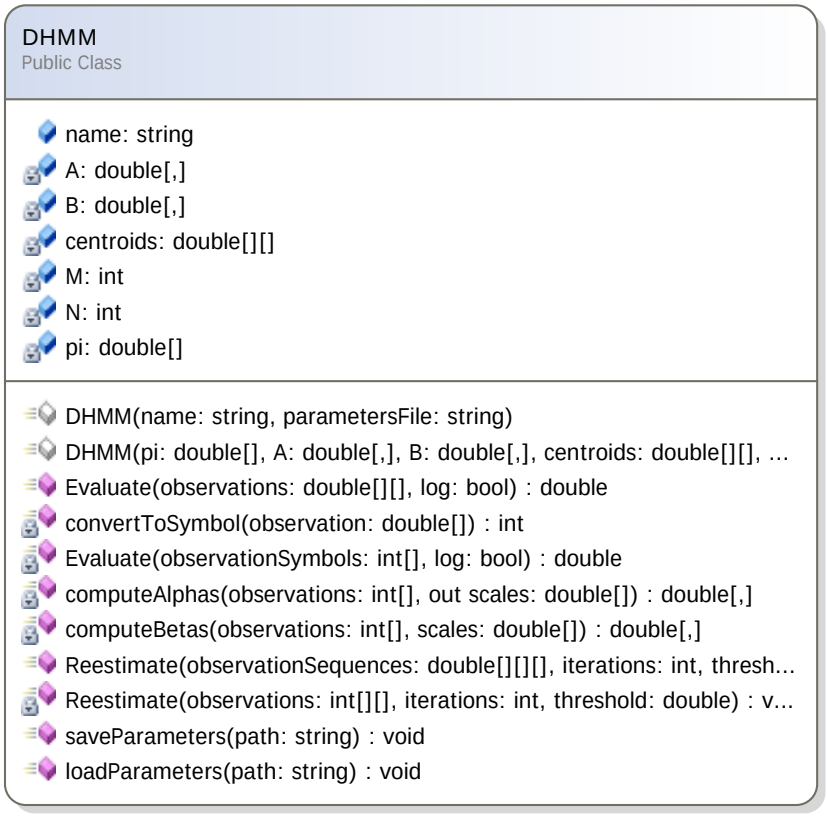


Figure 3.1: A UML skeleton of the DHMM class

training data sets to include not only spatial positions but other information as well, say velocity or positions relative to some fixed location.

Using this vector quantization method we were able to extend the `Evaluate` and `Reestimate` method of `DHMM` to take as input streams of (x, y, z) coordinates captured by the Kinect Sensor.

3.2 Implementing the signModel class

The main component of our sign classifier is a `signModel` object which, when trained for a specific sign, can take a Kinect input stream and return the probability that the input stream corresponds to that sign. Our main problem was determining how to combine `DHMM` objects to build an object which computes this

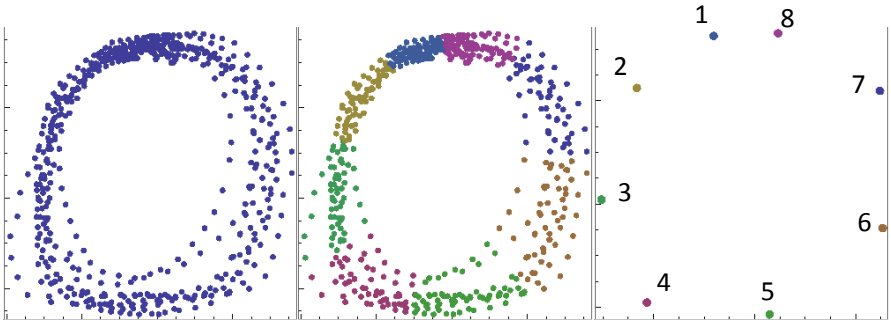


Figure 3.2: The K-Means method for vector quantization

probability by taking into account all of the information provided by the Kinect sensor.

One solution to this problem is to create an instance of `DHMM` which takes as its input streams vectors of $(\mathbb{R}^3)^J$ where J is the number of joints we choose to track. This method will allow us to detect signs using all of the joints tracked by the Kinect sensor however it does introduce two problems. The first is purely practical - the computations in the k-means clustering and training algorithms will become more and more expensive as the dimension of the observation vector grows and this will impact negatively on the performance of our sign recognition system.

The second issue is that this method ignores the prior knowledge we have about the joints of the body - that some are more dominant in the expression of a sign than others. For example, we know that the right hand is more dominant than the left and that both are more dominant than the elbows or shoulders. In fact the elbows and shoulders might be only worth considering when the hands alone cannot used to determine two different signs.

As such we should not let the importance of each joint be determined algorithmically and should specify these parameters with care. For this we create J separate instances of `DHMM`, each trained on a collection of observation sequences of a different joint. Then supposing we have trained a set of Hidden Markov Models $\Lambda = \{\lambda_1, \ldots, \lambda_J\}$ for each joint, and have observation sequences $\mathbf{\Theta} = \{\mathbf{O}_1, \ldots, \mathbf{O}_J\}$ which specify a stream for each joint over the course of one sign, we can compute a likelihood measure that this sequence corresponds to the sign used to train $\lambda_1, \ldots, \lambda_J$ as a weighted sum

$$L([\mathbf{\Theta}|\Lambda]) = \sum_{j=1}^{J} c_j \log(\mathbb{P}[\mathbf{O}_j|\lambda_j])$$

where the weights c_j are used to express the dominance of the j^{th} joint in expressing a sign relative to the other joints. Note that this value no longer satisfies all of the properties of probabilities (or their logarithms) even if we restrict the constants in some way, however L has one important property - that larger values correspond to more likely events. We choose to define L in this way as it simplifies the computations in determining the likelihood that a given joint observation collection $\mathcal{O}$ corresponds to a given sign.

