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Indian sign language recognition using wearable sensors and multi-label classification

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ABSTRACT

Sign language recognition is often carried out using hierarchical classification approach to reduce complexity and enhance accuracy. In this paper, mutli-label classification is proposed for categorization of a sign based on its lexical attributes followed by final classification of the sign. Results are presented for classification of 100 isolated signs from the Indian sign language recorded using multiple surface electromyogram and inertial measurement units on both the forearms of 10 different signers. Signals from both the hands are processed in an integrated manner to identify static or dynamic state of the two hands. Moreover, symmetry in the motion of two hands is also utilized for sign categorization using novel features. In the classic tree-based categorization of signs, there is error propagation, which results in a classification error of 6.22%. Whereas in the proposed mutli-label classification approach, error propagation is avoided and the average classification error of 2.73% is observed.

1. Introduction

A language provides humans with a structured means to exchange information with each other. While languages like Hindi and English use verbal or written mode of communication, sign languages, on the other hand, involve the use of visual gestures and signs. People with hearing and speech disabilities can communicate more naturally in sign language as compared to verbal languages. However, since most people do not understand sign languages, there is often a communication barrier experienced by a person wishing to converse in sign language. The use of a human interpreter or written form of communication is not always convenient. According to the Census 2001 of the Ministry of Home Affairs [1], there are around 1.26 million deaf people and around 1.64 million people with speech disability in India, while there are only 250 certified sign language interpreters in India. An electronic, wearable sign language recognition system shall be very useful in reducing the communication barrier that exists between a signer and a non-signer. There are several challenges in designing such a system.

Sign language is not unique worldwide and varies, at times significantly, in different countries and within a country. The Indian Sign language (ISL) and sign languages in general, consist of non-manual components such as facial expressions and body language as well as manual components related with configuration and motion of hands [2,3]. Since majority of signs can be recognized based on

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the manual components, this work is focussed on developing a wearable ISL translator using manual components of signing for classification. The manual components may further be categorized into one-handed or two-handed signs and static or dynamic signs [2,3]. In one-handed signs, the signer almost always uses the dominant hand, which is the right hand of a right-handed signer and the left hand for a left-handed signer. The dominant hand could be performing a static posture such as signing a numeral or the hand may follow a specific trajectory while held in the same or varying posture. In two-handed signs, the dominant hand may be more active as compared to the non-dominant hand, described as the *dominance* condition [4]. Then, the dominant hand may be dynamic while the non-dominant hand may be static. Otherwise, both the hands may be active and may have similar hand shape and movement, which is referred to as the *symmetry* condition [4]. In this work, the attributes explained above are utilized to design a multi-label classifier for initial categorization of an isolated sign, following which the final classification is carried out.

Sign language recognition has been reported with several sensing technologies and recognition algorithms. In [5], around 240 approaches for sign language recognition that use various sensing modalities as well as different machine learning algorithms have been reviewed. Based on the sensing technology, sign language recognition systems can be broadly classified as follows.

1. Vision-based systems: These systems track the motion of hands using camera mounted in front of the signer [6,7]. The Kinect sensor, that initially became popular for providing gesture-based control in Microsoft's Xbox gaming console, has been used to develop sign language recognition systems [6]. While Kinect provides the colour and depth video streams, Leap Motion sensors provide accurate hand and finger tracking, which is very useful for sign language recognition [6]. In [7], The authors used hand shape, velocity and position of hand as subunits to classify isolated signs and signed sentences from video stream with up to 97.3% accuracy. Use of skin tone or coloured gloves is also used in designing hand tracking algorithms [5]. However, vision-based recognition systems are not wearable and their performance may be affected by factors such as lighting condition, background, occlusion and limited view of capturing.
2. Wearable sensor-based systems: These systems consist of contact sensors such as those that can measure the bending of fingers, or motion and rotation of hand and/or fingers, such as accelerometers and gyroscopes [8]. The sensors may be placed in a glove. Sign language recognition using signals acquired from one Data Glove [9] and two CyberGloves, one on each hand [10] have been reported in literature. A precision and recall rate of 96.6% and 95.7%, respectively have been reported for classification of 74 distinct sentences based on 107-word vocabulary in [9]. For large databases with 5113 isolated signs and 750 different sentences, classification accuracies of 95.4% and 91.9% are reported in [10]. However, wearing a glove equipped with multiple sensors may interfere with natural signing, which requires different hand postures and motions.
3. Alternatively, armbands with multiple inertial measurement units (IMU) and surface electromyogram (sEMG) have been used for sign language recognition [11–13]. Surface electromyogram measures the electrical potentials generated in the muscles in a non-invasive manner from the sensors placed on the skin surface. Electromyogram provides rich information about hand gestures and has been used for health monitoring, studying muscle fatigue, developing prosthetic limb controls and in sign language recognition systems [8]. An IMU consist of a tri-axial accelerometer, which measures information related to linear acceleration and orientation, and a tri-axial gyroscope, which measures the turn rate about the orthogonal axis. Each sensing modality provides certain advantages as well as some limitations. In fact, the utilities of different sensing modalities for classification of signs in ISL have been assessed analytically in [14] and it is found that when multiple sensors and multiple modalities are used together, sign language recognition improves.

