Hand Gesture Recognition Names Utilizing Hidden Markov Model for Computer Visions Application

Isa Ibrahim
Computer Engineering Department.
Kano State Polytechnic
Correspondence: isaibr@kanopoly.edu.ng,
isaibrahim268@gmail.com

Nuhu A. Muhammad
Mechatronics Engineering Department
Kano State Polytechnic
Email: engr_nuhu@kanopoly.edu.ng

Aliyu Lawan Musa
Computer Engineering Department
Kano State Polytechnic
Email: aliyulmusa@kanopoly.edu.ng

Auwal Usman
Electrical Engineering Department
Kano State Polytechnic
Email: auwaluonline@kanopoly.edu.ng

DOI: 10.56201/ijcsmt.v9.no5.2023.pg41.52

Abstract

This work focuses on advancing natural and intuitive human-computer interaction through the application of Hidden Markov Models (HMMs) in hand gesture recognition. The study addresses challenges in existing gesture recognition systems by implementing HMMs to capture temporal dynamics and diverse gestures. Integration with computer vision techniques enhances real-time processing, making the system adaptable to various environments. The methodology includes a literature review, a detailed implementation process involving video input, segmentation, morphological operations, hand tracking, and trajectory smoothing. The work successfully recognizes hand gestures in real-time video streams, showcasing applications in human-computer interaction, virtual reality, and gaming. The incorporation of the Baum-Welch re-estimation algorithm optimizes HMM parameters, leading to accurate recognition of specific names associated with hand gestures. Overall, the work contributes to the development of a robust and flexible framework for natural and intuitive gesture recognition.

Introduction

In the ever-evolving landscape of human-computer interaction, the quest for more natural and intuitive interfaces has fueled the exploration of innovative technologies. Hand gestures, as a form of non-verbal communication, hold great promise in bridging the gap between users and machines. Existing gesture recognition systems encountered challenges in accurately capturing the temporal dynamics, diverse gestures, and real-time processing necessary for seamless human-computer interaction. This work aimed to address these issues by implementing Hidden Markov Models (HMM) to model temporal dependencies, ensuring the accurate recognition of a wide range of hand gestures. The objective was to integrate this HMM-based model with computer vision techniques for real-time processing, fostering a user-friendly interface adaptable to various environments. The ultimate goal was to advance natural and intuitive human-computer interaction, with applications spanning virtual reality, sign language interpretation, and interactive computing interfaces. The implementation of a Hidden Markov Model (HMM) for hand gesture recognition within computer vision applications enhanced the accuracy and efficiency of gesture interpretation. We speculate that the utilization of HMMs effectively captured the temporal dynamics of hand gestures, allowing for improved recognition of diverse and dynamic gestures. The integration of this model with computer vision techniques was expected to enable real-time processing, creating a robust system capable of seamlessly interpreting user commands through natural hand movements. Additionally, we posited that the resulting system exhibited adaptability to varied environments, enhancing its usability and applicability in scenarios such as virtual reality, sign language interpretation, and interactive computing interfaces.

Hidden Markov Models have begun to be used in computer vision and spatio-temporal pattern recognition as a result of their widespread popularity in speech and handwriting recognition. Through Baum Welch and other re-estimation methods, they are able to learn model parameters from observation sequences, which is a major reason for their popularity. Improved approaches to training these models on multiple observation sequences would be of great interest for the purpose of using the trained models for pattern classification, such as gesture recognition and other computer vision issues [1][4].