We implemented the class `SignModel` (Figure: 3.3) to correspond to this definition of Λ. This class contains a collection of `DHMM` objects with each corresponding to a joint of the skeleton provided by the Kinect Sensor, as well as a set of weightings corresponding to the $c_1, \ldots, c_J$. Further there is a method `trainModel` which trains an instance of `DHMM` for each joint observation sequence set stored in the training folder. The `signModel` class also contains a method to compute the likelihood that a given collection of joint observation sequences corresponds to this sign using the weighted sum of joints method described above.

3.2.1 Determining the Weightings

To ensure that the likelihood measures between signs are comparable we chose to use the same weighting constants for each sign model. Intuitively each constant c_j corresponds to the importance of the joint j in making a sign – for example, the constants corresponding to the hands should be higher than those for the

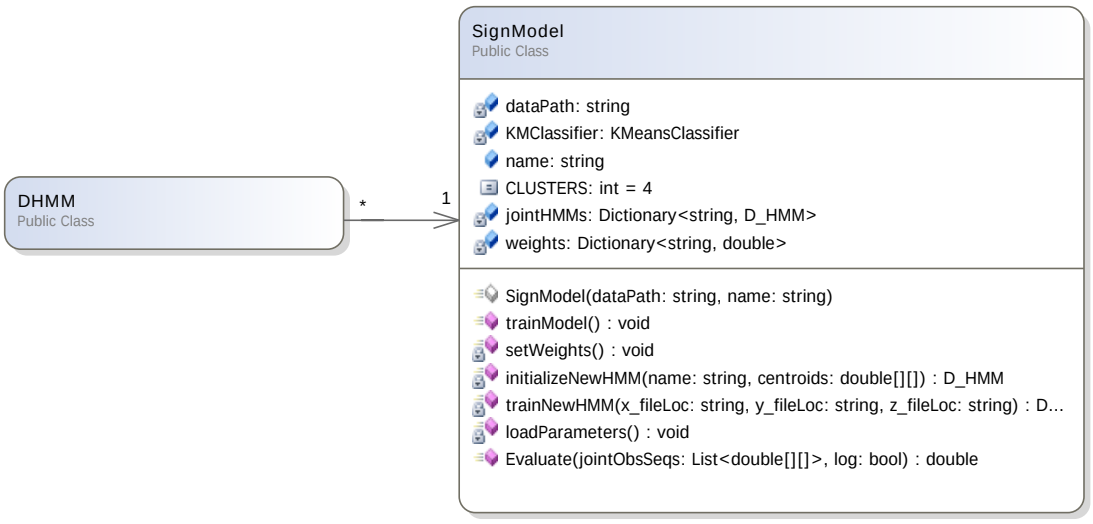


Figure 3.3: A UML diagram for the signModel class

shoulders. In the absence of any research into the influence of the joints in signed languages we make the assumption that every movement a signer makes through the course of a sign is important. As such we determined that a greater variance of a given joint over the set of all training data implies that that joint conveys more information each sign. Hence, assuming $\mathcal{T}_j$ denotes the set of all observations of the joint j, we set

$$c_j := \sigma_j^2 = \frac{1}{|\mathcal{T}_j|} \sum_{v \in \mathcal{T}_j} \|v - \mu_j\|^2 \qquad \text{(where } \mu_j = \frac{1}{|\mathcal{T}_j|} \sum_{v \in \mathcal{T}_j} \|v\|\text{)}$$

and then normalised the c_j to satisfy

$$\sum_{j \in J} c_j = 1$$

We decided that if a joint j has $c_j < 0.05$ then it is unlikely to impact the overall decision about which sign has been observed and that the calculation of $\mathbb{P}[\mathbf{O}_j|\lambda_j]$ would be a waste of computational resources. As such we decided to set $c_j = 0$ for these joints and forgoe the unnecessary calculations. Using this method we chose to ignore the head, chest and lower body joints provided by the Kinect

sensor.

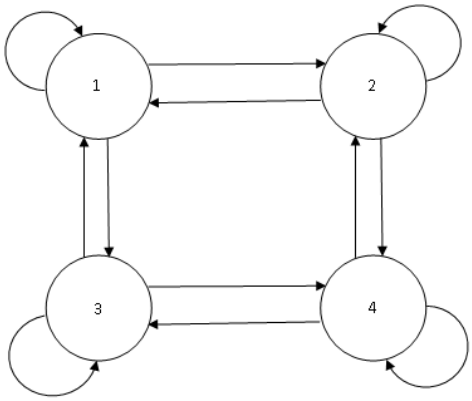
3.2.2 Determining The Initial Topology and Parameters

As our training method utilises a local search to improve our parameterisation its effectiveness will greatly depend on how we initialise our Hidden Markov Models. If the initial parameterisation is poor then even with a large training set we may fail to find a parameterisation which allows us to recognise signs with high accuracy.

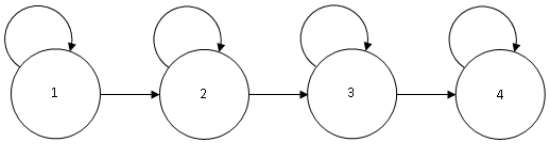
It has been shown that the topology of the underlying Markov Chain can greatly impact the effectiveness of a HMM for a given pattern recognition task (Jelinek, 1998; Rabiner, 1989). The two most common types of HMM (See figure 3.4) are the *ergodic model*, in which each state can transition to any other state in a finite number of steps and the *left-right model* or Bakis model (Bakis, 1976) in which the state sequence is (non-strictly) increasing. The left-right model can be viewed as modelling a signal which changes through time, with each transition representing a movement forward in time. For that reason it is more suitable for modelling gestures or speech than other Markov Chain topologies and is the topology we chose for our Hidden Markov Models.

