DACTYLOLOGY RECOGNITION SYSTEM
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Abstract.
Dactylology is the technique of communicating with signs made with fingers, especially in the manual alphabets used by the deaf. Sign Language is one of the oldest and most natural forms of language for interaction between normal and deaf & mute people, but since most people do not know sign language and interpreters are very difficult to find, we have come up with a real-time method using neural networks for fingerspelling based American sign Language. Sign languages are visual languages and consist of 3 major components: Fingerspelling, Word level vocabulary and Facial expressions.

In our project, we basically focus on producing a model which can recognize fingerspelling based hand gestures in order to form a complete word by combining each gesture.

We follow 4 steps in the hand gesture recognition: i) Data Acquisition, ii) Data preprocessing, iii) Feature extraction iv) Gesture classification. We aim to collect 600 RGB images each for 26 alphabets and apply a filter called Gaussian blur to each of the images. This filter gives a black and white outline of the hand gesture which makes it easier for computation. The images are then passed through a convolutional neural network classifier which predicts the class of the hand gestures. Our method provides 95% accuracy for the 26 letters of the alphabet.

Keywords: Dactylology, Image Recognition, Gaussian Blur Filter, Image Processing, Deep Learning, Convolutional Neural networks.

1. Introduction

1.1 About Project
Sign language is a form of communication used by people with impaired hearing and speech. People use sign language gestures as a means of non-verbal communication to express their thoughts and emotions. Sign languages generally do not have any linguistic relation to the spoken languages of the lands in which they arise. The correlation between sign and spoken languages is complex and varies depending on the country more than the spoken language. We use a custom recorded American Sign Language data set based on an existing data set for training the model to recognize gestures. We propose to use a CNN (Convolutional Neural Networks) named Inception to extract spatial features from the video stream for Sign Language Recognition (SLR). American Sign Language (ASL) is a characteristic language that fills in as the prevalent sign language of Deaf people. American Sign Language (ASL) is a visual language. With marking, the brain processes phonetic data through the eyes. The shape, arrangement, and movement of the hands, just as facial...
expressions and body movements, all play significant parts in passing on data, ASL has the same linguistic properties as spoken languages. We try understanding the precise meaning of deaf and dumb people’s symbolic gestures and converting it into understandable language (Text) and finally into speech using Google Text to Speech (gTTS) module.

1.2 Objectives of the project

The aim is to develop a user-friendly human computer interface (HCI) where the computer understands the human sign language. There are various sign languages all over the world, namely American Sign Language (ASL), French Sign Language, etc and work has been done on other languages all around the world. But, we focus on converting American Sign Language into speech, as ASL is a global sign language and can be understood by people all over the world. In recent years there has been tremendous research done on hand gesture recognition.

With the help of literature survey done we realised the basic steps in hand gesture recognition are: - Data acquisition, Data preprocessing, Feature extraction, Gesture classification.

1.3 Scope of the project

We are planning to achieve higher accuracy even in case of complex backgrounds by trying out various background subtraction algorithms. We are also thinking of improving preprocessing to predict gestures in low light conditions with a higher accuracy.

2. Literature Survey

2.1 Existing System

Sign Language is the most natural and expressive way for the hearing impaired people. Many new techniques have been developed recently in this area. But the existing system uses Linear Discriminant Analysis (LDA) algorithm was used for gesture recognition and recognised gesture is converted into text. LDA mainly used in statistics, pattern recognition and machine learning. It is used to find a linear combination of features that characterises or separates two or more classes of objects or events.

The current system has collected around 10 images for each sign. These images are included in the training and testing database. The captured image at a distance is adjusted by the signer to get the required image clarity. Due to fewer images given for training, the accuracy of such a system drops to 85-88%. The image components are extracted by Morphological Filtering tools which are useful for representation and description of shape. The features extracted from the segmentation operation used for gesture recognition. The smooth contour is obtained by removing the noise from the images with Morphological filtering techniques.
2.2 Proposed System

American Sign Language is a predominant sign language and is widely used by people all over the world. ASL alphabets are quite different from the gestures, alphabets involve manual letters from A-Z with each letter shown to convey a message, while gestures convey an entire emotional together. Creating an human interactive interface that takes ASL as the input and converts it into speech can be used by people all over the world without any barriers. The proposed system with a live video input is subjected to the trained sign recognition model, trained victimisation neural networks of deep learning, the model acknowledges the alphabet, combines recognised letters to words and finally combines words to sentences. A Hunspell spell checker is also included to suggest or correct words during the recognition process. The sentences are converted to speech/audio by using the gTTS library.

3. Proposed Architecture

The proposed architecture presents a model which captures images from the web camera, the image frame through which the desired input has to be taken can be manipulated from the software. The Image is then processed in the OpenCV platform to recognise the gestures through image processing algorithms. Spell checker package is included to correct the spellings in case of some erroneous inputs. The text is then passed to the gTTS library that converts the opened text into audio file.