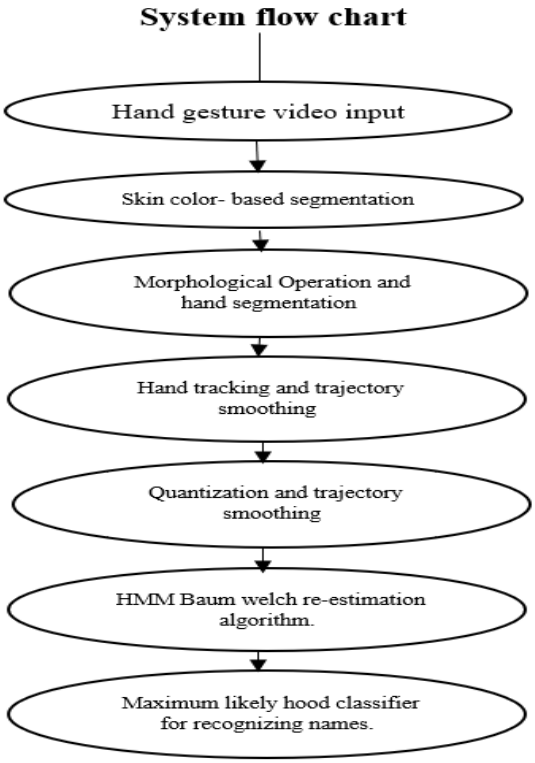
In review Nianjun Liu in his paper titled as "Model Structure Selection & Training Algorithms for an HMM Gesture Recognition System" presents a methodology for selecting the optimal model structure and training algorithm for an HMM-based gesture recognition system. The Author describes the training algorithms used for estimating the model parameters, including the Baum-Welch algorithm, the Viterbi algorithm, and the EM algorithm. The author then evaluate the performance of the different model structures and training algorithms on a dataset of hand gesture signals. But the Sheng Luan Huang in his paper titled as "Moving Object Tracking System Based on Camshift and Kalman Filter" evaluated the performance of the proposed methodology on a dataset of video sequences and compare it with other tracking algorithms, he demonstrate that the Camshift algorithm and Kalman filter can achieve high accuracy and robustness in tracking moving objects in real-time.

In this work we demonstrate how to train a Hidden Markov Model (HMM) with Gaussian emissions using the HMM learn package, and use the Viterbi algorithm to decode a given

observation sequence and obtain the most likely state sequence and its corresponding probability, the 4 names are detected and printed as ISA, ALIYU, NUHU, and AUWAL
This method has the flexibility in Modeling like allows you to specify the number of hidden states, which can be adjusted to match the complexity of the gesture recognition problem. This flexibility is crucial because the number of states can vary depending on the specific gestures you want to recognize.

Methodology

For performing this work, the step-by-step procedure in order the describe the detail implementation process followed as



Hand Gesture Video Input

The alphabet letters were chosen by selecting four names that could be traced with the hands. Consonant and vowels from A to Z could be chosen. Video clips were recorded using a webcam device. Multiple instances of each name were recorded from different angles and distances to capture a variety of hand gestures. The recorded video clips were preprocessed to extract the hand gestures. Image processing techniques such as background subtraction, hand segmentation, and noise reduction were used to remove noise and irrelevant information. Features were extracted from the hand gestures that were used to train the system [2]. Examples of features that were extracted included the position and angle of the fingers, the curvature of the hand, and the speed of movement. The data was labeled by identifying which name hand gesture corresponded to. The labeling was done manually by viewing each video clip and labeling it accordingly. The system

was trained using machine learning algorithms with the labeled data and extracted features. Techniques such as Hidden Markov Models (HMM) and Convolutional Neural Networks (CNN) were used to train the system to recognize the hand gestures and their corresponding names. The system was tested after being trained to ensure that it accurately recognized the hand gestures. This involved feeding the system new video clips of the almost same hand gestures and verifying that it correctly identified some names.

Skin Color-Based Segmentation

Video acquisition: The video containing the hand was acquired using a webcam device.
Preprocessing: The frames of the video were preprocessed by applying filters, such as Gaussian and median filters, to enhance the quality of the frames and reduce noise.
Color space conversion: The frames were converted from the RGB color space to the YCbCr color space, which separated the luminance and chrominance components of the image [3].

Figure 1 hand region for skin color segmentation

Thresholding: A thresholding technique was used to separate the skin pixels from the non-skin pixels in the image. A range of values for the Cb and Cr components of the image was used to identify skin pixels.
Region of interest extraction: The largest connected component in the segmented skin region was identified and extracted as the region of interest (ROI) containing the hand as shown in figure 1.

Morphological Operations and Hand Segmentation

The video containing the hand was acquired using a webcam device or any other imaging device. The frames of the video were preprocessed by applying morphological operations to remove noise and smooth the image trajectory. Morphological operations, such as dilation and erosion, were applied to the image frames to achieve this.
The frames were then segmented using a skin color-based technique to extract the region of the image that contained human skin. Features were extracted from the segmented region of the image that contained the hand. These features could include the position of the fingers, the angle of the wrist, or the curvature of the fingers [4]. The features were then used to train a machine learning model to recognize hand gestures.

