A Cost Effective Sign Language to Voice Emulation System

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Abstract— **Sign Language Recognition has been a field of great interest for researchers across the globe because of the wide variety of applications that can be developed with the results. This paper presents a holistic approach to develop a real time and cost effective glove based system, to convert the static subset of a sign language to voice, using statistical template matching. The proposed system aims to build an affordable assistive device for the disabled masses, affected with speech impairment or 'mutism'.**

Keywords— Gesture Recognition, Data Gloves, Sign Language to Voice, Statistical Template Matching, Java Swings.

I. Introduction

Various advancements in today's technical world have been helping the diverse disabled communities at large, in terms of research and product development in the field of assistive technologies – to help the differently abled carry out their daily activities. A gesture recognition system is one such product which aims to reduce the communication barrier that a mute person has to endure in his/her daily life [27][31][32], communication being the most basic and inherent of the human needs, as effective transaction of ideas and thoughts defines us as who and what we are.

Gesture Recognition gloves are available in abundance in the market, namely "AcceleGloves", "CyberGloves","5DT Data Gloves" etc. [21]. Unfortunately sign language to voice translation systems that have been developed so far using such gloves, have not been very efficient in terms of cost, as prices for these gloves ranges from about 1,000 to 20,000 US dollars per pair. In this paper we are presenting a design for a low cost sign language to voice conversion system comprising of highly cost effective gesture recognition gloves, costing about 70 US dollars per pair, and also explaining the software implementation for the system. This will thus enable even the economically weaker sections of such communities to afford this system.

The paper is organized as follows. Section II briefly analyzes the advantages and the disadvantages of the various models and techniques that can be implemented for capturing and recognition of gestures. Section III contains the hardware and software design specifications of the proposed system, discussing some key glove characteristics and explaining the various details of the statistical template matching model. Section IV follows with the implementation aspects of the system and describes a method of manufacturing highly cost efficient gloves using self-developed uni-directional flexion (bend) sensors and provides insight into the Java-Swings implementation details of the "Sign Language Trainer & Voice Convertor" software. The paper concludes with the results and findings of using this inexpensive system.

II. Background

This section of the paper discusses different methods of data collection and the various algorithms which can be applied on the data to successfully recognize gestures. There are three basic approaches for collection of data related to a gesture required for recognition viz. glove based system, vision or camera based systems or a hybrid of the two, with each of these methods having their individual advantages and disadvantages [21].

The vision based systems use a camera source as their primary input for obtaining the necessary data [30][37]. Various problems are inherent to this system vis-à-vis limited field of view of the capturing device, high computational costs [2][21] and the need to setup multiple cameras in order to obtain robust results (due to problems of depth, occlusion, etc.) [27][45], rendering the entire system futile for development of real time recognition applications.

The alternative approach for acquiring data related to gestures makes use of a certain type of instrumented gloves [21] which are fitted with a variety of sensors, namely, flexion (or bend) sensors, accelerometers, proximity sensors, abduction sensors and the like which are used to measure accurately the bend angles of the fingers and the thumb, abduction angles between the fingers, thumb crossover, arching of the palm and the roll, pitch and yaw of the wrist for orientation of the hand. The degrees of freedom (DOF) that can be realized using such gloves varies from 5 to 22, depending on the number of such sensors embedded on the glove (refer Table I for summary of various historical and commercially available gloves in the market) [9][14][16][18][21][22][25][26][33][40][41][47][48].

The major advantage of using the glove based systems over vision based systems is that, gloves can directly report relevant and required data (degree of bend, roll, pitch, yaw of the wrist, etc.) in terms of voltage values to the computing device, thus eliminating the need of processing raw data into meaningful values, unlike vision based systems which need specific tracking and feature extraction algorithms to be applied to raw video stream(s), thereby escalating computational overheads [21].