In this work, the signals are recorded using multiple sEMG and inertial sensors placed on both the forearms of the subjects so that the system is wearable and convenient to use when conversing in sign language. A novel multi-label classification (MLC) aided sign recognition is proposed, where the labels are selected according to the lexical attributes of signs as reported in [4]. Novel features are proposed for classification of static and dynamic motion of hands during signing as well as for determining symmetric motion of hands. Hence, the signals recorded from the two hands are processed in an integrated manner to improve recognition. Results are reported for 100 commonly used words from the Indian sign language. The proposed approach is compared with tree-classification approach reported in literature.

The remaining paper is organised as follows. Section 2 contains a brief overview of the techniques used in sign language recognition. The details of the experimental setup used in this work and the proposed algorithm are presented in Section 3. Novel features are also proposed for categorization of one- or two-hand signs into static and dynamic, and for determining symmetric motion in two-hand signs. Performance of the proposed MLC-aided classification is compared with the classic tree-classification as well as flat classification approach in Section 4. Results indicate that accuracy improves, while execution time is comparable with the existing algorithms. Section 5 concludes the paper.

2. Related literature

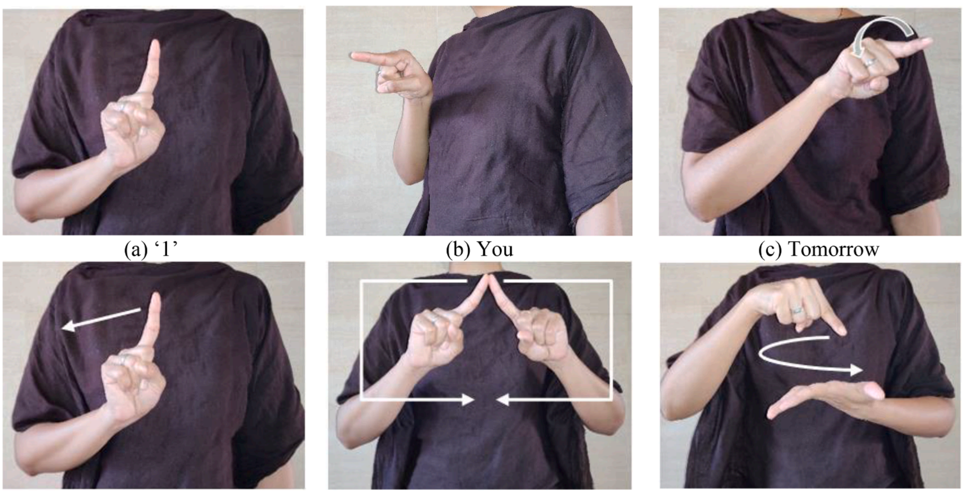
2.1. Use of sign language models in sign recognition

Sign language, like any other verbal language, has been studied for its phonological and lexical construction. Various models have been reported in literature to describe the structure of signs in terms of subunits, which is equivalent to a phoneme in a verbal language [15,5]. According to the Stokoe model, subunits of a sign language may be categorized according to shape, location and movement of the hand [16,15,2]. The handshape is described by the configuration of the fingers and orientation of the palm, while location of the hand is determined relative to the body. For example, as shown in Fig. 1a and 1b, a one-hand (index finger pointing out and other fingers forming a fist) facing up is the sign for the digit ‘1’, whereas one-hand facing front is the sign for ‘you’ in ISL [17]. Also, a sign may require a local movement, such as that of fingers or wrist, or movement of complete hand along a trajectory in space. For instance, one-hand is moved in an arc and only the orientation of the hand is changed from down to up, it means ‘tomorrow’ in ISL (shown in Fig. 1c), while to sign ‘week’ one-hand facing out at chest level is moved to right, as shown in Fig. 1d. Continuous signing has been described to consist of sequential organization of movement and static posture, termed as the Movement-Hold model [16].