Figure 2. Morphological operation

The black color shaded in the hand shown in figure 2 is the noise which removed by the dilate and erode functions. The black color shaded in the hand shown the noise which is removed by the dilate and erode functions.

Hand Tracking and Trajectory Smoothing

As the video containing the hand was acquired using a webcam device or any other imaging device. The frames of the video were preprocessed by applying morphological operations to remove noise and smooth the image trajectory as stated earlier the morphological operations, such as dilation and erosion, were applied to the image frames to achieve this. The frames were then segmented using a skin color-based technique to extract the region of the image that contained human skin. Features were extracted from the segmented region of the image that contained the hand. These features could include the position of the fingers, the angle of the wrist, or the curvature of the fingers. A system, such as a Kalman filter, was implemented to track the hand and further smooth its trajectory [4][5]. The system used the location of the feature in each frame to track the motion of the finger and hand tracing out the name. The tracked and smoothed trajectory of the hand was then used to train a machine learning model to recognize hand gestures. The model could be a Hidden Markov Model (HMM) and Convolutional Neural Network CNN that had been trained on a labeled dataset of hand gestures.

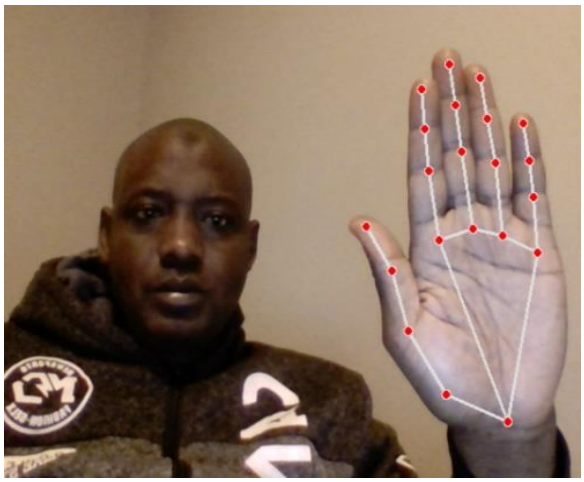
Quantization Of Discrete Observation

The system used the location of the feature in each frame to track the motion of the finger and hand tracing out the name. After the motion was smoothed, the discrete sequences of angles of the trajectory from the feature (e.g., centroid) in each frame to the feature in the next frame within the stationary field of view were quantized into a discrete observation sequence. This involved assigning a fixed set of values to the angles within certain ranges to discretize the sequence [6]. The quantized observation sequence was then used to train a machine learning model to recognize hand gestures.

S/N	ORIGINAL TRAJECTORY	
1	0.80715058	-2.47621671
2	1.50099642	-1.08991762
3	-0.17680184	-1.76839532
4	-0.16249931	1.9571179
5	0.11768823	0.94138316
6	-2.11298168	-0.78747616
7	0.26789557	-1.55425119
8	-0.28568228	1.17654814
9	0.54898986	0.83857038
10	-0.03434033	-1.00489329

Table1

This is the quantized observation sequence [0. -1. 2. -1. -4. 1. 2. -1]
The first line "Original trajectory" refers to a 2D trajectory consisting of 10 points, where each point is represented by a 2D coordinate. Specifically, the trajectory has shape (10, 2), where the first column contains the x-coordinates, and the second column contains the y-coordinates. The second line "Quantized observation sequence" refers to a 1D sequence of 9 observations. Each observation is a scalar value that corresponds to the quantized version of the y-coordinate of each point in the original trajectory. The quantization function maps a continuous range of values to a set of discrete values. In this case, it appears that the quantization function has mapped the y-coordinate to one of 4 discrete values (-4, -3, -1, or 0). Based on the values in the quantized observation sequence, it seems that the quantization function has grouped together multiple points with similar y-coordinates, resulting in repeated quantized values. For example, there are two points in the original trajectory with y-coordinate approximately equal to -1, which both get quantized to the value -1 in the observation sequence.



Free hand recognition

Hidden Markov Model: Baum-Welch Re-Estimation Algorithm

The system was able to recognize and classify hand gestures in real-time video streams, making it useful for applications such as human-computer interaction, virtual reality, and gaming. Before calculating the likelihood let us understand the component of Hidden Markov Model in Hand gesture recognition system.