TABLE I. COMPARISON OF VARIOUS LEGACY (L) AND COMMERCIALLY (C) AVAILABLE GLOVES

S.NO.	PRODUCT (DEVELOPERS)	NO./ TYPE OF SENSORS USED	DEGREE OF FREEDOM PROVIDED	COST PER PAIR (in US $)
1 (L)	Sayre Gloves (Thomas Defanti and Daniel Sandin)	7- Light-based sensors with flexible tubes with a light source at one end and a photocell at the other.	7	N/A
2 (L)	DataGloveTM and Z-GloveTM (VPL Research)	5(to 15)- Flex sensors made up of flexible tubes with a reflective interior wall, a light source at one end and a photosensitive detector at the other.	10	N/A
3 (L)	Power Glove (Mattel/Nintendo Games)	4- Piezo resistive flex sensors.	4	100 $
4 (L)	Space GloveTM (W Industries)	6- Fiber optic flex sensors.	6	N/A
5 (C)	CyberGlove TM (Stanford University/Virtual Technology)	18(to 22)- Piezo resistive flex sensors.	22	10,000 $ - 15,000 $
6 (C)	5DT Data Glove TM (Fifth Dimension Technologies)	5- Fiber optic flex sensors. 2- Tilt Sensors.	7	1,000 $ - 20,000 $
7 (C)	Super Gloves TM (Nissho Electronics)	10(to 16)- Piezo resistive (proprietary technology) flex sensors.	10	5,000 $ - 20,000 $
8 (C)	PinchTM Gloves (Mapes, University of Central Florida)	5- Electrical contacts on the inside of the tips of the four fingers and the thumb.	5	2,000 $

The third approach of collecting raw gesture data uses a hybrid approach by combining glove and camera based systems [21]. Such a system uses mutual error elimination to enhance overall accuracy and precision. However, a great deal of work has not been carried out in this direction due to cost and computational overheads of the entire setup. Nevertheless, augmented reality systems [6][38] have shown promising results with the use of hybrid tracking methodology.

For the purpose of developing a real time gesture recognition system various popular models like Feature Extraction, Principal Component Analysis, Learning Algorithms, Template Matching, etc. can be used.

A robust technique, as used by Wexelblat [47], to recognize hand posture and gestures is Feature Extraction. This technique's main disadvantage being that when a large number of features are to be recognized, the proto-feature detectors become computationally very expensive for the system.

Another approach for gesture detection is the Principal Component Analysis [20]. This method has not been widely used in gesture detection using gloves, and requires extensive training for efficient results.

Artificial Neural Network may also be used to recognize hand gestures [3][35]. Neural network requires extensive training of the network before the model can be built, and for every new gesture which has to be added, the entire model needs to be retrained.

Another popular choice for gesture recognition is the Hidden Markov Model (HMM), which is different from the regular Markov Model in the sense that the states are not directly visible to the observer [8].

It is a statistical approach which has been proved to achieve high accuracy with adequate training. Disadvantages of this method are that the training required is very extensive and it is computationally expensive for real-time detection.

One of the most straightforward models to implement static gesture recognition is Statistical Template Matching or Prototype Matching [2][42], which works on the fundamentals of statistics and calculates the closest match of the incoming data values with pre trained samples known as 'templates'. The advantages of using this model lie in the fact that it neither requires extensive calibration/ training, nor do the calculations require a fast processor. Thus, the statistical model proves to be an ideal choice for implementation in our approach, as it can also be employed for mobile processors due to its lower computational complexity, thereby enhancing scalability for future.

III. DESIGN OF THE PROPOSED SYSTEM

A. *Hardware Design*

There are a total of 5 Flexion (Bend) sensors (for the 5 fingers) used in each glove which are used to detect the movement of joints in fingers and thumb. As the sensor is flexed, the resistance across the sensor increases. Also, a single tri-axial accelerometer is fitted on the back of the palm of each glove so as to capture the orientation of the hands along with the bend angle of the fingers.

B. *Software Design*

The "Sign Language Trainer & Voice Convertor" software receives the values given by the flex sensors and the accelerometers on the two gloves through an Arduino

Duemilanove Microcontroller Board. The software end has the following features:

- Visualization of the gloves on real time graphs
- Calibration of gloves
- Creation of libraries
- Saving of multiple samples for each gesture in a library
- Gesture recognition and voice emulation.

