A Review on Arabic Sign Language Translator Systems

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Abstract. Deaf and dumb peoples are suffering difficulties most of the time in communicating with society. They use sign language to communicate with each other and with normal people. But Normal people find it more difficult to understand the sign language and gestures made by deaf and dumb people. Therefore, many techniques have been employed to tackle this problem by converting the sign language to a text or a voice and vice versa. In recent years, research has progressed steadily in regard to the use of computers to recognize and translate the sign language. This paper reviews significant projects in the field beginning with important steps of sign language translation. These projects can be classified according to the use of an input device into image-based and device-based. Image-based is used the traditional methods of image processing and features extraction, by using a digital camera such as a webcam. Device-based uses different devices like (Microsoft Kinect sensor, electronic glove and leap motion controller). These devices are used to reduce the time of both image processing and extraction features. Then the accuracy rates of using device-based are ranged between in 90%-99% where the accuracy rates of using image-based are ranged between 85%-93%.

1. Introduction
The language is a mental mechanism through which human can transform mental images into symbols. Thus, it is one of the most important means to achieve social integration, education and learning.

Language is a gift to humans and a means of communication between people. Since some people have hearing and speech disabilities, they need a way to communicate with each other, and with normal people, so sign language appeared [1].SL (Sign Language) is a widely recognized method for people with hearing impairment in order to communicate and integrate with their community. SL is a series of grammatically organized human gestures, so it's a kind of visual language. [2].

The history of sign language extends into Western societies of the 16th century, the Arabic sign language (ArSL) for the deaf was developed and introduced in 1972 by the Egyptian National Society for the Care of Deaf and was followed by many attempts and individuals’ studies to define this language. in 1991 the sixth conference of organizations working in the care of the deaf, which was held in the UAE, the ArSL became the essential language of deaf and dumb. In 1999, ArSL dictionary has released contains the 3200 signs by cooperation League of Arabian countries and (ALECSO) Organization [3].
According to the statistics of the World Federation of the Deaf and the World Health Organization, about (466 million) people worldwide have a hard hearing, and (34 million) of those are kids. Hearing failure may result from genetic problems, dilemmas at birth, contagious diseases, recurrent ear contagions, using particular medications, exposure to extreme noise, and aging [4].

As in the spoken language, SL varies from one country to another. But still easier to communicate using different sign language in compared to using different spoken languages. Sign language is not international, but there are several sign languages, for example, American, British, Arabic and others [5].

The references of sign language are usually taken from the customs and traditions of the country [6].

Normal people have troubles in learning sign languages, and on the other hand it is difficult for deaf and dumb people to be taught the vocal languages. Sign language recognition systems (SLRS) can enable communication between these two communities. So, there is a need, for a translation system that can transform SL into written or spoken language and vice versa, so that the deaf and mute can properly communicate with normal people [7].

This paper will introduce the important subject which is the translation of sign language into text, which includes both image processing, feature extraction, and machine learning. The aim of this paper is to present the most important studies that have been conducted in this issue with the most important technologies used and these studies are limited to the period from 2019 to 2010. This paper is constructed as follows: Section 2 Sign Language Translators, section 3 reviews some related works of ArSLSR (Arabic Sign Language System Recognition). Section 4 present discussion and conclusion.

2. Sign Language Translators

Sign language are different around the world like written languages, but they share the same four main components: hand movements, facial expression, lip movements and body movement

1. Hand movements: such as the movements of the fingers indicating numbers and letters, can be one hand or two.
2. Facial expressions: to express personal feelings and tendencies, which are often combined with hand movements to give new compositions and multiple meanings.
3. Lip movements: This skill is considered one of the advanced skills, due to the strength of observation you need, so deaf people read the words directly from the lips.
4. Body movement: the movement of the body uses major movements, such as referring to the shoulders, head, chest, or abdomen in a suggestive use; to clarify desires and meanings in general for self-expression, and they differ from one country to another [8].
Translating Sign Language to a text one, this indicates to capture video from signers, process the frames to extract important features, and map these features to the corresponding text sentence. So the sign language translation consists of many steps as shown in figure 1 create a dataset by using one or many capturing devices, image processing, pattern recognition and finally used classification algorithms to recognize each sign [9].