For one-handed signs, the aforementioned models are sufficient, however, in two-handed signs, the relation between the movement and posture of the two hands has also been modelled [16,18]. Battison in 1978 proposed two constraints on the lexical of two-handed signs, namely the symmetry condition and the dominance condition [18]. According to the symmetry condition, when both the hands have dynamic motion, they must consist of same handshape and movement, which may be alternating. Under the dominance condition, if handshapes are not same for the two hands, then one hand must be in static posture, while the other hand articulates the meaning. In this case, the static hand is the non-dominant hand of the signer, which is the left hand for a right-handed signer and the right hand for a left-handed signer. For instance, in the sign for ‘rectangle’, both hands are in one-hand posture and move away from each other as shown in Fig. 1e, while in the sign for ‘plate’, the right one-hand facing down moves in a circle on top of the left hand, which remains static, open and facing up, as shown in Fig. 1f. Another point to be noted is that left-handed signers perform mirror image of the signs performed by right-handed signers [16].

There are certain sign language recognition systems where the signals recorded using various wearable sensors during signing are simply used for feature extraction and classification, without considering the language model. For instance, in [11], sEMG and IMU data was collected from four subjects in multiple sessions for 80 signs in the American sign language. The sensors were placed only on the dominant hand and processed for feature extraction, feature selection and classification. An average classification accuracy of 96.16% was achieved using support vector machine (SVM) classifier. In [12], the signals from Myo armbands on both hands were processed for feature extraction and classification using a multi-dimensional HMM and classification accuracy up to 96.15% was achieved for 13 gestures from the American sign language. On the other hand, sign language models such as Stokoe model and the Movement-Hold model have been employed during classification of signs [3,9,10,13]. For instance, the video streams for both hands were segmented into static and dynamic subunits and handshape information was also incorporated to improve classification accuracy [3]. In [9,10], the data from a CyberGlove and position trackers on both hands were segmented into sign and movement epenthesis, which is the transition phase between two adjacent signs. Also, the sign descriptors given by Stokoe have been used during classification. In [13], sign attributes were used to design an optimized-tree structure for hierarchical classification of signs using wearable armbands with sEMG and IMU sensors. In the first stage, the sign was classified as one- or two-handed. From the signs belonging in the selected category, the sign was then classified according to hand orientation in the second stage. In the third stage, the sign was classified according to signal amplitude to further limit the set of signs from which a multi-stream HMM identifies the sign being performed. For two-handed signs, the data from both hands was processed independently and the final recognition was achieved by probabilistically combining the decisions of classifiers for each hand.

In literature, sign attributes and the movement-hold model have been utilized extensively. However, the relative motion of two hands as described by Battison [4] has not yet been employed for sign language classification, to the best of our knowledge. In this paper, the signs are first categorized according to one- or two-handedness, static or dynamic state of both dominant and non-dominant hand, and also symmetric or asymmetric motion of the two hands. Moreover, MLC approach is proposed for categorization, as described in the following section.



(a) ‘1’ (b) You (c) Tomorrow
(d) Week (e) Rectangle (f) Plate

Fig. 1. Some common signs in Indian Sign Language.

2.2. Multi-label classification

Multiclass classification problem may be handled using flat classification, hierarchical classification or multi-label classification. In flat classification, the classifier assigns one of the multiple classes to an instance or the input feature vector in a single stage of classification [19]. In the learning phase, a function $h : \mathcal{X} \rightarrow \mathcal{Y}$is learned from the training data $(\boldsymbol{x}_i, y_i), i = 1, \ldots, m$, where $m$is the number of observations in training data, $\mathbf{x}_i \in \mathscr{X}(= \mathbb{R}^d)$is the input feature vector from the d-dimension feature set and class label is denoted by $y_i \in \mathcal{Y}$, where $\mathcal{Y} = \{y_1, y_2, \ldots, y_q\}$. For an unseen feature vector $\widehat{x}$, $h(\widehat{x})$is used to predict the associated class label $\widehat{y}_i$. Flat classification approach has been used for sign language recognition in [11,12]. Since relations among classes are not exploited, the complexity of a flat classifier increases as the number of classes increase. In hierarchical approach, classification is carried out in multiple stages and in each stage, there could be a binary or multiclass classifier at a parent node [19]. The classifier at each parent node may be designed using features more discriminative for the possible labels in that stage. For instance, an optimized tree is proposed for hierarchical classification of signs in [13], as explained in Section 2.1above. Here, the number of signs to which the input feature vector may be associated with in the final classification step progressively reduce with each stage of classification, in turn decreasing the complexity of the classifier. However, if there is an incorrect decision at any parent node, the error propagates downwards into the remaining stages of the hierarchy.