The software is based on the statistical template matching model and the entire model can be divided into three parts, namely: calibration of the sensors, training of the model and gesture recognition.

1) Calibration of the sensors is achieved by taking the minimum and maximum sensor values and then normalizing and quantizing the values, so as to convert the read sensor values into a pre-defined range of discrete data set, according to a scale down factor as:

$$N_i = (S_i - S_{i\,min}) \times \frac{(R_{max} - R_{min})}{S_{i\,max} - S_{i\,min}} + S_{i\,min} \tag{1}$$

$$F = \frac{(R_{max} - R_{min})}{L} \tag{2}$$

$$Q_i = N_i - (N_i \bmod F) \tag{3}$$

where, N_i is the normalized value for the i^{th} sensor, R_{max} & R_{min} (set to 500 and 0 respectively, for the proposed system) define the required range, $S_{i(min)}$ & $S_{i(max)}$ are the read minimum and maximum sensor values, S_i is the actual value of the i^{th} sensor, F is the scale down factor, L (set to 40 for the proposed system) is the number of required quantization levels and Q_i is the final quantized and normalized value of the i^{th} sensor.

2) The data collection phase of the model is called 'Training' in which all the quantized sensor values are taken as input and stored in the database as samples for a particular gesture in the library.

3) The third phase of 'Recognition' involves building of the statistical template matching model by calculating the mean and standard deviation of each sensor, for each gesture stored in the library and only recognizing those input samples as correct which lie within the threshold times the standard deviation bounded mean of a particular gesture in the selected library.

The gesture boundaries [2] are calculated as:

$$\mu_{i,j} = \frac{1}{n} \times \sum_{k=1}^{n} x_{i,j,k} \tag{4}$$

$$\sigma_{i,j} = \sqrt{\frac{1}{n} \times \sum_{k=1}^{n} \left(x_{i,j,k} - \mu_{i,j}\right)^2} \tag{5}$$

$$\mu_{i,j} - \alpha.\sigma_{i,j} < Q_j < \mu_{i,j} + \alpha.\sigma_{i,j} \tag{6}$$

where, $\mu_{i,j}$ and $\sigma_{i,j}$ are the mean and standard deviation of the i^{th} gesture's j^{th} sensor, $x_{i,j,k}$ is the value of the k^{th} sample, n is the total number of samples stored for a gesture, α is the user defined threshold and Q_j is the j^{th} sensor's quantized and normalized value from the input sample.

For a large threshold value (α), there are frequent cases when more than one gesture matches the classification due to overlapping recognition ranges. In such a case, the closest match can be calculated by using the technique of Least Mean Square Error (LMSE) [21], amongst all the chosen gestures, as in the Boltay Haath Project [2]. Mean square errors for all the available gestures of a particular library are calculated and then, the least value amongst them is selected as the LMSE. If 'i' be the total number of available gestures, $\mu_{i,j}$ be the mean of i^{th} gesture's j^{th} sensor and x_k be the j^{th} sensor's value from the k^{th} sample of a particular gesture, then LMSE would be given by:

$$LMSE = \min_i \left\{ \left(\sum_j \sum_k \left(x_k - \mu_{i,j}\right)^2 \right) \ \forall\ i \right\} \tag{7}$$

In spite of using the LMSE technique, the statistical model's accuracy is effectively reduced as the dataset grows in size due to overlapping of boundary conditions.

IV. Implementation

A. Hardware Implementation

A startling inference that can be drawn from Table I is that all of the commercially available gloves cost anywhere between 1,000 – 20,000 US dollars, consequently rendering production of sign language translation systems infeasible for general masses, in terms of production cost. To overcome this issue as well as, to enhance the overall user experience of using glove based technology, the proposed system uses specially designed cotton gloves embedded with self fabricated bend sensors and standard accelerometers, which measure the bend of each finger separately and the orientation of the hand as gestures are made. This results in highly reduced manufacturing costs and greater user comfort.