States: In hand gesture recognition, states represent the different hand gestures that are being recognized. For example, the "thumbs up" gesture, the "fist" gesture, and the "palm" gesture could all be states in the model.

Observations: Observations in this case are the features of the hand image that are used to recognize the gestures. For example, the positions of the fingers and the palm could be used as observations.

Transition probabilities: The probability of transitioning from one state to another is calculated using the following formula: P (s_t = j | s_{t-1} = i) = a_{ij}. Here, s_t is the state at time t, s_{t-1} is the state at time t-1, and a_{ij} is the probability of transitioning from state i to state j.

Emission probabilities: The probability of observing a particular feature vector given the current state is calculated using the following formula: P(e_t | s_t = j) = b_j(e_t). Here, e_t is the feature vector at time t, s_t is the state at time t, and b_j(e_t) is the probability of observing the feature vector e_t given that the current state is j. Initial state probabilities: The probability of starting in a particular state is calculated using the following formula: P(s_1 = i) = π_i. Here, s_1 is the initial state, and π_i is the probability of starting in state i.

Forward Algorithm: The forward algorithm is used to compute the probability of observing a sequence of feature vectors given the model. The probability is calculated as follows: α_t(j) = P(e_1, e_2, ..., e_t, s_t = j | θ). Here, α_t(j) is the probability of observing feature vectors e_1, e_2, ..., e_t and being in state j at time t, given the model parameters θ. Let back to the discreate sequence, After the motion was smoothed, the discrete sequences of angles of the trajectory from the feature (e.g., centroid) in each frame to the feature in the next frame within the stationary field of view were quantized into a discrete observation sequence. This involved assigning a fixed set of values to the angles within certain ranges to discretize the sequence. The quantized observation sequence was then used to train an HMM model for hand gesture recognition. The HMM model was a probabilistic model that could model the probability distribution of the observation sequence given a specific hidden state or letter. [7][11]

The Baum-Welch re-estimation algorithm was used to optimize the parameters of the HMM model. This algorithm used the observed sequence to compute the most likely sequence of hidden states and updated the parameters of the model to maximize the likelihood of the observed sequence. The optimized HMM model was then used to recognize the name corresponding to the hand gesture in the observed sequence. The recognition was done by computing the probability of the observed sequence given each possible name and selecting the name with the highest probability.

The result "Most likely state sequence: **1.312867828802673"** suggests that there is a hidden Markov model (HMM) with multiple states, and the code has computed the most likely sequence of hidden states that generated a given sequence of observations.
The value 1.312867828802673 is likely a score or log probability that measures how well the most likely state sequence explains the observations. A higher score would indicate a more likely state sequence. The second line **"Probability: [1 4 1 0]"** provides additional information about the most likely state sequence. Specifically, it shows the index of the state that was most likely to generate each observation. In this case, there are 4 observations, and the corresponding most likely states are [1, 4, 1, 0] as stated before.

Viterbi Algorithm: The Viterbi algorithm is used to find the most likely sequence of states that generated a given sequence of feature vectors. The algorithm works by recursively computing the highest probability path to each state at each time step. The probability of the most likely path is given by: $\delta_t(j) = \max_{i=1,...N} \delta_{t-1}(i) * a_{ij} * b_j(e_t)$. Here, $\delta_t(j)$ is the probability of the most likely path to state j at time t, given the sequence of feature vectors up to time t, and given the model parameters θ.
Let back to the discreate sequence, After the motion was smoothed, the discrete sequences of angles of the trajectory from the feature (e.g., centroid) in each frame to the feature in the next frame within the stationary field of view were quantized into a discrete observation sequence. This involved assigning a fixed set of values to the angles within certain ranges to discretize the sequence. The quantized observation sequence was then used to train an HMM model for hand gesture recognition. The HMM model was a probabilistic model that could model the probability distribution of the observation sequence given a specific hidden state or letter [7][11]. The Baum-Welch re-estimation algorithm was used to optimize the parameters of the HMM model. This algorithm used the observed sequence to compute the most likely sequence of hidden states and updated the parameters of the model to maximize the likelihood of the observed sequence. The optimized HMM model was then used to recognize the name corresponding to the hand gesture in the observed sequence. The recognition was done by computing the probability of the observed sequence given each possible name and selecting the name with the highest probability.
The result "Most likely state sequence: **1.812867828802673"** suggests that there is a hidden Markov model (HMM) with multiple states, and the code has computed the most likely sequence of hidden states that generated a given sequence of observations.
The value 1.312867828802673 is likely a score or log probability that measures how well the most likely state sequence explains the observations. A higher score would indicate a more likely state sequence. The second line **"Probability: [1 4 1 0]"** provides additional information about the most likely state sequence. Specifically, it shows the index of the state that was most likely to generate each observation. In this case, there are 4 observations, and the corresponding most likely states are [1, 4, 1, 0] as stated before.