2.1 Capturing devices
The common devices used for the data acquisition are vision, glove, kinect and leap motion-based, as shown in figure 2:

2.1.1 Image-based (Vision based) systems
these systems apply the image processing algorithms on images and videos of hand gestures. They fall into two kinds: The first type relies on the use of colored gloves as shown in figure 2. The second type is based on images that capture hand gestures without using any glove or device. These systems recognize either static or dynamic gestures.[10].
2.1.2 Microsoft Kinect sensor

Microsoft developed in 2010 a set of sensors called Microsoft Kinect that were originally designed as an input device to the XBOX gaming device. It has three sensors: RGB, sound, and depth as shown in figure 3, allow motion detection, define user’s faces, and also players to play games using their bodies as a controller without sticks. while its original purpose was the input device to the XBOX gaming devices, but it is possible to use Kinect sensor in many useful applications in the computer vision scope, like motion recognition, gestures recognition, virtual reality, and robotics,[11].

![Figure 3. Color Glove[12]](image)

2.1.3 Electronic Glove

uses glove with fabricated sensors that identify hand signs Deaf and dumb people must wear a glove that is joined to sensors that collect data as shown in figure 4, the data get from finger flexion and 3D hand direction with gloves. The data glove is limited by ten flexible sensors, two on each finger. The data glove is highly suitable in looking at both fingerspelling and sign motions, which includes static and movement signs[13].

![Figure 4. Microsoft Kinect[14]](image)
2.1.4 Leap motion controller
It is a tiny and easy device as shown in figure 5, for track hands and hand fingers. It has three Infrared lamps that release light with a wavelength of 850 nm, and two cameras that catch the mirrored light in this spectrum. The sensor area of the device is a quarter of a cubic meter in the form of an inverted pyramid with a maximum distance of 80 cm. The jumping movement has two tracking modes: normal (table top) or head-mounted device [16].

2.2 Pre-processing
In this step, the sign data is prepared to the next step. The sign data can be video or image. There are many techniques of pre-processing video for examples, video segment and select the best frame which contains sign data [18], or can be used Haar-like classifier to track the hand movement per frame to decide on the final region to be processed [19].

Techniques of pre-processing of the image that can be used, for example hand segmentation followed by morphological operations [20]. Crop and resize, low pass filtering using a Gaussian filter to remove noise and fine edges, and segmentation to isolate the object from the background [21]. The pre-processing of the Trajectory (obtained by Kinect) includes noise elimination and compression, the joints positions are noisy and hold some outliers [22].

2.3 Features Extraction
In this step, the features which are determined in the previous step will be selected, these features are rich in sign data. there are many methods use for feature extraction like computed the features of intensity histogram: mean, standard deviation, skewness, kurtosis. gray level co-occurrence matrix GLCM correlation, entropy, contrast, and homogeneity [23]. Or extract
the features from the images was collected by using Fourier, Hartley, and log-Gabor transforms [24]

2.4 Classification
In this stage, the sign is recognized by using different classification algorithms like super vector machine, Euclidean distance algorithm, convolutional neural network, k-nearest neighbors, artificial neural network, classification tree, and naïve Bayes. Classification algorithms can give different accuracy rate depend on the capturing device and select good features.

3. Literature Review
Many researches have been done on Arabic sign language translation, most of these works are focused on utilizing the input device, selected features, and machine learning algorithms. The following are the most recently works in this respect.

In [25], the ArSL system introduced through the development of current studies in feature extraction and pattern identification. In this system, two distinct datasets are used: one for isolated gesture recognition and another for continuous sentence recognition. Feature extraction is calculated based on Spatio-Temporal that begins with pixel differences of consecutive images that are computed. These image differences are then converted into binary images by applying an appropriate threshold. Next, the frequency domain conversion such as the DCT is applied to the binary image variations. The hidden Markov model is used to classification.

