Real-time Embedded Recognition of Sign Language Alphabet Fingerspelling in an IMU-Based Glove

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ABSTRACT

Data gloves have numerous applications, including enabling novel human-computer interaction and automated recognition of large sets of gestures, such as those used for sign language. For most of these applications, it is important to build mobile and self-contained applications that run without the need for frequent communication with additional services on a back-end server. We present in this paper a data glove prototype, based on multiple small Inertial Measurement Units (IMUs), with a glove-embedded classifier for the french sign language. In an extensive set of experiments with 57 participants, our system was tested by repeatedly fingerspelling the French Sign Language (LSF) alphabet. Results show that our system is capable of detecting the LSF alphabet with a mean accuracy score of 92% and an F1 score of 91%, with all detections performed on the glove within 63 milliseconds.

Author Keywords

Sign language recogntion; Inertial sensing; Data glove

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI)

INTRODUCTION

For the past two decades, research in input technologies for wearable computers has proposed a large amount of systems that rely on hand gestures. The advantages of these gestures are that they are easy to learn and enable the adoption of existing alphabets (sign language) that already have a significant user base. However, as these gestures tend to use the full articulation of the hand, requiring the detection of the exact position and motion of all fingers, such systems are not straightforward to implement. Systems that are placed in the environment tend to suffer from occlusion and are not mobile. Previously-proposed wearable approaches on the other hand, have used reduced alphabets, less-accurate but small-enough sensors, and offline processing of the sensor data.

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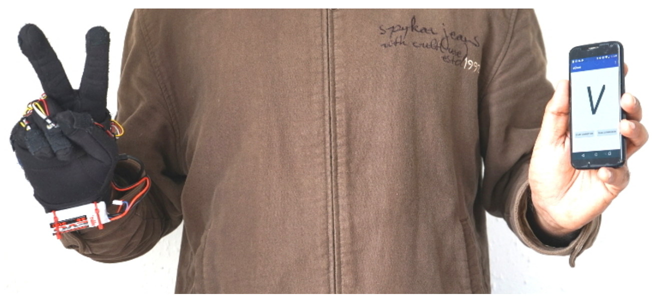

Figure 1. This paper's self-contained glove is capable of detecting fine-grained signs in real-time through a set of 9D IMU units, one per finger. Detection is done on an integrated microcontroller placed in the back of the glove, powered from a flat Li-Po battery integrated under the wrist.

Although many glove-based systems have been proposed in this area, most of them are focusing on bend sensors that are straightforward to integrate in the fabric but offer less precision on the fingertips and suffer from a hysteresis effect. Few systems have thus far integrated 9D IMUs on the fingers, while none have been designed or evaluated for distinguishing different hand articulations on the glove itself in real-time. In this paper, we introduce a sensing glove which can detect its wearer's hand postures and motion at a high accuracy while keeping the size and amount of hardware components to a minimum. Our proposed system is designed around handling the data from IMUs positioned on each finger as efficiently and fast as possible. This is evaluated by detecting all handshapes from the LSF alphabet, as well as a background class, on the glove itself, allowing it to be used as a basic text entry system. We illustrate this by connecting the glove to a smartphone for immediately displaying the glove's output.

RELATED WORK

We focus in this paper on gloves that serve as input devices: The earliest sensor glove was developed in 1977 by de Fanti and Sandin [16], based on flexible tubes with a light source and photocell. Finger movements modulated the amount of light passing to the photocell causing a change in voltage. By the end of the decade, advancements in camera-based approach that can track the LEDs placed on the hand were designed at the MIT Media Lab [16].