A left-right topology Markov chain is characterized by an upper triangular stochastic matrix A. We can further restrict our model to only allow jumps from a state i to states $i \leq j \leq i + \Delta$ for some Δ. This restriction can prevent the model being pushed, through re-parameterisation, into a trivial Markov chain which remains at the final state N at all times. This can be seen as imposing a restriction on the velocity we can expect a signer's hand to move at - not allowing him to pass by too many states in quick succession.

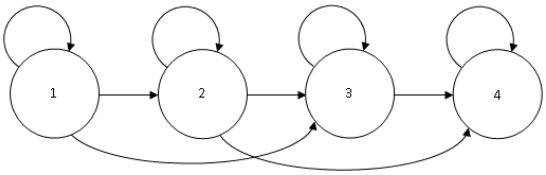
As such we choose to intialize the HMMs in the `signModel` class as left-right



(a) An Ergodic Markov Chain



(b) A $\Delta = 1$ Left-Right Markov Chain



(c) A $\Delta = 2$ Left-Right Markov Chain

Figure 3.4: Different Markov Chain Topologies

models restricted to $\Delta = 1$ and initialise the stochastic matrix with form

$$A = \begin{pmatrix} a_{11} & a_{12} & 0 & \cdots & 0 \\ 0 & a_{22} & a_{23} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & a_{(n-1)(n-1)} & a_{(n-1)n} \\ 0 & 0 & \cdots & 0 & 1 \end{pmatrix}$$

and define $\pi = [1, 0, \ldots, 0]$. Clearly if we initialise the non-zero a_{ij} of A deterministically then we restrict ourselves to single outcome from the re-estimation procedure regardless of how many times we retry it, as such we choose to intro-

duce some stochasticity by setting

$$a_{ii} = 0.5 - r \qquad\qquad a_{i(i+1)} = 0.5 + r$$

for some r chosen uniformly from the interval $[-0.3, +0.3]$. This interval is chosen to ensure that none of the links are set too weakly causing the forward transitions to be broken during re-estimation.

As we expect the system to differentiate a large number of signs it would be a major task to tailor the initialisations of each Hidden Markov Model to the sign it is expected to recognise. Hence, we choose to use the same initial estimation procedure for each HMM and do not make any inferences about the structure of the emissions matrix B given the sign it is expected to model. We initialise B almost uniformly with

$$b_{ij} = 1/M + r_{ij} \qquad \text{for each } 1 \leq i \leq N \text{ and } 1 \leq j \leq M$$

where each r_{ij} is some small random number and subject to the condition that the matrix B remains stochastic.

The benefit of introducing stochasticity into the initial parameter estimations is that if the re-estimation procedure does not produce a sufficiently good parameterisation we can re-initialise our HMM and try again. That is to say we may use the forward-backward algorithm as part of a random restart hill climbing algorithm (Russell et al., 1995) to increase the chances that we will find a good parameterisation for the model.

3.3 Building a Sign Classifier

A `signModel` object, when trained using suitable set of training data from a single sign, allows us to evaluate how likely a new observation sequence is to be an instance of the sign used to train the model. Hence if we have a trained `signModel` instance m_s for each sign s in some dictionary D and a collection of joint observation sequences $\mathbf{\Theta} = \{\mathbf{O}_1, \ldots, \mathbf{O}_J\}$ read from the Kinect Sensor then

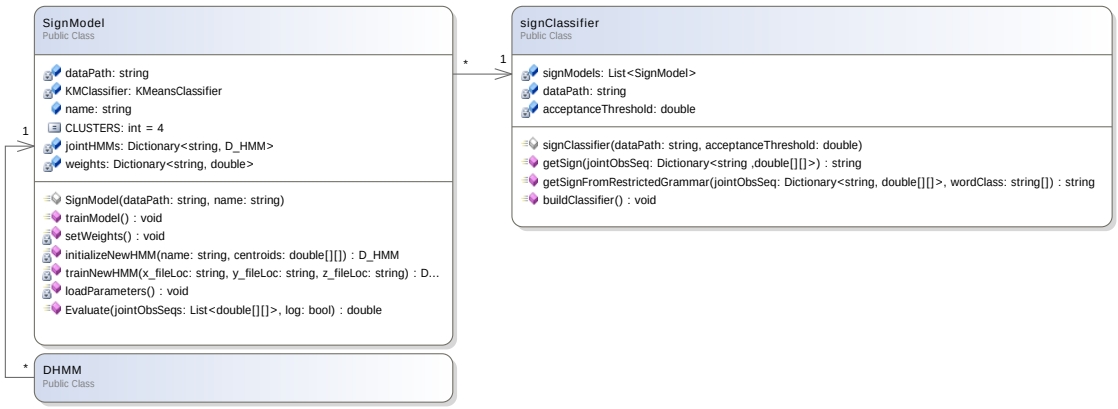


Figure 3.5: The signClassifier in UML

we can determine which sign model was most likely to have generated $\mathcal{O}$ as

$$m = \text{argmax}_{s \in D}\{L[\mathcal{O}|m_s]\}$$

where the value $L[\mathcal{O}|m_s]$ is computed by the `Evaluate` method of the `signModel` object. Then if $L[\mathcal{O}|m]$ is sufficiently large, say greater than some threshold τ, we can conclude that $\mathcal{O}$ corresponds to the sign used to train m.