In [26], an automatic Arabic sign language (ArSL) recognition system is introduces based the dataset contains 20 isolated words from the Standard Arabic sign language. The hand represents by a model consisting of the palm, the five fingers as ridges at finer scales and fingertips as even finer scale blobs. in the hand tracking and recognition, three main phases for hand detection and tracking; skin detection, edge detection and hand fingertips tracking. In the classification phase Hidden Markov Models are used.

In [27], automatic Arabic sign language translator system is produced. The system begins with converting video to frames and choose the best frame by calculating the distance between frames using Euclidian distance role. This system sorts the alphabetic Arabic sign language as three groups depending on the apparent direction of the hand wrist after located the group of letters, the system crops the image at each good frame to resize the hand area. Edge-detection and feature-vector-creation are used for feature extraction. Finally, minimum distance classifier (MDC) and multilayer perceptron (MLP) neural network is used for recognition.

In [12], identification of ArSL system is produced. In this system a digital camera and a colored glove are used for input devices, colored glove has a different color for each finger. The colors HSI system is used as the basis of image processing, next each image is segmented to six parts that represent the five fingertips and wrist. Then, the features are extracted according to the color layers, the color centers are specified by using the Fuzzy C-means clustering method. Finally, feedforward NN with backpropagation and RNN are used for gesture recognition purposes.

In [19], the real-time ArSL recognition system is proposed using the High- resolution video camera. In hand detection, a Haar-Like classifier is used for object detection. Next, features are extracted from Six alphabets signs, then classification is performed through the K Nearest Neighbor (KNN) algorithm.
In [28], a system is suggested for dynamic hand sign identification of ASL (20 different signs). The system takes the dynamic signs (video) as input, the input video is segmented to frames, the best frame is selected. Hand area is selected from the best frame for computing the hand motion features. The feature extraction module calculates (14) features like (center of gravity, velocity, perimeter, and Angle Calculations) for the hand motion trajectory. Then, matching the features of the input gesture to the stored ones by using the correlation coefficient.

In [29], a system is developed to recognize Arabic alphabet signs using the leap movement controller (LMC). The LMCs data acquisition stage returns twenty-three features for each frame of data. However, in this system, select 12 features that Naive Bayes (NB) and Multilayer Perceptron (MLP) are used for classification.

In [30], introduces Arabic Sign Language Recognition that recognizes hand gestures from image input. this system is proposed fast algorithm for gestures of manual Arabic letters for the sign language. The proposed system applies the concept of hand geometry for classifying by divided the letters into four groups based on the direction of hand appear on the screen.

In [31], the proposed Arabic sign language is automatic Interpreter using Microsoft Kinect Sensor Depth Camera. The features used are 3D information. The system has been trained to recognize 40 signs from the standard Arabic sign language using the Hidden Markov Model classifier.

In [32], the Android mobile application is designed to translate Arsl in real-time using the Leap Motion controller, which is use to capture signal words. The application contains many functions including sign-to-speech language, speech to sign language and sign language test game. Features is extracted by using statistical features. The classifier uses the minimum distance algorithm.

In [24], the ArSL recognition system was produced. The input video is segmented to frames, the best frame is selected. Then in the feature extraction step, different types of transformation methods are used to extracted features such as the Fourier, Hartley, and Log-Gabor. Finally, the features are classified by using KNN, SVM and MLP classifiers.

In [33], a system is presented for recognition of the Arabic sign language alphabet. Skin color segmentation is used as pre-processing, based on the results of the skin segmentation can be applied the Hull Convex color. The Hull convex step is followed by the drawing of the convexity defect three points for each sign, then calculate the distance between these three points to produce the features the vector includes the number of error points, the distances, and the different locations of the point of the defect. Finally, different classification methods are applied such as Stochastic Gradient Descent, Random Forest, Logistic Regression, KNN, Decision Tree, SVC and Linear SVC.

In [21], Translating Arabic Sign Language system is presented, by using an Artificial Neural Network. This system uses the morphological features that extracted from the captured sign of 3 alphabets Arabic.