The idea of sensing the flex of finger was then continued by Zimmerman *et al.* [20] in 1987, who commercialized the first data glove. Five to fifteen resitive flex sensors measured each finger and provided a novel interface to PCs. Kuroda *et al.* 2004 [11] proposed a StrinGlove equipped with 24 Induct-coders and 9 Contact sensors on the fingertips of both hands. Around 48 finger characters were examined and the accuracy was found to be about 85%. Khambaty *et al.* [9] had presented Ges-TALK in 2008 - a glove to capture the finger movements for 24 sign language static gestures and further processed to output the corresponding voice of the respective gesture. An assembly of 11 resistive bend sensors were setup to gather the readings. Here, a potentiometer is used to calibrate the system for every new user. Results showed an accuracy of 90% with a response rate of 750 ms based on template matching along with statistical pattern recognition. Huang *et al.* 2011 [5] used a 5DT(Dimensional Technologies) data glove with 5 flex sensors.

Different materials allowed better integration into gloves, and sign language applications were targetted increasingly to evaluate such systems. In 2011, Jeong *et al.* [6] made a gesture recognition glove with Velostat material, which can measure the finger flexion through change in resistance. The glove also embedded a 5-Degrees of Freedom(DOF) IMU to measure motion angle for American Sign Language (ASL) and Korean Sign Language. Voltage differences are noted for the finger movements and used to recognize the gestures. The sign language letters were recognized using the velostat with a short delay to obtain stable readings. In [13] 2014, Park *et al.* used 10 linear potentiometers, flexible wires and linear springs on each finger to calculate the joint angles and thereby measuring the motion of fingers. In 2012, Kadam *et al.* [8] made a bend sensor-based glove that emulates a sign language teacher for those who would like to learn the language.

A system using inertial MEMS sensors to estimate individual finger motion and position has been argued for as a wearable interaction system in as early as 1999 in [15]. Most proposed systems, however, relied on combining multiple modalities to achieve higher accuracies. Jiangqin *et al.* [7] recognized in 1998 for instance 26 chinese sign language words using Cyberglove with 18 sensors and a 3D-Tracker, employing a multi-layer perceptron to remove noise from the sensor data that can be passed as input to Hidden Markov Models to classify the words. In [4] , Hrabia *et al.* study the linear angular bio-mechanic relationship between finger joints studied and report that it is possible to track the hand gesture using eight motion sensors with 9 DOF comprising accelerometer, gyroscope and magnetometer.

Several projects have combined an inertial unit with bend sensors. In [2], the 5DT Data Glove 5 Ultra along with an accelerometer was used to obtain each fingers flexion degree and information about wrist orientation. These readings were processed offline afterwards and with an artificial neural network, classification of 24 ASL static hand gestures for fingerspelling was tested. A classification rate of 94.07% accuracy was obtained on 1,200 test patterns provided the network was trained on 5,300 patterns. In [19], Vutinuntakasame *et al.* recognized fingerspelling with 5 flex sensors and a 3D accelerometer connected to a Body Sensor Network (BSN). They proposed a hierarchical framework using multivariate Gaussian distribution coupled with bigram and set of rules to detect a particular padgram and found an accuracy about 72.7%-73.6%. Tanyawiwat *et al.* 2012 [17] designed a glove to recognize ASL fingerspelling hand gestures with 5 Contact sensors, 5 Flex Sensors and a 3D accelerometer installed on it and also presents a concept of combined sensory channel. A combination of Multivariate Gaussian Distribution and the multi-objective Bayesian Frame network is used to classify the gestures and helped to improve the recognition accuracy rate with 77.4%. Here, six calibration steps were defined to adapt to different hand sizes. More recently, Tubaiz *et al.* [18] worked on the DG5-VHand data glove system, which consists of 5 bend sensors and a three-dimensional accelerometer for both the hands to recognize 40 sentences in the Arabic sign language. The data glove communicates with a computer through Bluetooth and a camera is used to collect the data. Sentences were classified with K-Nearest Neighbour with resampled feature vectors, achieving a 98.9% accuracy.