Bend sensors and accelerometers that are available in the market cost about 16 US dollars per sensor and 30 US dollars respectively. However, this cost can be brought down drastically by self fabricating the bend sensors instead of purchasing the same from the market. Each bend sensor then costs under $1. The total optimized cost for a pair of gloves using this approach = 10 * 1 + 2 * 30 = 70 US dollars (excluding cost of gloves themselves).

Steps for constructing a flex sensor:

Materials Required: Velostat, Brass Foil, Conducting wires and Electrical Tape.

1) Wires are soldered to the ends of two brass foil strips, which act as the two electrical terminals (Fig. 1)

2) 3 layers of Velostat (Eonyx) is sandwiched between the two brass strips using electrical tape (Fig. 2 and 3)

3) Different bend sensors are then customized according to the relative ratios of the finger lengths and then embedded onto the cotton gloves (Fig. 4)

B. Software Implementation

The software end of the system has been developed in Java, along with Java Swings to provide a rich user interface. Every program in Java has a set of initial threads, where the application logic needs to begin. However, the Swing elements are processed only on the Event Dispatch Thread (EDT) which handles the events from the Abstract Window Toolkit (AWT) graphical user interface (GUI) event queue.

In case of multi threaded programs, it is of utmost importance to not run time consuming tasks on the EDT, otherwise the entire GUI becomes unresponsive. Thus, any computationally intensive application, which needs to have a long running task in the background providing updates to the UI, either when done or during processing, needs two threads, one to perform the lengthy task (known as swing workers) and also the EDT for all the GUI related activities [7]. Since our application needs to handle computations of large amounts of incoming data, as well as, needs an active user input at the same time, therefore we implemented Java Swing Workers for this purpose, which also help in maintaining a near real time simulation of the system.

V. SIMULATION

To convert sign language to speech, the user needs to wear the gloves (Fig 4), which are then connected to a computer through Arduino Duemilanove microcontroller boards. These boards send the different sensor values to the hand gesture recognition software which implements the components of the statistical model while providing a simple interface and real time graphical display of sensor values (Fig. 5.) Prior to using the software, the gloves need to be calibrated by the user and this is achieved through the “calibration” section of the software. After successful calibration, the software can be trained using the ‘Edit / Add Library’ feature provided in the ‘File Menu’ of the software. On adding a library, a new table gets created in the database by its name, and all the samples for each and every gesture are stored within this table. At run-time, a threshold value can be specified by the user and any trained library can be loaded into the recognition engine. When a library is loaded the software builds a model by calculating the mean and standard deviation of each sensor value for each gesture which is then used for recognizing user gestures. When a gesture is matched, the text-to-speech engine (FREETTS) converts the name of the gesture to mechanical speech.

The proposed system was tested for the standard American Sign Language with a gesture database of 2250 samples. Different values of threshold defined by the users lead to different accuracies in recognition. Excluding ambiguous gestures [2] increased the accuracy as there are no abduction sensors fitted in these gloves. Addition of such sensors can help in increasing the range of gestures that this system can successfully recognize.

Table II compares the performance of the proposed system with the Boltay Haath project [2] which uses the DataGlove5 developed by 5DT. It is clearly inferable from the table that the specially designed flex sensors used in this system matches the performance levels of commercially available gloves and can thus be used for developing cost efficient sign language to voice conversion systems.

VI. CONCLUSION

Sign language is used all over the world by the mute and hearing-impaired to communicate with each other. It is a combination of finger spelling and facial expressions. Sign language has crossed barriers because of its beautiful expressive characteristics. The facial expressions and gestures that accompany sign language have opened the way for visual articulation in art, drama, therapy, and many other non-traditional settings. It has become a language for both the hearing-impaired and the mute.

Research in the area of assistive technologies is progressing at a good pace. Our Glove-based sign language recognition system using Statistical Template Matching Technique was implemented successfully with accuracy comparable to those of commercially available systems and that too at a highly optimized cost.