In [34], The proposed system is developed and implemented in 40 medical sign words, by using Microsoft Kinect. The feature selection method uses frames that collected, and selects 32 features which are the most effective features. KNN, ANN, and SVM classification algorithms are applied to recognize signs.

In [22], a system for identification of ArSL was proposed by using the 3D trajectory of hand signs as a polygon, then extracted the features that define this polygon. Two types of features
are used in this system: Polygon Description and Positional Trajectory. Finally, features are tested by classifier KNN on a dataset of (100) words assembled using the Kinect sensor.

In [14], the Real-Time system is presented for an automatic Arabic sign language recognition system based on the Kinect sensor using the Dynamic Time Warping algorithm to compare signs, to recognize 30 isolated words from standard Arabic sign language signs.

In [35], skin tracking technique is proposed for identifying and tracking hands. The hand is segmented using a dynamic skin-based detector based on the color of the face. Then, segmented points are used to recognize hands with the help of the head. Geometric features are used to create feature vectors. Finally, the Euclidean distance classifier is implemented in the classification stage.

In [36], a system is introduced for Arabic Sign Language Recognition using a pair of leap motion controller (LMCs). The LMC gives data as a sequence of frames, and each frame contains N geometric information describing the movement of the object in the scope of view. Data was collected from two signers, for (100) Arabic dynamic signs. To combine the information from the two LMCs, introduced the Dempster-Shafer (DS) theory of evidence. The features are extracted from the double LMCs were tested by using a GMM together with a Bayesian classifier.

In [37], a system is proposed to recognize numbers and letters of ArSL. this system based on the Residual Neural Network (ResNet) CNN, with a real dataset.

In [38], a static hand signs recognition system of the ArSL alphabets is presented. The system uses a Histogram Of visual Words (HOW) descriptor and (SVM). First, the images of static hand signs are transformed into HOW features and grouped using k-means clustering to build histograms. Next, they are transformed from non-linear space into linear space using a Chi-squared kernel. Then the SVM classifier used for classification. Three different databases are used: ArSL database, marcel static hand postures database, and ArSL hand posture database.

In [39], a system has been proposed for ArSL recognition based on deep learning. Input images are sizing to increase the image data. After that, pre-trained networks can be used with two methods, the first method depends on holding the first pre-trained layers, the second method is based on retraining the network again without retaining the primary layers. Deep features are selected by processing input images with various layers. Finally, the SoftMax function is used to classify target classes, it determines a normalized probability score for each class.

In [40], a system is provided to identify dynamic gestures isolated and translated, which is performed using one or both hands with facial expressions. Arabic video signals are used as input. Each sign is treated as an isolated gesture. The features are extracted using the intensity histogram and integrating with the Gray Level Co-occurrence Matrix (GLCM) features and Euclidean Distance is used to classify them.

There are many studies on translating foreign sign languages. The following papers are examples of these studies:

In [41], the ASL system is presented for the identification of fingerspelling in real-time using image-based. The system begins by using the inbuilt camera to detect the user's hands movement, the images are processed to distinguish the area of hands, the area of the hands is tracked by using the color thresholding method, in which color region is segmented. Each sign will have a different set of fingertip locations. The recognition of a static sign is done based on the position of the finger in the bounding box. in this method each alphabet (A-Z) and the number (0-9) have a particular flow of hand postures. A threshold value is set for the
highest difference between the input sign and the dataset, if the difference is below the highest limit, a match is observed and the sign is identified. In [42], an ASL alphabet translation system is presented.

The first step in the translation system is cropping that applied on a perimeter square as a border from the upper left corner to the lower right corner of the skin area. Feature extraction is applied to the binary image, so the canny edge detection method is used. The Generic Fourier Descriptor (GFD) system is used as a method to extract the feature and K-Nearest Neighbor (KNN) is used as a classification to recognize the signs.

In [43], the Indonesian Sign Language System has been proposed to identify Inflectional words in Indonesian Sign Language (ISL). Microsoft Kinect sensor used as an input device to record hand signs. The outcome from the depth sensor and the skeleton tracking from Kinect is used to extract features. Two angles are used: the first angle between (shoulder center, elbow) and the angle between (shoulder center, hand). Next, skeleton features are used by modifying the Hidden Markov Model (HMM) for classification.