Glove-based accelerometers and inertial units have also been combined with several other modalties to achieve more accurate detection of gestures. In [10], a 3-axis accelerometer and Electromyogram (EMG) was examined to figure out their complementary functionality and their potential in recognizing a small set of 7 German sign language words collected from 8 subjects. Classification results using KNN produced an average of 98.9% accuracy on subject-dependent recognition whereas subject-independent resulted in 54.82% accuracy. A vision based sign language recognition using a hat-mounted camera coupled with the integration of an accelerometer was proposed by Brashear *et al.* [1] to rule out the noise in recognizing hand gestures on 5 set of words representing a vocabulary along with calibration gestures. It was shown that the accuracy is 90.48% on using these multiple sensors. In [12], Oz *et al.* translated 60 ASL words into English using the Cyberglove and a 3D motion tracker in 2007 where gesture classification was performed by two artificial neural net classifiers obtaining a 95% accuracy.

In contrast to the above approaches, we focus on designing a data glove to primarily sense the articulated hand via IMUs placed on the fingertips. Rather than capturing the raw data and processing it elsewhere, we developed an embedded sensor fusion technique that combines the data of each of the five IMUs to obtain stable and accurate information about the articulated hand. The classification is carried out through onboard computation as well, making the system function in real-time without needing any external processing units.

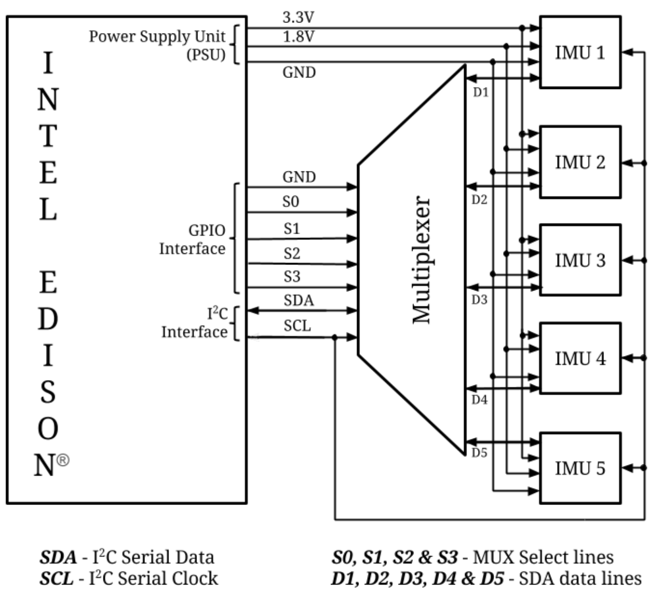

Figure 2. The hardware design of the system, showing the combination of the Edison module and five IMU sensors, through the I^2C interface bus. Connections for the IMU are as follows: VCC - 3.3V, V_{LOGIC} - 1.8V, SDA, SCL and Ground GND. The Edison's SDA is shared among the IMUs through a multiplexer, where all IMUs have a common address. Power is sourced by the Edison's internal Power Supply Unit.

SYSTEM DESIGN

Our goal is to design our glove with on-board computation capability, while being comfortable to wear and modularly built. The hardware components of the glove are shown in Figure 2 and described as below:

Microprocessing Unit (MPU): A powerful on-board computation unit is the key component to make the glove functionally independent: Intel's Edison was chosen, as it provides both processing and integrated wireless capabilities. Delivering high performance, the Edison features a dual-core CPU along with integrated WiFi and Bluetooth support. The MPU runs Ubilinux, a stripped-down version of the Debian Linux distribution for embedded applications. These characteristics enable the MPU to perform gesture recognition in real-time.

Inertial Measurement Unit (IMU): The IMU comprises a 3D accelerometer (ACC), 3D gyroscope (GYRO) and 3D magnetometer, which can measure acceleration, rate-of-turn and magnetic field respectively. For signs, the orientation of each finger relative to magnetic north are less critical, so the magnetometer readings are ignored and only orientation in the vertical planes are used. ACC and GYRO readings are 16-bit in resolution and are fused using a Complementary Filter to generate Euler angles (Roll and Pitch) as will be specified in the Sensor Fusion section. The MPU-9250 by Invensense is used to collect 9D inertial data from each finger.