In hierarchical classification, multiple labels are assigned to the input feature vector, but one at a time in each stage of classification. However, in MLC, an input feature vector may be associated with more than one label in a single stage of classification. The training data consist of $(\boldsymbol{x}_i, Y_i), i = 1, \ldots, m$, where $\boldsymbol{x}_i$ is the feature vector as defined earlier and $Y_i \subseteq \mathcal{Y}$is the set of labels associated with $\boldsymbol{x}_i$. For a new observation $\widehat{x}$, the learned function may predict a set of labels $\widehat{Y}_i \subseteq \mathcal{Y}$as true. MLC has been used in various applications such as text categorization, recommender systems, and annotation of multimedia such as music and images [20,21]. MLC may be designed using problem transformation approach or algorithm adaptation approach. In problem transformation, MLC is redefined to transform it into conventional classification problems, such as a multiclass classification problem [20,21]. Some examples of MLC using problem transformation are binary relevance, classifier chain and label powerset. In algorithm adaptation, the conventional learning techniques are adapted to handle MLC. For example, multi-label k-nearest neighbour classifier (ML-kNN), multi-label decision tree and rank-SVM can assign more than one label to an unseen observation. In this paper, problem transformation approaches are employed for initial categorization of a sign due to their simplicity and applicability in the considered scenario.

In binary relevance (BR), one binary classifier is learned for each possible label, $y_1, y_2, \ldots, y_q \in \mathcal{Y}$[20]. Given an observation in the training data $(\boldsymbol{x}_i, Y_i)$, label associated with $\boldsymbol{x}_i$in the k^{th} binary learner, $k = 1, 2, \ldots q$, is given as

$$z_k = \begin{cases} 1, & \text{if } y_k \in Y_i \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

An unseen feature vector $\widehat{x}$, is tested with all the q-binary classifiers and a true prediction implies the presence of that label in the label set associated with the unseen feature vector, that is $\widehat{Y}_i = \{y_k | \widehat{z}_k = 1\}$. BR technique treats each label as distinct and does not utilize the relations that may exist between labels. In classifier chain (CC) technique, q-binary classifiers are trained in a specific order depending on the ranking of labels [20]. Also, $\boldsymbol{x}_i$is stacked with the actual label relevance (z_k) of the previous label in the chain to utilize label dependence during classification. Let $\{y_{r1}, y_{r2}, \ldots, y_{rq}\}$ be the rank-ordered label set. The ith input feature vector for the kth binary learner is $[\boldsymbol{x}_i, z_{r(k-1)}]$. For a new observation $\widehat{x}$, the kth binary learner in the chain uses $[\widehat{x}, \widehat{z}_{r(k-1)}]$ as the input feature vector to determine $\widehat{z}_k$. Another MLC technique that uses problem transformation and label dependencies is Label Powerset (LP) [20]. In LP approach, each unique label combination in the training data is assigned a pseudo-label and a single-label multiclass classifier is learned with the input feature matrix and the pseudo-labels. The learned model can predict a pseudo-label for a new observation, which is associated with a set of labels in $\mathcal{Y}$. The limitation of this method is that the number of possible pseudo-labels 2^qmay be very large for a large number of labels$q$. Also, the model can only be trained to classify the label combinations that are present in the training data.

Twelve different MLC techniques have been tested with eleven publicly available multi-label datasets derived from domains such as biomedical, multimedia and text categorization in [21]. Among the problem transformation approaches, LP-approach namely hierarchy of multi-label classifiers (HOMER), BR and CC are found to perform the best in terms of 13 evaluation measures. HOMER is a computationally efficient LP approach for handling large number of labels. The LP approach may be employed when there are only a few labels in the multi-label set, as in the case of the dataset used in this work. In [22], authors used BR, LP and CC approach to classify phonemes in Tamil language from audio signals and achieved the best accuracy of 93.6% with the LP approach. MLC has been used for human walking activity recognition in [23] using an accelerometer that may be placed in four different locations on the body. The authors combinedly classified the signal for different sensor placements and activities using LP approach to achieve a Hamming score of 99.6% for 10 walking activities, which was better than the score achieved with multiclass classifiers for individual sensor placements. In this paper, a sign is first categorized according to four attributes using MLC on signals recorded from multi-modality, wearable sensors. Then, the sign is recognized from the set of signs in the determined category, using multiclass classification, as explained in the following section.