In [44], American Sign Language (ASL) system is presented to translate 10 Welcome words by using Microsoft Kinect for Xbox with its Windows SDKK-curvature algorithm is used to isolate and track the hands. Euclidian distance and j48 algorithm are used to learn and recognize any Sign Language.

In [20], An identification system is introduced to the Indian Sign Language (ISL) in real-time by using the camera. The system interprets signs that represent with one hand for the numbers (0-9) and the alphabet (A-Z). The pattern recognition methods depend on the method used to process the image. For example,

1. a color threshold is used followed by the position of the fingertip is extracted, so the position of the finger is recognized by the bounding box.
2. Finger counting Logic is used, in this method, active fingers are involved in the input gestures that are determined using the centroid variable distance features. The maximum Euclidean distance is computed between Two points, these points are centroid, and a point located on a counter the edge image.
3. Pattern matching Algorithm is used if the image is black and white treated Image, the dataset must be established using black and white images only. In this way, the input image is matched with database images.

In [45], a system is suggested for recognizing the dynamic and static gesture for sign language using "moments". The system begins by dividing the entered video into frames, then applies the skin color segmentation to reveal body parts as well as to detect hand gestures. Zernike Moments are used to extract features. Finally, the K-Nearest Neighbors (K-NN) and Hidden Markov (HMM) models are used for classification.

In [46], an American Sign Language Recognition System is introduced to translate the ASL alphabets. This system has two phases: cognition phase and recognition phase.

In the cognition phase, signed gestures are captured by the digital camera. Color conversion, resizing the gesture, noise removal, and the segmentation of hand gesture is used to prepare the input data. The various features of hand gesture are extracted with respect to several factors like gesture size, roundness, centroid, mean, entropy, local phase quantization, a histogram of oriented gradients, and Gray level co-occurrence matrix. All features are combined for use in the second phase.

In the recognition phase, the initial four steps of processing are alike as in the cognition phase. In the fifth step of the recognition phase, in which the machine learning algorithms like (SVM), (k-NN), self-organizing map (SOM), (ANN) are used to recognize the signs.

In [47], mobile application is improved to translate the Kannada sign language to the text Kannada language. A video is split into frames, and these frames are more processed by
implementing noise removal filter and blurring images using median filter. After the elimination of noise, the features of images are extracted and these features are connecting with training videos to identify text.

The system contains two steps: training and testing. In the training step, each image is processed through the filter (noise removal technique, edge detection or detection format) and histogram-oriented gradient (HOG) is used to extract feature. Then all images are trained using SVM. In the testing stage, undergoes preprocessing with using the median filter, the canny operator for edge detection, HOG for feature extraction. SVM takes input as HOG features and predict the class label based on the trained SVM model.

In [48], the Indian Sign Language Interpretation System is developed to recognize symbols A-Z and 0-9. The input data is normalized by using the histogram. The external effects of lighting and the noise are removed from the normalized images. The feature of the hands can be found by the following step 1: The given image is passed to detected the edge area. step 2: a close contour is derived. Step 3: the closed contour curvature was developed and the peak feature was selected. Finally, the SVM is used for classification.

In [49] an automated American sign language (ASL) system is introduced by using Microsoft Kinect 2.0 sensor as an input device to capture a video of 50 sign. The system begins with a segment of the video to frames. Two types of features are extracted for all frames: hands 2D coordinate feature and Deep Hand hand-shape feature. Finally, to classify an input video clip, two label probabilities were calculated for each feature type using the K-means clusters.

4. Discussion

There are many systems used in sign language translation, these systems can be classified according to the applied capture devices. Cameras are the main element in obtaining data. The most important characteristic of cameras is available on laptops and smartphones, in addition to the cost of cameras is low. All of these reduces the cost of building the system. However, there are many problems that disturb the work and development of the system, including: the limited field of vision of the capture device, the high computational cost, the need for several cameras to obtain good results, the need for appropriate capturing environments.