Multiplexer (MUX): The IMU has only 2 selectable addresses and on the MPUs side there are two I2C buses available for communication, allowing at most 4 IMUs to be interfaced. Introducing 5 IMUs thus requires to multiplex the I2C data line of the MPU to transceive data between the IMUs. To facilitate this, a 16-bit bi-directional multiplexer is used.

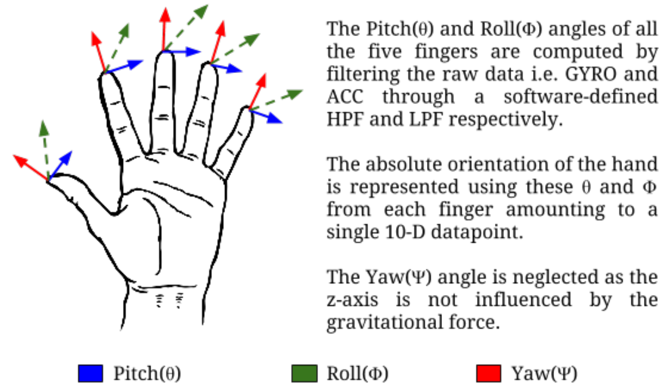

Figure 3. Euler Angle representation of each finger for measuring the absolute orientation. The IMUs are placed on the finger tip of the glove and track the hand motion.

Power: The power consumption of the glove at 5V is approximately 130mA without WiFi or 250mA with WiFi connection. Bluetooth connectivity is used to send the detected signs to the Smartphone. Since WiFi is used only for debugging, a Lithium Polymer battery with 7.2V @1000mAh is used, which can provide continuous power for at least 8 hours.

Glove: A cotton glove was extended with added elastic pockets on the finger tips, to accommodate the IMUs. Cable hooks along the length of the finger manage the cables.

SENSOR FUSION APPROACH

Our goal is to obtain precise readings from the orientation of each finger. The raw readings from the ACC and GYRO obtained from the IMU can be unreliable when used independently. The ACC unit measures the acceleration due to gravity or linear motion. In a static state, the ACC is under constant influence of the earths gravitational pull causing a $1g$ ($g = 9.8m/s^2$) acceleration to act on the axes to which it is oriented. Moreover, the ACCs on the glove are under constant minor fluctuations due to involuntary quivering of the hand, registered as high-frequency noise. The GYRO is a measure of the angular rotation. Unlike the ACC, it is not affected by any external force, but the GYRO tends to drift from its mean value in the long run as it lacks a reference frame.

Sensor fusion combines the sensor data from different sources to reduce the uncertainty and improving the quality of individual series of readings. In our case, ACC and GYRO data are fused together to eliminate problems caused by noise and drift respectively. The implementation is carried out by employing a digital filter which is performed on the ACC and GYRO data. Among different available filters, the Complementary Filter (CF)[3] is best suited for the problem at hand, as it primarily operates on signals having opposite noise levels. In other words, a low-pass filter is used to remove the high frequency noise in the ACC and a high-pass filter to eliminate the low frequency drift of the GYRO. The CF acquires the orientation of each finger from both the sensors and delivers the desired signal with less noise and a low drift.

To formulate the orientation, one should provide a form of representation in 3D Euclidean space. Among a multitude of ways to illustrate the orientation, Euler angles (EA) are sim-

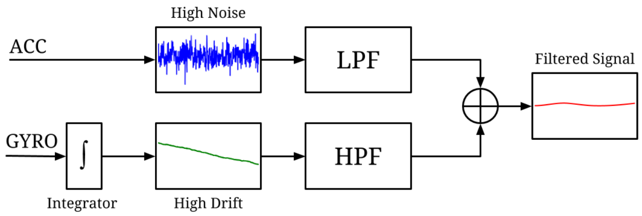

Figure 4. Working model of the Complementary Filter: The block diagram depicting the use of digital filters for improving the quality of the angle data. Sensor fusion is performed on both accelerometer and gyroscope, which is integrated with sampling time using low pass and high pass filters to obtain the filtered signal.