We implemented this means of determining a signs as the class `signClassifier` (Figure: 3.5) which contains for each sign a trained `signModel` object and a method `getSign` which performs the above calculation.

A trained instance of `signClassifier` forms the basis of SignAlign and provides a means of recognising signs using the Kinect Sensor as input. We implemented the `buildClassifier` method to search for any parameterisations for `signModels` on disk and load them and then to search for any new training sets and create new `signModel` instances from them (saving their parameters to disk). As such the SignAlign dictionary can be extended by simply providing more training data without the need to retrain the rest of the model. This is a particularly desirable feature as a full re-estimation can take considerable time for a large dictionary and it would be inconvenient to perform each time the dictionary is expanded.

The `signClassifier` and `signModel` classes contain a number of contants which we have not yet given a specified value, for example M the number of

observation symbols or the acceptance threshold τ for detecting a sign. There is no *a priori* reason we should choose any particular value for these signs and hence chose to determine them through experimentation (Chapter 5). Before this was possible we were required to build a catalogue of training data and test cases by recording Kinect sensor streams.

Chapter 4

Interfacing With The Kinect Sensor

The Kinect SDK provides access to the Kinect Sensor from within C# code by defining a `KinectSensor` object which interfaces directly with the hardware. When this object is instantiated, and provided a Kinect Sensor is connected via the USB port, it provides access to the depth, RGB and skeletal streams of the camera. The `KinectSensor` object also provides an event `AllFramesReady` which fires each time the streams have successfully updated. The streams update at approximately 30 frames per second but this rate can be significantly reduced if the sensor attempts to track too many skeletons. Using this `KinectSensor` object we built a general purpose skeletal tracking controller class `GestureController` (Figure: 4.1) which initialises a `KinectSensor` object to provide a single skeletal stream and subscribes to the `AllFramesReady` event via a method `KinectAllFramesReady`.

4.1 Recording Training Data

In order to record the training data we implemented a class `GestureRecorder`, which extends `GestureController`, and a class `GestureRecording` which stores a single recording of the skeleton over time (Figure: 4.1). This second class contains a hashmap from `JointType` (an enum listing the different possible joints tracked by the Kinect Sensor) to lists of vectors representing the readings of that

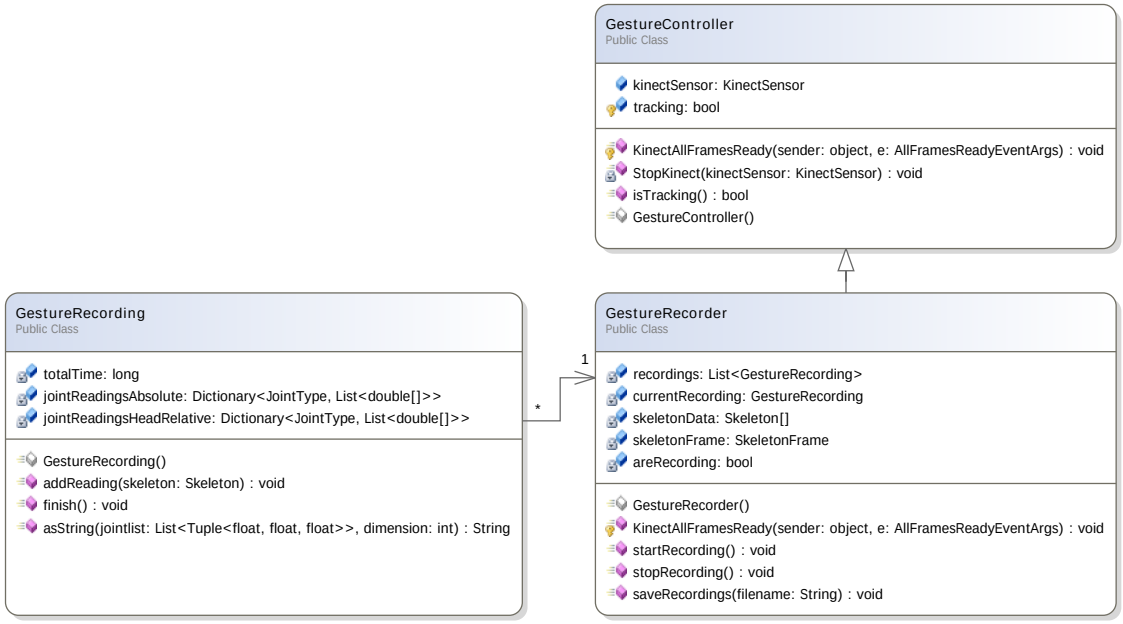


Figure 4.1: A UML diagram of the gesture recording classes

joint through time, and a method `addReading` which takes a `Skeleton` object and adds each joint location to the appropriate list. The `GestureRecorder` class stores a list of completed `GestureRecording` objects along with a current recording and extends the `KinectAllFramesReady` method to pass the Skeleton provided by the sensor to this current recording. This class also provides methods to start and stop the current recording (adding it to the list of recordings when stopped) and to save the list of recordings to file. Thus the `GestureRecorder` class allows us to record the movements of the hands, wrists, elbows, shoulders and head over time and save them as training or test data. Further we implemented two methods for storing the data – as positions relative to the camera or as positions releative to the signer's head.

Using this controller we implemented a small program which can be used to record a collection of training data by repeating a sign the desired number of times and giving a start/stop signal between each. For convenience we defined this signal to be when hands are raised a certain distance above the waist, a signal consistent with the pose a signer takes whilst pausing between sequences of signs.