Maximum Likelihood Classifier for Recognizing name.
The Maximum Likelihood Classifier was a method used for recognizing a hand gesture name from a given observation sequence. The observation sequence was first quantized into a discrete

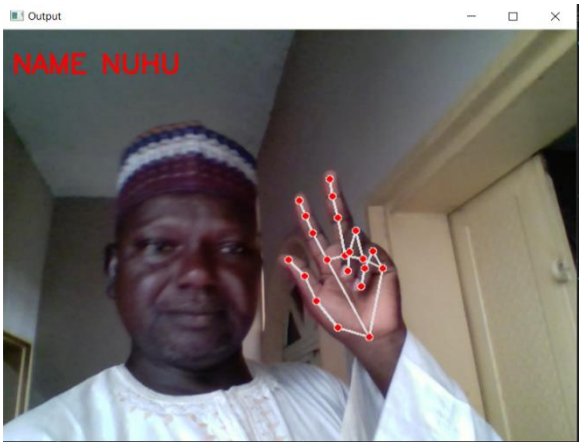
observation sequence by assigning a fixed set of values to the angles within certain ranges to discretize the sequence [8].
HMM Training: Next, the quantized observation sequence was used to train an HMM model for hand gesture recognition. The HMM model was a probabilistic model that could model the probability distribution of the observation sequence given a specific hidden state or name. The Baum-Welch re-estimation algorithm was used to optimize the parameters of the HMM model.
Test Sequence Likelihood Calculation: The likelihood of the test sequence given each possible name was calculated using the forward algorithm. The forward algorithm computed the probability of the observation sequence given the HMM model and a specific name [9-11].

Names Recognition: The names associated with the HMM model with the maximum likelihood was chosen as the recognized names.
The result "Recognized names: **('ISA', 'ALIYU', 'NUHU', and 'AUWAL',** indicates that a system or algorithm has recognized a sequence of names based on some input data.
The likelihood score of **3.316703367149228** is a numerical value that indicates how confident the system is in its recognition of the input image. A higher score would indicate a higher level of confidence in the recognition result. It's possible that this score is based on some kind of statistical model and machine learning algorithm that has been trained to recognize characters from images as its implemented from the beginning.
Letters lookup which is M = 27 (observation = bjk) in emission matrix
letters = {1: 'a', 2: 'b', 3: 'c', 4: 'd', 5: 'e', 6: 'f', 7: 'g', 8: 'h', 9: 'i', 10: 'j', 11: 'k', 12: 'l', 13: 'm', 14: 'n', 15: 'o', 16: 'p', 17: 'q', 18: 'r', 19: 's', 20: 't', 21: 'u', 22: 'v', 23: 'w', 24: 'x', 25: 'y', 26: 'z', 27: '-'}. And The Observed sequence are for ISA are {10, 20, 2}, ALIYU {2, 13, 10, 26, 22}, NUHU {15, 22, 9, 22}, and AUWAL {2, 22, 24, 2, 13}