ple and allow a 3D orientation description for a body using a sequence of rotations around different axes, namely Pitch(θ), Roll(ϕ) and Yaw(ψ) which corresponds to X, Y and Z axes respectively as shown in figure 3. Euler angles can be calculated from inverse tangent of the ACC data. The Yaw angle is neglected as the Z-axis is not affected by the gravitational force as it acts parallel to yaw axis of reference.

$$Pitch(\theta) = atan\left(\frac{ACC_x}{\sqrt{ACC_y^2 + ACC_z^2}}\right) * \left(\frac{180}{\pi}\right)$$

$$Roll(\phi) = atan\left(\frac{ACC_y}{\sqrt{ACC_x^2 + ACC_z^2}}\right) * \left(\frac{180}{\pi}\right)$$

The Gyro rate gives the measure of the angular position obtained by integrating angular velocity over time.

$$Gyro\_X\_Rate = \int_0^t Gyro\_X(t) * dt$$

$$Gyro\_Y\_Rate = \int_0^t Gyro\_Y(t) * dt$$

where, $dt \rightarrow$ Sampling Period, $Gyro\_X(t)$, $Gyro\_Y(t) \rightarrow$ raw GYRO angular velocities in the θ and ϕ axes respectively, $Gyro\_X\_Rate$, $Gyro\_Y\_Rate \rightarrow$ uncompensated θ and ϕ angular positions respectively.

The filter introduces a coefficient factor to decide the amount of influence of ACC and GYRO against one another. This coefficient (α) was empirically determined as 0.93.

$$\theta_t = \underbrace{\alpha * (\theta_{t-1} + Gyro\_X(t) * dt)}_{HPF} + \underbrace{(1-\alpha) * (ACC\theta_t)}_{LPF}$$

$$\phi_t = \underbrace{\alpha * (\phi_{t-1} + Gyro\_Y(t) * dt)}_{HPF} + \underbrace{(1-\alpha) * (ACC\phi_t)}_{LPF}$$

where, θ_t & $\phi_t \rightarrow$ Current estimate of Pitch & Roll by CF, θ_{t-1} & $\phi_{t-1} \rightarrow$ Previous estimate of Pitch & Roll by CF, ACCθ_t & ACC$\phi_t \rightarrow$ Current estimate of ACC Roll & Pitch.

The Pitch and Roll angles are calculated for the readings obtained from each finger continuously through polling. For every new GYRO and ACC data, the angles are iterated using the CF in the following manner. The HPF allows the GYRO readings to pass through if the rate of change of these readings are large enough to be captured within the sampling period.

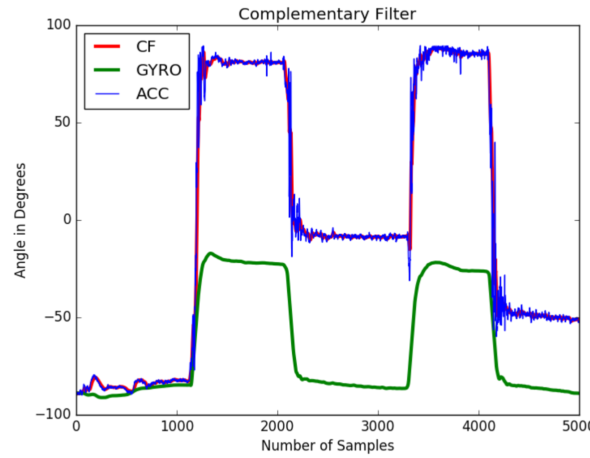

Figure 5. The Complementary Filter returns a smooth and consistent signal, by fusing both accelerometer and gyroscope data.

Likewise, if the rate of change of ACC data is small, the readings are permitted by LPF. Finally, 93% of the previous angle integrated with the current angular position given by GYRO and 7% of the current ACC angle are fused to filter out the short-term noise and long-term drift.