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TABLE II. COMPARATIVE PERFORMANCE RESULTS

	ACCURACY %					
THRESHOLD	***2σ***		***4σ***		***6σ***	
CRITERIA	***Boltay Haath***	***Proposed System***	***Boltay Haath***	***Proposed System***	***Boltay Haath***	***Proposed System***
Including Ambiguous Signs	23.8	21.6	68.5	67.9	71.3	70.6
Excluding Ambiguous Signs	25.4	23.7	73.3	72.4	78.2	77.9

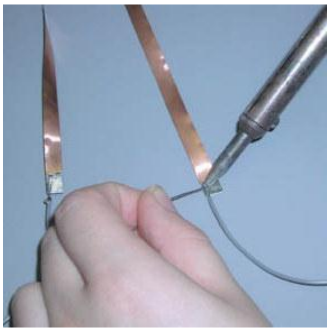

Figure 1. Step 1 in fabrication of Bend Sensors

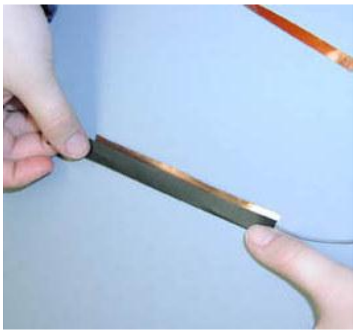

Figure 2. Step 2 in fabrication of Bend Sensors

Figure 3. Completed Bend Sensor

Figure 4. Completed Pair of Gesture Recognition Gloves with 10 flex sensors and 2 Accelerometers

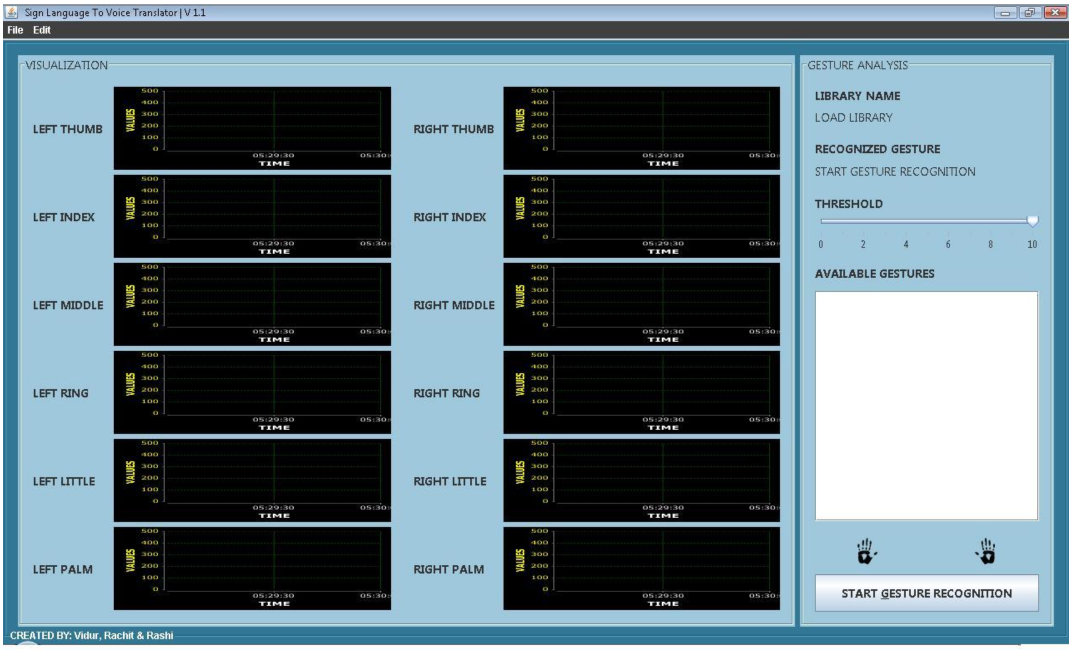

Figure 5. Software Interface