4.1.1 The Training Data

Using this controller we recorded for each of a collection of 20 British Sign Language (see figure: 4.2) signs a set of 40 training examples, 10 hold-out examples and 10 testing examples. Each sign lasted between 1 and 3 seconds and was recorded at the maximum skeletal frame rate – 30 frames per second.

4.1.2 Limitations in the Training Data

The quality of the training sets was degraded by two factors. The first is that the signer (myself) who performed the training sets is not fully fluent in sign language and hence does not reproduce the signs consistently. The second factor is a limitation of the Kinect Sensor. The Kinect can track joints well when they are isolated but performs poorly when two parts of the body, for example the hands, are in contact (see figure: 4.3) and as many common signs require the hands to be placed together this issue caused a significant amount of the noise in the training data for those signs. The hand tracking issue is expected to be fixed in an upcoming SDK release but the contact issue could still cause noise in certain signs; for example those that require the signer to touch their elbows, shoulders or face.

Figure 4.2: The collection of 20 signs we recorded training data for (image credit: www.british-sign.co.uk)

Figure 4.3: An example of the broken hand tracking with the hands placed together. The yellow joints are inferred by the sensor incorrectly, the actual location of the hands is just below the chin.

Chapter 5

Testing and Experimentation

5.1 Determining the Classifier Parameters

In building the `signClassifier` we introduced parameters to determine how the sign likelihoods are calculated. For example in the `signModel` class we used k-means clustering to quantize the continuous Kinect sensor reading and hence had to chose a value for k (and hence the number of observation symbols M). Further, in the `signClassifier` we introduced a threshold value τ which determined whether the likelihood that a sign was observed was high enough to conclude that it indeed was observed. The choices of these parameter values have a significant impact on the performance of our classifier and for this reason we determined their values by experimentation. To avoid overfitting our model by training on the test data set we instead used a hold-out set for these experiments.

In carrying out our experiments we used several standard measures to quantify the performance of our classifier, for example measures of *true positives*, *true negatives*, *false positives* and *false negatives*. We take the definition of negative here to mean that no sign was/should be detected. Hence if the input for one sign is erroneously classified as a different sign this does not count as a false positive but rather as a *misclassification*. The definitions of these terms are summarised in table 5.1.

		Hypothesised Sign					
		1	2	3	...	20	No Sign
Actual Sign	1	TP	MC	MC	...	MC	FN
	2	MC	TP	MC	...	MC	FN
	3	MC	MC	TP	...	MC	FN
	⋮	⋮	⋮	⋮	⋱	⋮	⋮
	20	MC	MC	MC	...	TP	FN
	No Sign	FP	FP	FP	...	FP	TN

Table 5.1: A confusion matrix showing when different performance measures occur in a classifier trained to recognise 20 signs. Key: MC - misclassification, TP - true positive, TN - true negative, FP - false positive, FN - false negative.

5.1.1 The Cluster Number

As each choice of cluster number, k, defines a different classifier we decided to test these different classifiers to find a value for k which optimises the perfomance of our system. There are a number of methods to measure how well a given classifier performs in comparison to others. One technique is to plot ROC curves - plots of true-positive rate against the false-positive rate - of the different classifiers and use these to determine the best performance (either by observation or calculation of the area under the curve). This method is well documented for binary classifiers and has been extended for use with multiple bin classifiers, for example by considering higher dimensional ROC curves (Landgrebe and Duin, 2006). As we tested our system on a dictionary of 20 signs, this method would require us to consider a hypersurface in at least 20 dimensions and would require a very large hold-out data set to provide meaningful insight into the performance of our classifier. Due to the time restrictions of this project it was not possible to collect sufficiently large data sets and hence this method for comparing classifiers was unsuitable.

A second method for comparing classifiers is to consider a one class vs all others binary classifier for each class and to generate a 2-dimensional ROC curve for each. We attempted to use this method to determine the ideal cluster number but quickly found it to be innappropriate as for a given sign the number of false positives (that is test data streams that are incorrectly classified as that sign) was extremely low; regardless of the thresholding value and cluster number. As a

result the ROC plots were mostly degenerate, providing only information about the true positive rate, and could not be use to determine an appropriate number for k.

As such we decided to use the accuracy, defined to be

$$\text{accuracy} = \frac{\text{true positives} + \text{true negatives}}{\text{number of tests}}$$

as our measure of performance for each classifier. For cluster numbers ranging from 3 to 8 we retrained the classifier, tested it on the hold-out set for different threshold values and recorded its accuracy measure (see figure 5.1). This experiment provided some unexpected results, showing that a cluster number of 4 made for a more accurate classifer. We had assumed that a higher cluster number would make for a more accurate classifier because a more fine grained discretisation of the continuous input stream should allow the classifier to utilise more information about the input stream. However this was not the case and we found that the smaller cluster number of $k = 4$ yielded an accuracy of 85.9% (for $\tau = -800$) which was better than classifiers trained with a higher cluster number; as such we chose a cluster number of $k = 4$. Further inspection of the parameterisations of the `signModel` objects with higher cluster number found that many clusters contained few or no points and this may have caused the translation from continuous space to observation symbol space to translate very similar continous streams to considerably different symbol streams.