The user gives input from the video capture with the help of the in-built camera on the computer. This camera helps in capturing the required images for each alphabet. This involves the image acquisition phase where the input from the user is taken. These images acquired are then preprocessed. The preprocessing involves converting the images into gaussian blur images.
1st Convolution Layer - Input 128*128 image, using 32 filters, output 126*126 image. 1st Pooling Layer - Downsampled using 2*2 max pooling to 63*63 pixels image. 2nd Convolution Layer - Input 63*63 image, using 32 filters, output 60*60 images. 2nd Pooling Layer - Downsampled using 2*2 max pooling to 30*30 images. The outcome of the CNN layers is 28,800 units. The 1st Fully Connected Dense layer consists of 128 units and this is followed by 2 fully connected layers of 96 units and 64 units respectively. Finally, there is the output layer which consists of 27 units, one for each alphabet and last one neuron for the blank space.

4. Implementation

4.1 Data Collection
We created a dataset which has 27 gestures and these gestures are made up of 26 alphabets and 1 blank space. There are 500 images for each alphabet in the 27 different folders. From the 13,000 images, 11070 images were given for training and 2755 images are given for testing.

4.2 Preprocessing
In preprocessing the image data is improved which reduces unwanted deviation or enhances image features for further processing. Preprocessing is also referred to as an attempt to capture the important pattern which expresses the uniqueness in data without unwanted data which includes cropping, resizing and grey scaling. Cropping removes the unwanted parts of an image to improve framing.

4.3 Designing the CNN (Convolution Neural Networks)
This step is the most important part of the entire process as we design the CNN through which we will pass our features to train the model and eventually test it using the test features. We have used a combination of several different functions to form a CNN which we will discuss one by one. Building and training a CNN in Keras:
Sequential() - A sequential model is just a linear stack of layers which is putting layers on top of each other as we progress from the input layer to the output layer.

- classifier.add(Conv2D()) - This is a 2D Convolutional layer which performs the convolution operation as described at the beginning of this post. To quote Keras Documentation "This layer creates a convolution kernel that is convolved with the layer input to produce a tensor of outputs." Here we are using a 3x3 kernel size and Rectified Linear Unit (ReLU) as our activation function.

- classifier.add(MaxPooling2D()) - This function performs the pooling operation on the data as explained in Literature Review. We are taking a pooling window of 2x2 with 2x2 strides in this model.

- classifier.add(Flatten()) - This just flattens the input from ND to ID and does not affect the batch size.

classifier.add(Dense()) - According to Keras Documentation, Dense implements the operation: output=activation(dot(input, kernel)) where activation is the element-wise activation function passed as the activation argument, kernel is a weights matrix created by the layer. In simple words, it is the final nail in the coffin which uses the features learned using the layers and maps it to the label. During testing, this layer is responsible for creating the final label for the image being processed.

4.4 Algorithm

Our approach uses two layers of algorithms to predict the final symbol of the user. Algorithm Layer 1: Apply Gaussian blur filter to the frame to get the processed image after feature extraction. This processed image is passed to the CNN model for and if a letter is detected for more than 50 frames then the letter is printed and considered for forming the word. Space between the words is taken as blank symbol.

Algorithm Layer 2: The symbols which look alike of each other, special classifiers will be applied to them depending on the accuracy obtained.

4.5 Tkinter Implementation

Tkinter is lightweight and relatively painless to use compared to other frameworks. This makes it a compelling choice for building GUI applications in Python, especially for applications where a modern sheen is unnecessary, and the top priority is to quickly build something that’s functional and cross-platform. The foundational element of a Tkinter GUI is the window. Windows are the containers in which all other GUI elements live. These other GUI elements, such as text boxes, labels, and buttons, are known as widgets. Widgets are contained inside of windows.
In our implementation a video capture is opened which takes input from the user and displays the recognised letter in the form of character. This character is then passed to the word. On receiving blank as an input, the obtained word is passed to the sentence. On clicking the click to convert into speech button, the sentence is converted to speech.

5. Results

![Output for the given Sign in the form of sentence](image)

Fig 5.1: Output for the given Sign in the form of sentence

![Sign Language to Speech Conversion](image)

Fig 5.2: Sign Language to Speech Conversion

6. Conclusion
In this project, a functional real time vision based American sign language recognition for Deaf and Dumb people have been developed using ASL alphabets. We achieved final accuracy of 95% on our dataset. We are able to improve our prediction after implementing two layers of algorithms in which we verify and predict symbols which are more similar to each other.

We started from collecting the data by using OpenCV video capturing. This followed preprocessing the data and smoothing the images by using Gaussian Blur Filtering. The cleaned data was then trained using 2 CNN layers and 3 Densely connected layers. Training was done in 2 steps, one for all the alphabets and second step for alphabets looking similar to avoid confusion.

A front-end GUI was then developed using the Tkinter window to capture inputs. The output is a sentence which is converted to audio, on click of a button present on the window. This way we are able to detect almost all the symbols provided that they are shown properly and there is no noise in the background and lighting is adequate.

7. Future Scope

We are planning to achieve higher accuracy even in case of complex backgrounds by trying out various background subtraction algorithms.

We are also thinking of improving the preprocessing to predict text in low light conditions with a higher accuracy. Currently, our project uses manual alphabets where each letter is shown to combine it to a word and then into a sentence, we plan to add gestures in the future which would convey emotions like Thank you, I Love you, Hello etc. We plan to add dactylology recognition to online meetings as well using which deaf and dumb people and communicate, an algorithm can be applied to online meetings where a gesture shown is converted to text and shown to the others in the meeting.

Finally, we would like to improve the time efficiency of our system in order to make it appropriate to use in different applications.

8. References


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