Various systems are using Microsoft Kinect sensor which is part of the Xbox game that can capture body joints based on depth of images. This is what enables sensor to sense small hand movements. The most important feature of the Kinect sensor is the ability to get data directly from the input signals, in addition to reducing pre-processing time. One of the problems with this method is the high cost of the device, as well as the device connected and operated complexity, also the leap motion systems suffered these problems. There are systems that adopt the electronic glove in their work, the wearable glove contains sensors that contact the hand. Sensors capture hand movements and positions.

It provides accuracy in the position and direction of the fingers of the hand. This method requires physical communication with computers, which makes it very convenient technology, but it is quite expensive. The vision-based used the traditional steps for sign classification, which include: the pre-processing, features extraction, and classification. The device-based (Microsoft Kinect sensor, leap motion controller, and electronic gloves) can directly extract features without pre-processing, which means the Device-based can minimizes the time for preparing sign language dataset and also can give a good accuracy rate in compared with vision-based as shown in table (1).
Table 1. Input device and classification algorithms

| Paper No. | Input Device          | Input Sign                          | Classify Method                                      | Accuracy  |
|-----------|-----------------------|-------------------------------------|------------------------------------------------------|-----------|
| [26]      | camera                | 20 words of Arabic sign letters     | Hidden Markov Models                                 | 82%       |
| [27]      | camera                | alphabet of Arabic sign letters     | (MDC) and (MLP) classifier,                         | 91%-83%   |
| [12]      | camera                | Alphabet of Arabic sign language    | Feed-Forward Neural Networks and Multilayer Feedforward Neural Networks | 95%       |
| [19]      | camera                | Alphabet of Arabic sign language    | K Nearest Neighbor (KNN)                             | 90.50%    |
| [28]      | camera                | 20 words of Arabic sign letters     | correlation coefficient                             | 85.60%    |
| [29]      | Leap Motion Controllers | Alphabet of Arabic sign language   | Multilayer Perceptron (MLP) neural networks and Nave Bayes classifier | 99%       |
| [30]      | camera                | Alphabet of Arabic sign language    | inner circle classifier                             | 81.60%    |
| [31]      | Microsoft Kinect depth camera | 40 signs from standard Arabic sign language | HMM                                                   | 90%       |
| [21]      | camera                | 3 from Alphabet of Arabic sign language | ANN                                                   | 73%       |
| [24]      | camera                | 23 signs from standard Arabic sign language | Support Vector Machine (SVM), K- Nearest Neighbors (KNN) and MLP classifiers. | 99%       |
| [35]      | camera                | 30 words from regular ArSL          | Euclidean distance classifier                        | 97%       |
| [14]      | Microsoft Kinect depth camera | 30 words from regular ArSL        | Dynamic time warping matching                        | 97.58%    |
| [34]      | Microsoft Kinect depth camera | 40 medical sign words             | (SVM), (KNN) (ANN)                                  | 91%       |
| [40]      | Camera                | 100 Arabic signs from regular ArSL | Euclidian distance                                  | 95%       |
| [37]      | Camera                | Alphabet of ArSL                   | Deep learning (ResNet18)                             | 99%       |
| [38]      | Camera                | Alphabet of Arabic sign language   | Support Vector Machine (SVM)                         | 97%       |
5. Conclusion

Sign language is a means of communication for people with hearing and speaking disabilities. Human-computer interaction and computer vision play a very important role in sign language translation. This paper discusses the different algorithms and techniques used to recognize sign language. We discussed the various systems used in sign language translation. Vision based systems use cameras as primary tools to obtain input data. The main advantage of using a camera is that it eliminates the need for wearing devices. Other systems use sensors including (the Microsoft Kinect sensor, the Leap motion controller, and the electronic glove device) to capture the input mark. The main advantage of the device-based approach is that the data can be obtained directly, thus eliminating the need for pre-processing data, and this approach is not subject to Environmental impact. Hence, the data is more accurate. Despite the accuracy of the data that can be taken from devices, devices remain uncomfortable, whether they are wearing gloves or attached to a computer like a Leap motion or Microsoft Kinect.

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