3. Proposed ISL recognition

3.1. ISL database

Three sEMG sensors and two 6 degree-of-freedom IMUs were placed on both the forearms of the signers in an armband configuration, as shown in Fig. 2a. The sEMG and IMU signals were recorded at 90μs and 6.7ms sample intervals, respectively using the Delsys Trigno wireless system, shown in Fig. 2b. The sensors are synchronized in time and they transmit the signals wirelessly to a base station, which is connected to a PC via USB where signals are recorded and later processed. The skin was cleaned and the sensors were placed on the skin using double-sided adhesive interface to limit motion artifact. 10 volunteers comprising of 7 females and 3 males in the age group of 21–35 years of which 3 were left-handed and remaining right-handed gave informed consent to participate in the study. Each volunteer performed 20 repetitions of 100 commonly used signs in ISL, as given in the ISL video dictionary [17]. The volunteers were comfortably seated on a chair and an audio stimulus was used to indicate the beginning of a signing duration. The volunteers were given 3 s to complete a repetition of a sign and 5 s rest between each repetition, during which the volunteers were asked to keep the hands on the thighs in a resting position. Additional 5 min rest was given between each sign recording to avoid muscle fatigue. Hence, 20,000 samples of observations were collected containing around 15 hrs of usable recording.

ISL signs with different lexical attributes were selected; details of which are mentioned in Table I. Inspired by the sign language model given by Battison explained in Section 2.1, a sign is labelled as follows:

(i) Two-handed: A sign is two handed if the non-dominant hand is also used during the sign. In all the signs, the dominant hand is either required to make a posture with or without motion along a trajectory. If the non-dominant hand remains in rest position during the signing duration, the sign is considered to be one-handed. For instance, as shown in Fig. 1, the signs for 'rectangle' and 'plate' are two handed and the remaining four signs are one-handed.

(ii) Dynamic dominant hand: If a sign requires the dominant hand to undergo a local motion or motion along a trajectory, it is considered to be dynamic. Otherwise, it is considered to be static. For instance, as shown in Fig. 1, the dominant hand is in dynamic motion in the signs for 'tomorrow', week, 'rectangle' and 'plate', while it is static in signs for 'one' and 'you'.

(iii) Dynamic non-dominant hand: The condition for dynamic dominant hand is also applicable for the non-dominant hand for two-handed signs. For one-handed signs, the non-dominant hand is always considered to be static. In Fig. 1, all signs except the sign for 'rectangle' have static non-dominant hand.

(iv) Symmetric: For two-handed signs, the sign may require that the hands move in mirror symmetry. Otherwise, the hands have asymmetric motion such as for one-handed signs, non-dominant hand static signs or even when both hands are in motion. In Fig. 1, the sign for 'rectangle' has symmetric motion of both hands, while the remaining signs will be categorized as having asymmetric motion.

The possible sign categories according to the four sign attributes and the corresponding labelling used for sign categorization are listed in Table 1. The signals recorded during signing are pre-processed and MLC is used to categorized into a category using MLC. The final classification for recognition of the performed sign is carried out from amongst the signs in the identified category.

3.2. Signal processing

The signals recorded using the sEMG sensors and IMUs were processed as follows, before carrying out feature extraction.

1 Missing sample interpolation: Missing samples in the recorded signals were determined using linear interpolation of adjacent samples.
2 Baseline removal: A moving-average filter of length 125 ms was used to estimate the baseline of sEMG signals, which was removed.
3 IMU calibration: For each IMU, the accelerometer and gyroscope signals were calibrated to compensate the bias and scale factors.
4 Detection of activity duration: Activity duration for each repetition of the sign was determined using gyroscope signals, for each hand. To perform a sign, the signer must lift the active hand(s) in a space in front of the torso, referred to as the signing space [17].

Fig. 2. (a) Placement of sensors on forearm, (b) Recording setup.

Table 1
Sign categories and sign attributes for MLC labelling.

Sign Categories	Sign Attributes Examples (Number of signs in the category)	A1: Two-Handed	A2: Dynamic dominant hand	A3: Dynamic non-dominant hand	A4: Symmetric
C1: One-hand static	Good, 1, C, you (16)	0	0	0	0
C2: One-hand dynamic	Bad, right, key (29)	0	1	0	0
C3: Two-hand static	A, Doctor, Pray (10)	1	0	0	1
C4: Dominant dynamic, non-dominant static	Plate, bank, lock (19)	1	1	0	0
C5: Two-hand, both dynamic and symmetric	Rectangle, shop, pipe (19)	1	1	1	1
C6: Two-hand, both dynamic and asymmetric	Meat, work, add (7)	1	1	1	0