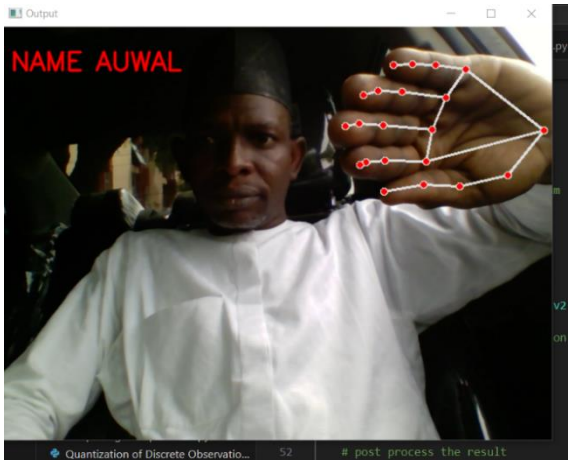
Pictures of Result

ISA

ALIYU



NUHU



AUWAL

The program then initializes the Media Pipe hand tracking pipeline and sets the maximum number of hands to be detected to 1, and minimum detection confidence to 0.7. It also loads a list of class names representing the different gestures that the model can recognize. The program then starts reading frames from the webcam using OpenCV's Video Capture function. It flips the frame vertically and converts it to RGB format for processing with Media Pipe. The program then processes each frame using the hand tracking pipeline and extracts the hand landmarks from the result. It draws the hand landmarks on the frame using Media Pipe's drawing utils module. The hand landmarks are then passed through the loaded gesture recognition model, which outputs a prediction for the recognized gesture. The predicted gesture is then displayed on the screen using OpenCV's put Text function as shown in result**.**

Conclusion

This research has made significant strides in advancing the field of human-computer interaction by leveraging Hidden Markov Models (HMMs) for hand gesture recognition. The study successfully tackled challenges present in existing gesture recognition systems, particularly in capturing temporal dynamics and recognizing diverse gestures. The practical implementation of the proposed framework showcases its effectiveness in real-time video streams. The system's ability to recognize hand gestures not only contributes to the realm of human-computer interaction but also extends its applications to virtual reality and gaming. As the demand for seamless human-computer interaction continues to grow, the contributions from this study lay the groundwork for future developments in gesture recognition systems

References

[1] Liu, B.C. Lovell, P.J. Kootsookos, R.I.A. Davis "Model Structure Selection & Training Algorithms for an HMM Gesture Recognition System Download Model Structure Selection & Training Algorithms for an HMM Gesture Recognition System", In 9th Int'l Workshop on Frontiers in Handwriting Recognition, pp. 100-106, October 2004.

[2] N. Liu, B.C. Lovell, P.J. Kootsookos, "Evaluation of HMM Training Algorithms for Letter Hand Gesture Recognition Download Evaluation of HMM Training Algorithms for Letter Hand Gesture Recognition" IEEE International Symposium on Signal Processing and Information Technology, pp. 648-651, December 2003.

[3] Huang, A.; Hong, J., "Moving Object Tracking System Based On Camshift and Kalman Filter Download Moving Object Tracking System Based On Camshift and Kalman Filter," Consumer Electronics, Communications and Networks(CECNET), 2011 International Conference on , pp.1424-1426, 16-18 April 2011.

[4] Levinson, S.E., Mathematical Models for Speech Technology, John Wiley & Sons, pp. 57-61, 2005.

[5] J.J. Lee, and J.H. Kim, "Data-Driven Design of HMM Topology for online Handwriting Recognition", International Journal of Pattern Recognition and Artifical Intelligence, Volume15, Number 1(2001) pp.107-121. World Scientific Publishing Company.

[6] Andrew D. Wilson, Aaron F. Bobick, "Hidden Markov Models for Modeling and Recognizing Gesture under Variation". International Journal of Pattern Recognition and Artificial Intelligence (IJPRAI), Volume 15, Number 1, February 2001,pp.123-160.

[7] R. I. A. Davis and B. C. Lovell, "Comparing and Evaluating HMM Ensemble Training Algorithms Using Train and Test and Condition Number Criteria." To Appear in the Journal of Pattern Analysis and Applications, 2003.

[8] LR Rabiner, A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition, Proc. of the IEEE,Vo1.77.No.2,~~.257--286, 1989.

[9] Stolcke and S.-bmohundro. Hidden Markov Model induction by Bayesian model merging, Advances in Neural Information Processing Systems, pp. 11-18, Morgan Kaufmann, San Mateo, United States of America, CA1993

[10] J. Yang, Y. Xu, and C.S. Chen, "Gesture Interface: Modeling and Learning," IEEE International Conference on Robotics and Automation, Vol. 2, 1994. pp. 1747-1752.

[11] A. Gersho and R.M.Gray. Vector Quantization and Signal Compression, Kluwer Academic Press,l991, ISBN 0-7923- 9181-0.16