5.1.2 The Acceptance Threshold

Given a collection of joint observations $\mathbf{\Theta}$, the sign classifier determines the sign model m which is most likely to have generated it and, if $L[\mathbf{\Theta}|m]$ is larger than some threshold τ, concludes that $\mathbf{\Theta}$ corresponds to the sign that trained m. However there is no *a priori* reason to choose a given value for probability threshold τ. If τ is chosen too small then the classifier is more likely to associate a non-sign observation sequence with a sign, resulting in a false positive. Conversely, if τ is chosen too great then the classifier may fail to associate the observation sequence of a sign with the appropriate sign model, resulting in a false negative. To determine the appropriate value of τ we trained the classifier on the half of

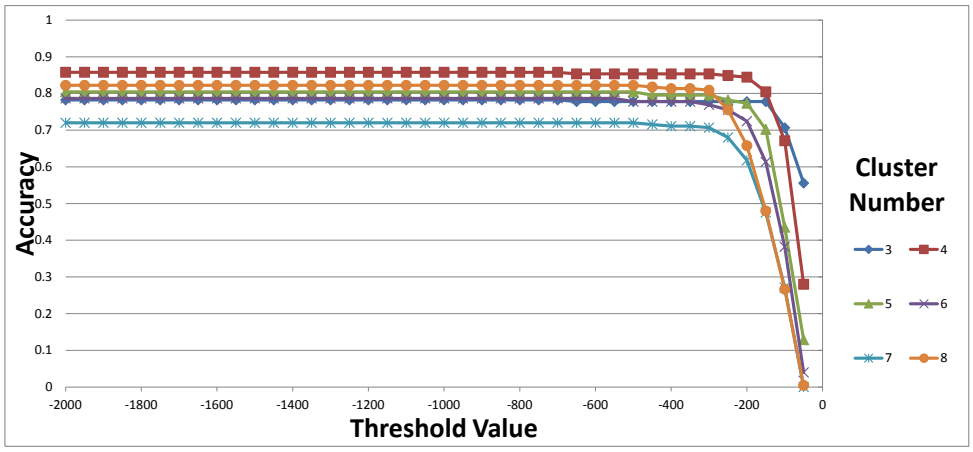


Figure 5.1: Recognition accuracy of classifiers with different cluster numbers

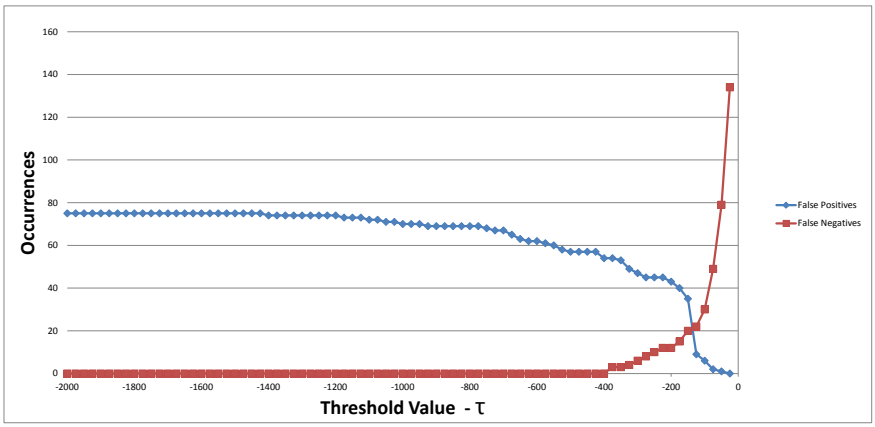


Figure 5.2: The trade off between false positives and false negatives

the training set and tested the classifier on the full hold-out data set for values of τ from -2000 up to 0 in increments of 50. In training our classifier on only half of the training data we essentially designated the signs from the other half as signs that should be classified as "No Sign" by our classifier and hence provided a large enough data set to test for false positives. The rationale here is that recording a large test data set of nonsense gestures is particularly time consuming and adds little value beyond this specific test. We recorded for each value of τ the number of false postives and false negatives and plotted them together (see figure: 5.2), from this experiment and by considering the accuracy measure we determined $\tau = -300$ to be an appropriate choice.

5.2 Lowering the Misclassification Rate

Whilst false positive and false negatives can be altered by changing the threshold value it is considerably more difficult to prevent misclassifications - the situation where the input sign for some sign is classified as another. From experimentation

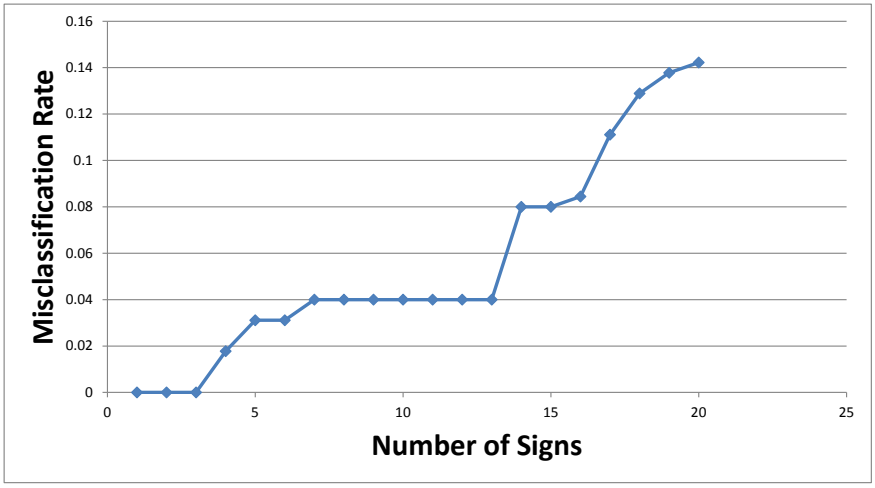


Figure 5.3: A graph comparing the number of signs the classifier decided between to the misclassification rate. As expected if there are more possible signs to decide between the misclassification rate increases.

we find, predictably, that the misclassification rate increases with the number of signs (see figure: 5.3).