Also, after performing the sign, the signer brings his hands down in the resting position. A tri-axial gyroscope measures the turn rate ω along the x-, y- and z- axis of the sensor in deg/s. For the kth IMU, $k = 1, \ldots, 4$, the square root of Euclidean norm of gyroscope signals was evaluated as,

$$\| \boldsymbol{\omega}_k(n) \| = \sqrt{\omega_{kx}^2(n) + \omega_{ky}^2(n) + \omega_{kz}^2(n)}, \tag{2}$$

where n denotes the time sample. Fig. 3a and 3b show the norms of gyroscope signals for IMU1 and IMU3 placed on the dominant and the non-dominant hands, respectively for the sign 'Plate'. When the hand is in rest position or in a static posture, norms of gyroscope signals remain close to zero. Amplitudes of signals are high during any motion and peaks are observed between adjacent pauses. Hence, the beginning of the first peak and the end of the last peak in the norm of the gyroscope signals was detected to determine the activity duration, which are marked in dotted black lines in Fig. 3a and 3b. Since dominant hand is used in all signs, peaks are always observed in gyroscope signals of IMU1 and IMU2. However, when no peaks of at least 50°/s were detected in the signals from gyroscopes placed on the non-dominant hand, for instance for one-handed signs, the activity duration detected on the dominant-hand was selected as the duration over which the signals from the non-dominant hand are processed.

5 Detection of signing duration: As shown in Fig. 3c and 3d, the duration between the instances when the amplitude of first peak of the norm of the gyroscope signal drops below 50°/s and the amplitude of last peak increases above the same, was determined. This is the actual signing duration, where the duration of hands being lifted to the signing space and being taken back to the rest position are removed from the detected activity duration. The signing duration detected for the dominant and the non-dominant hands are plotted in dotted black lines in Fig. 3c and 3d, respectively.

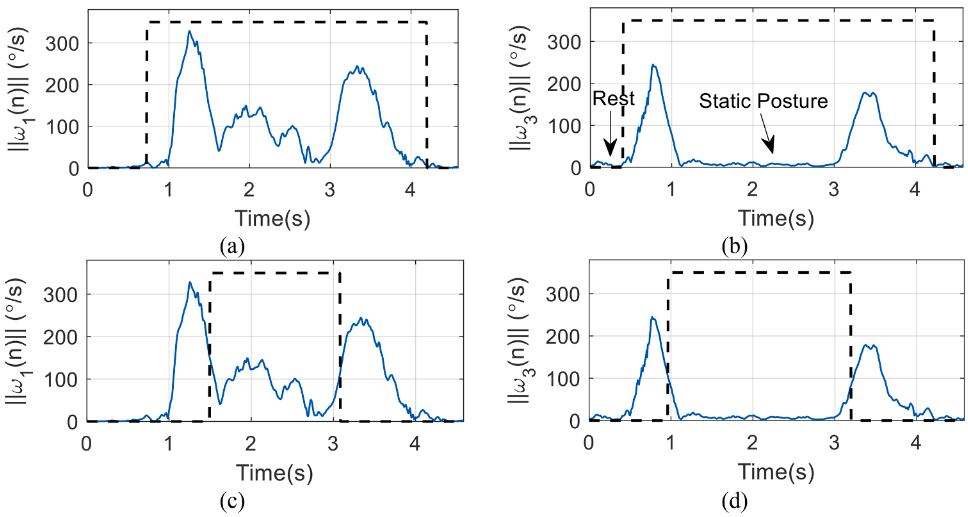


Fig. 3. Detected durations for the sign 'Plate' (a) Activity duration of dominant hand, (b) activity duration of non-dominant hand, (a) signing duration of dominant hand, (b) signing duration of non-dominant hand.

Novel features are proposed to categorize a sign according to the four attributes mentioned in Section 3.1 based on the recorded signals. Let the specific force vector of tri-axial accelerometer of the kth IMU after calibration, be

$$\mathbf{f}_k(n) = \left[f_{kx}(n) \quad f_{ky}(n) \quad f_{kz}(n) \right]. \tag{3}$$

Normalized peak-to-peak values: The peak-to-peak value of accelerometers on the non-dominant hand, normalized with respect to the maximum of the peak-to-peak values of all accelerometer signals is evaluated over detected activity durations, as given in (4). Similarly, the normalized peak-to-peak values for gyroscope signals of non-dominant hand sensors are evaluated.

$$p^s_{kl} = \frac{\max(s_{kl}(n)) - \min(s_{kl}(n))}{\max(\{\max(s_{mr}(n)) - \min(s_{mr}(n)),\ \forall m \in \{1,2,3,4\}\ and\ r \in \{x,y,z\}\})}, \tag{4}$$

where $s_{kl}(n)$ is the specific force $f_{kl}(n)$ when $p^s_{kl}$is evaluated for accelerometer signals and it is turn rate $\omega_{kl}(n)$ when $p^s_{kl}$is evaluated for gyroscope signals. In (4), $k\in\{3, 4\}$ corresponding to sensors on the non-dominant hand, $l\in\{x, y, z\}$, $n = 1, \ldots N$and N is the number of samples in activity duration. For one-handed signs, since the non-dominant hand is not lifted to the signing space, the normalized peak-to-peak values for accelerometer and gyroscope signals is expected to be lower as compared to that of two-handed signs.