EVALUATION

Each gesture can be represented by a set of values within a range gathered from the readings of all the five IMUs. In order to make our model more adaptive, a large amount of data including all possible orientations in which a user could perform to enact a sign language gesture were recorded. Each gesture made by different users might have minor offsets from the ideal finger positions. Hence it is highly important to capture these slight deviations from each person for every gesture. Each participant was shown a short demonstration to make them familiar with the LSF signs before gathering the samples. After obtaining the filtered data from sensor fusion, we collected 1000 samples for each alphabet gesture in the sign language from 57 people. Of these 57 participants, one native LSF instructed the hand gestures and movements of each gesture to the remaining 56 participants, so that our dataset would amount to 57000 highly varying samples for each sign. The dataset contains approximately 1.25 million samples for all handshapes, excluding the dynamic gestures J, P, Y, Z. Each sample is represented by a 10-dimensional vector, where individual pairs of dimensions describe roll and pitch angles of a finger of the right hand. Manual annotation of the data samples was carried out afterwards to prepare the dataset for a supervised learning task.

Different machine learning approaches like Support vector machines (SVM), Naive bayes (NB), Multi layer perceptron (MLP) and Random forest (RF) models [14] were examined to classify the hand gestures. Among them, MLP and RF showed the most promising results The MLP had been reconfigured with different number of hidden layers and neurons and also by tuning various hyperparameters to achieve satisfactory results. A stochastic gradient descent algorithm with a learning rate of $1e^{-5}$ and 0.5 momentum along with the total of 100 neurons in each of the two or three hidden layers was shown as a best MLP classifier for our task. On the other hand, the performance of RF was tested with different number of trees varying from 5 to 75. A trade-off was observed in evaluating the significance of trees. The accuracy of validation results on the dataset showed minor improvements with the increase in number of trees in RF. Since the aim of our work is to design a real-time gesture recognition glove, an RF with 15 trees was found to be a reasonable decision to balance accuracy and response rate. The performance and accuracy produced by both MLP with 100 neurons and RF with 15 trees on the validation data was comparable. The rate of false positives for MLP was relatively high in comparison with RF and thus the RF with 15 trees was chosen as a final classifier.

An android App integration was made to facilitate the communication with the glove's Intel Edison over Bluetooth and to visualize the handshapes as letters of the sign language alphabet classified by the system. The recognized sign is displayed in the Android app interface provided the certainty of prediction is high, otherwise a null character would be shown to indicate the undefined gesture. The glove and a Smartphone(SP) are paired with each other at the beginning of the control routine via Bluetooth, where the glove acts as a server and waits for a Bluetooth-enabled glove to start sending.

We evaluated the dataset by assessing the results using 57-fold cross validation by following a leave-one-user-out approach. The model was trained with all the gestures of 56 subjects' data for each fold and 22000 samples (1000 samples for each of the handshapes) of a single subject was used for testing. The accuracy of each correctly recognized gesture observed in each fold was noted. The confusion matrix for all the signs can be seen in Figure 6. A number of 1000 samples representing a gesture is predicted in each fold, the confusion matrix depicts the average prediction count of each sign over 57 iterations. The overall mean accuracy of all the gestures was 92.4% with a standard deviation of 0.042, the F1 score was 91.3% with a standard deviation of 0.048. The per-class accuracy results are promising, with 12 of the handshapes having an average accuracy of more than 95%, six of them account in the range of 89% to 95% and four handshapes vary between 75% to 80%. With the evidence provided by the confusion matrix, the reason for the accuracy drop found in the gestures 'F', 'T', 'L', 'U' can be analyzed more thoroughly: The trained model has most diffulties with the 'F'-'T' and 'L'-'U' handshapes. The gestures of the signs 'F' and 'T' find more similarity with each other resulting in a mean prediction count of 'F' as 'T' for 184 times and 'T' as 'F' for 163 times out of 1000 in the confusion matrix. While measurements from all the other fingers remain the same, pitch angle readings from the thumb are the only apparent measurements that would differentiate both of the gestures. On the other hand, a similar behavior can also be observed for 'L' and 'U'. Here, uncertainity is introduced since the difference of orientation can be noticed only for the thumb and middle fingers. As we gathered data from distinct people having different hand structures varying in length, width and thickness, the pitch of the thumb and the roll of middle finger for a few subjects