In face it is possible to reduce the number of signs considered in each classification without reducing the total number of signs the system is able to recognise. To do this we can restrict the grammar of the sentences our classifier will recognise to so that it need only look into a certain subclass of words when attempting to recognise a sign. As BSL uses a topic-comment sentence structure we could restrict to a simple sentence structure, for example *noun-pronoun-question* which encapsulates questions such as "what is your name?" (name-your-what). Then when the classifier receives the first input stream it will need only look amongst the sign models for nouns to try and place the sign and will not suffer from misclassifications between nouns and other sign types. Following this the classifier, having just recognised a noun, will need only look amongst the pronoun sign models to classify the next input sequence.

To test the difference a grammar restriction could make to our classifier we grouped our signs by word class into one of *pronoun, question, noun* or *adjective*. We then retested the classifier on the hold-out set but this time only considering sign models with the same word class as the test case. This method reduced our misclassification rate from 14.2 % to 4.0% and increased the accuracy of our classifier to 95.6%.

Using a restricted grammar for our system certainly impacts on its utility and expressiveness and this is undesirable. The results of this experiment do however show us that we can significantly improve our classification accuracy by removing one of our most restrictive assumptions – that signs will be performed independently of one another. By restricting to a specific grammar we have reversed this assumption entirely and insisted that signs can only occur in one of a number of predetermined orders, an assumption that again is deleteriously restrictive but this time impacting the expressiveness of our system rather than the accuracy. It seems the ideal solution lies somewhere between the two approaches, allowing each sign model knowledge of the previously recognised signs so that it can be factored in to the likelihood calculation. This approach requires a great deal of knowledge of the grammar of sign language to be made useful and was hence beyond the scope of this project. It does however suggest an avenue of further research – building a model of the grammar of sign language and using it to predict the most likely word class of the next word in a partial sentence.

Chapter 6

Analysis and Conclusions

In this project we have implemented a sign classifier able to distinguish between signs performed in front of the Kinect sensor. To do this we implemented classes which extend Hidden Markov Models to accept continuous input streams and translate them via k-means clustering to a sequence in a discrete observation space. We then combined left-right topology HMMs in a novel way to form `signModel` objects which use information about all of the joints the Kinect sensor tracks to determine the likelihood that a given sign was performed. Finally we trained these models on a training set and used a hold-out data set to determine optimal parameter values for the acceptance threshold value and number of clusters in the quantization algorithm.

When tested on a test set of 10 instances of each of the 20 signs we found the classifier had an accuracy of 81.6% or 92.3% with a grammar restriction applied. These values are not drastically lower than the recognition accuracy when tested on the hold-out set or training set and suggest that the classifier has not suffered too much from overfitting. These recognition rates are quite impressive as our classifier differentiates between actual signs of British Sign Language without ever considering the hands and are better than we had expected to achieve when we began the project.

Whilst certainly of some use, the classifier implemented in this project is not anywhere near a full translation system for BSL as it does not account for the fingers, hand shape of non-manual features of the language. As we have seen this greatly restricts the expressiveness of our system as we require information

about the fingers to distinguish certain signs or information about the face to pose questions. Further we have seen that as the number of signs in the dictionary increases the misclassification rate also increases and it follows that the methods used to build our classifier will perform considerably worse when expected to recognise signs from a full lexicon of thousands of words in BSL even if a strict grammar is enforced.

Our classifier's overall accuracy was lower than that of Yamato et al. (1992) which had an average accuracy of 96.0% for six full body gestures. As our classifier was expected distinguish between more gestures it is no surprise that it has overall accuracy lower than this. However when restricted to a set of only six signs our classifier can have an accuracy between 94% and 100%, depending on the choice of signs, which suggests our model is at least as effective as that of Yamato.

Starner and Pentland (1995) used continuous distribution Hidden Markov Models to build a sign classifier which achieved an accuracy of 90.7% without a grammar restriction and 97.0% with a grammar restriction on a test set of 496 sentences drawn from a vocabulary of 40 words of American Sign Language. However their classifier also made use of the shape of the hands during the sign and if such information were available to the our classifier the accuracy would certainly be improved. Nevertheless their results suggest that the method of continuous distribution Hidden Markov Models is worth considering.

6.1 Further Work

6.1.1 Improvements to the Current Classifier

An immediate improvement that could be made to the sign recognition system is to gather training data from a user fluent in British Sign Language. This would likely improve the recognition accuracy of our system as the training sets would be more consistent. As we have implemented an efficient way to gather training sets through the Kinect Sensor this could be achieved fairly easily for a small training set, however it would still be prohibitively time consuming for a single user to generate the training sets for a large dictionary of signs. As the Kinect

Sensor is widely available this problem might be solved by crowd-sourcing the training database and allowing users of the system to submit their own training data for new signs.

In building our system we decided to use Hidden Markov Models with discrete observation space over those with continuous observation space. It could be argued that continuous density HMMs might be more suitable for the task of gesture recognition as each individual rendition of a sign can be considered as being normally distributed about some "true" path which defines the actual sign. As such we may be able to model the sign much more effectively by using a continuous density Hidden Markov Model in which the probability distribution is some mixture of Gaussians. Failing this we might attempt to implement a more effective discretisation of continuous space. At present we are using Lloyd's algorithm to cluster the input space and this can create small or empty clusters if the cluster number is too high. We could see significant improvements if we implemented a clustering algorithm which ensures no empty clusters and attempts to make clusters evenly sized where possible.