Normalized standard deviations: The standard deviation (std) of signal from an accelerometer, gyroscope or sEMG sensor (denoted by e) on the non-dominant hand, normalized with respect to the maximum standard deviation of the corresponding signals from sensors on both hands is evaluated over the detected activity duration, using

$$\overline{\sigma}^s_{kl} = \frac{\mathrm{std}(s_{kl}(n))}{\max(\{\mathrm{std}(s_{mr}(n)),\ \forall m \in \{1,2,3,4\}\ and\ r \in \{x,y,z\}\})}, \tag{5}$$

where k, l and n have same meaning as in (4) and $s_k(n)$ are the signal samples in activity duration. If non-dominant hand is not in activity, the normalized standard deviations are expected to remain low.

Euclidean distance to determine symmetric motion between two hands: The accelerometer signals $f_{kl}(n)$, $k\in\{1, 2, 3, 4\}$ and $l\in\{x, y, z\}$ are normalized to make their mean over the activity duration as zero. Then, Euclidean distance is evaluated over corresponding accelerometer signals from either hand, that is between the accelerometer signals of IMU1 and IMU3, and IMU2 and IMU4, as

$$d(f_{1z}, f_{3z}) = \sqrt{\sum_{n=1}^{N} \left(f_{1z}(n) - f_{3z}(n)\right)^2}, \tag{6}$$

where n are the samples in activity duration. Fig. 4a and 4b show the signals for signs 'rectangle' and 'plate', respectively recorded from accelerometers in IMU1 and IMU3. The corresponding accelerometer signals have similar variation with time in Fig. 4a. By removing the mean, the difference in accelerometer signals due to difference in orientation is compensated. Hence, only the variation of specific

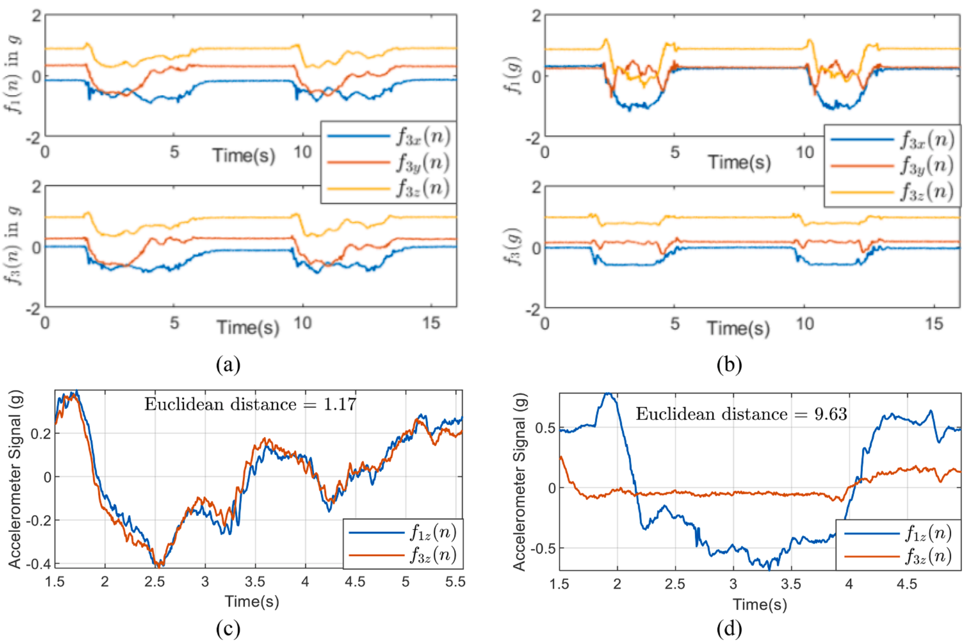


Fig. 4. Accelerometer signals, (a) $f_1(n)$ and $f_3(n)$ for sign 'Rectangle', (b) $f_1(n)$ and $f_3(n)$ for sign 'Plate' (c) $f_{1z}(n)$ and $f_{3z}(n)$ for sign 'Rectangle' after mean-removal, (d) $f_{1z}(n)$ and $f_{3z}(n)$ for sign 'Plate' after mean-removal.