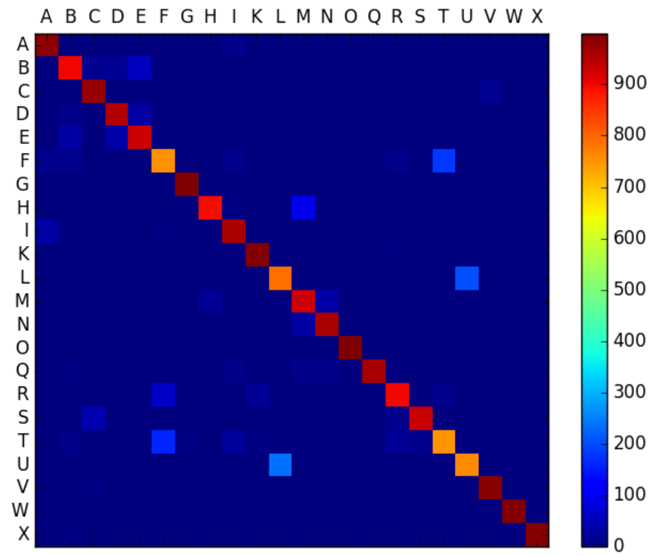

Figure 6. Confusion matrix of the recognized signs. Visible are minor confusions between 'L' and 'U', and 'T' and 'F'.

would not reveal great variance in the measurements, with the same holding for 'F' and 'T. Hence, the random forest classifier exhibited some ambiguity in recognizing these four handshapes during cross validation.

Apart from these validation results, the glove-based system has been tested on different new people in real-time studies: the time taken to predict the gesture was found to be performed within 65 ms, where 23 ms were spent on gathering the sensor readings from all 5 IMUs, and the random forest classifier predicting the handshape from the obtained readings within 42 ms. In order to understand the importance of large variety of data, we evaluated results on a dataset from less subjects and compared with the above scores. We trained the RF model with five subjects' data who were randomly chosen and found a drop in the accuracy and F1 score to 79% and 77% respectively. We also noticed the poor performance demonstrated by this training model during real-time testing.

CONCLUSIONS AND FUTURE WORK

This paper has contributed with a data glove design that includes IMU sensors on all fingers, to detect fine-grained handshapes. It takes advantage of recent System-on-Chip designs that are powerful enough to perform data fusion and classification routines in realtime within the glove. By using 5 IMUs along with a multiplexer, the amount of components is minimized, making the glove more comfortable to wear. The readings from IMU sensors suffer from noise and drift respectively: A complementary filter was employed to generate a smooth consistent signal by fusing the data and thereafter obtaining precise orientation of the finger orientation and movements. A dataset from 57 people was collected to capture the different variations of gestures made while fingerspelling letters from a sign language alphabet, to account for the differences in individuals' hand movements. The system is trained and executed fully on the glove, making it thus capable of recognizing any static sign language hand gesture defined in LSF signs. The performance was evaluated using 57-fold (leave-one-user-out) cross-validation, resulting in 92% mean accuracy and an F1 score of 91%. An android app was developed to immediately visualize the recognized gestures that are sent over Bluetooth by the glove, as well as start and stop the system. The proposed system has shown a real-time detection performance with gesture recognition being performed on-board within 65 milliseconds.

Both data set and source code for the system and evaluations in this paper are publicly available on-line on:
`http://ubicomp.eti.uni-siegen.de/home/datasets`
to facilitate reproduction of our results.

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