6.1.2 Extensions of SignAlign

An extension of the system to track hands and factor their positions into predicting signs would likely yield significant improvements to sign recognition. For example the signs for "you" and "your" which are essentially the same if the hand is ignored and are differentiated by a pointing finger or the hand forming a fist cannot be accurately differentiated by the current system. At present the Kinect SDK does not provide information about the locations of the fingers or shapes of the hands and so the system cannot be extended to use hand shapes without using third party software or implementing our own finger tracking; however it is expected that the Kinect will soon be updated to provide hand tracking and so we may be able to use hand tracking in the near future using only the Kinect SDK.

If hand tracking is implemented then we will be able to significantly extend the functionality of our sign recognition system to detect finger spelling. Finger spelling is commonly used in sign language to communicate words with no sign

equivalent and is a key part of communicating in sign language. As such the ability to accurately finger spell is integral to a full sign language translation system could be used to overcome the problem of not having training data for a large dictionary. The finger spelling problem consists of distinguishing between 26 distinct letter signs and could be solved using a similar Hidden Markov Model technique to the one presented in this project: By replacing joint tracking with finger and knuckle tracking. As we have obtained a good accuracy in classifying a small dictionary of signs it suggests that this method might produce good results in classifying the different letter signs of finger spelling.

Another feature of sign language which we have ignore in this project is facial expressions. Facial expressions are often used to modify the signs being communicated by the hands. For example the sign "you" can be converted to "are you ...?" by raising the eyebrows. The Kinect SDK has been used to track facial expressions (Microsoft, 2013a) and this work could be integrated with the sign recognition to produce a more robust sign recognition system.

Appendix: Technical Details

.1 Program Architecture

This project was implemented in C# using the Kinect SDK for Windows to provide access to the Kinect skeletal stream. The system was implemented using a Model-View-Controller architecure. The model here was the sign classifier which constitutes the majority of the project presented in this report whilst the controllers are the collection of classes we wrote to interface the Kinect sensor to the classifier. The view component consisted of a collection of simple user interfaces built using Windows Presentation Foundation to allow the user to record training, test and hold out data or to translate signs in real time by performing signs in front of the Kinect sensor.

Throughout the course of this project it became evident that there are a range of models we could have used in place of the discrete observation HMM. As such we used object oriented programming principles to ensure that the underlying workhorse statistical model which is used to build the `signModel` class was easily interchangeable. For brevity we chose to forgoe the details of how interfaces were defined and used within the main report. Figure 1 shows the full class hierarchy of the SignAlign system and how the Hidden Markov Model could be swapped for a different model easily.

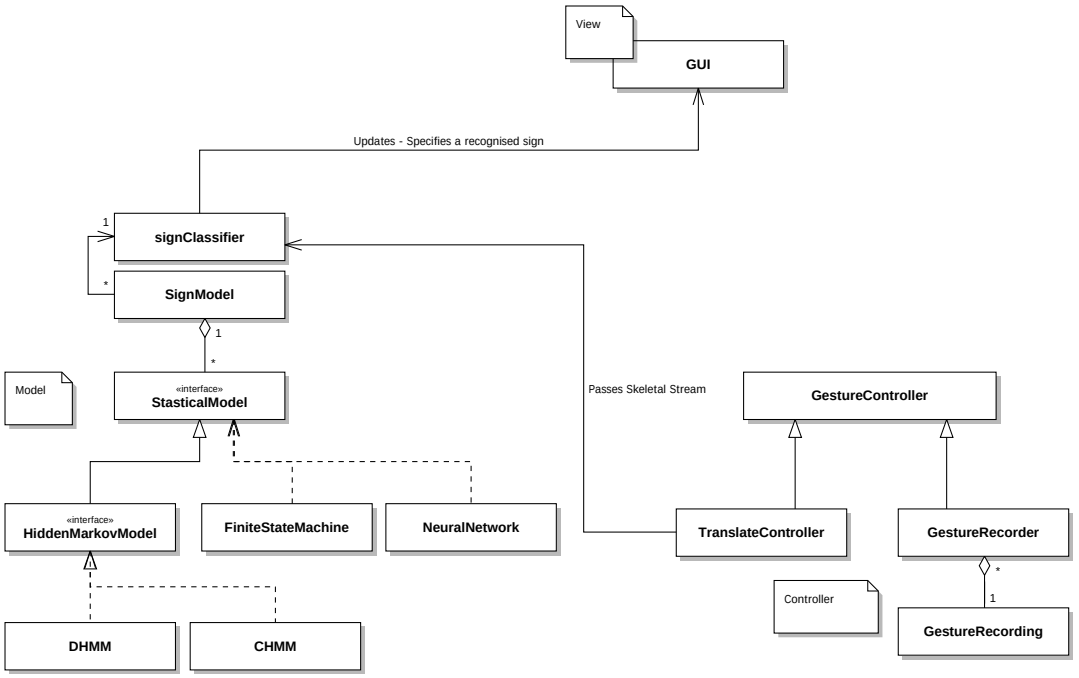


Figure 1: A UML diagram of the full SignAlign system

.2 Correctness Testing

After implementing the `DHMM`, `signModel` and `signClassifier` classes we verified their correctness by writing a collection of unit tests. However as we have built a statistical model the extent of our automated testing was limited to simple "sanity checks" and for this reason we omitted the details from the main report. We began by testing the likelihood evaluation and re-estimation procedure of the `DHMM` class by comparing its results on a collection of predetermined test cases against those of the RHMM package written in R (Taramasco and Bauer, 2013). Following this we went on to test the `signModel` class by writing a collection of test re-estimations on a collection of observation sequences to ensure that the re-estimation procedure does indeed increase the likelihood of that `signModel` generating those observation sequences.

.3 Program Listing

A full program listing for the SignAlign system is available at `https://github.com/Daniel-Nichol/sign-align`.

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