force of the corresponding accelerometers with time would affect the Euclidean distance. The mean-removed signals for accelerometers along *z*-axis in IMU1 and IMU3 are shown in Fig. 4c and 4d, respectively. In the sign for 'rectangle', the hands move in mirror symmetry and the Euclidean distance evaluated using (6) is 1.17, whereas in the sign for 'plate', the hands have asymmetric motion and the Euclidean distance is 9.36. The Euclidean distance is also low for two-hand static signs, since both hands lift into the signing space and then remain static.

Statistical features evaluated over signing duration: Mean and median are estimated over the signing duration for the Euclidean norm of gyroscope signals defined in (2). Also, standard deviation of accelerometer and gyroscope signals for all sensors is evaluated over the signing duration. These features yield significantly lower values for static postures as compared to when estimated over dynamic motion, provided the durations of signer lifting his hands to signing space and taking them back to rest position are excluded from the evaluation.

Features for multiclass (MC) classification: Other than the features proposed above, the features commonly reported in literature are also evaluated for final classification from the set of signs in the determined category. Since it is required to capture the variation of motion with respect to time, the sEMG and IMU signals are segmented into windows of 500 ms. The MC-related features listed in Table 2 are evaluated for each window. For sEMG signals, time domain features such as mean absolute value (MAV), variance (VAR), zero crossing rate (ZCR), skewness (SkewT), kurtosis (KurtT), frequency domain features such as mean frequency (MNF) and median frequency (MDF) have been reported for classification of signs [11,13]. In Table 2, $\overline{e}_k = \frac{1}{N}\sum_{n=1}^{N} e_k(n)$is the mean of sEMG signal for sensor $k\in\{1, \dots, 6\}$, over a signal segment having Nsamples. The threshold μ for detecting ZCR is taken as twice the standard deviation of the sEMG signal recorded during rest duration. The power spectral density (PSD) of an sEMG signal, P is weighted using the corresponding frequency f to evaluate MNF, whereas MDF is the frequency at which the area under the PSD is divided into half. The AR coefficients a_q are evaluated for segments of sEMG signals such that the prediction error $w(n)$ is uncorrelated, white noise. Skew and kurtosis are also evaluated for sEMG signals as given in Table 2, where μ_n is the n^{th} order central moment evaluated using the probability density function (PDF) of the signal [24]. Spectral skewness (SkewF) and spectral kurtosis (KurtF) reported in [24] for classification of finger gestures are also evaluated. The spectral moments are evaluated just like central moments, however, PSD of the signal is used in place of PDF. For accelerometer and gyroscope signals, mean and standard deviation are evaluated. In the next section, the proposed MLC-aided classification of signs is presented.

3.3. Proposed MLC aided SLR

For SLR, signals recorded using sEMG and IMU sensors placed on the hands of a signer were processed as depicted in Fig. 5. Basic pre-processing steps, explained in Section 3.2 were carried out for handling missing values and signal biases. Then, activity duration and signing duration were detected separately for sensors on the dominant and the non-dominant hands. The features proposed MLC and MC classification, as stated in Table 2, were extracted. The features were standardized so that the values of each feature have zero mean and unit variance. Also, principal component analysis (PCA) was applied on the MLC-related features to select reduced feature sets, while maintaining 99% variance. Different MLC techniques were employed to compare their performance for sign categorization. In BR, one probabilistic SVM [25] with Gaussian kernel was learned for each attribute mentioned in top row of Table 1. In CC, the label chain was created using the same sequence of attributes as mentioned in Table 1, with two-handed categorization as the first label in the chain. Here too, probabilistic SVM was used for categorization of a sign according to each attribute, but the true labels from the previous label in the chain were concatenated with the feature vector, as explained in Section 2.2. In LP, only one multiclass SVM was trained for MLC by assigning a pseudo-label to each of the six categories mentioned in the first column of Table 1.

For a new observation, MLC was first used to determine the label for each of the four attributes. In BR and CC approaches, it is also possible that the predicted attribute labels do not correspond to any of the 6 possible categories. Then, the new observation was classified from the set of all signs, following the flat classification approach. Also, if the posterior probability estimated using probabilistic SVM of an MLC label taking a value 0/1 was less than 0.8, the estimated MLC label was ignored and the remaining MLC labels were used to determine the set of signs for the final classification stage. For example, if the labels for attributes A1, A2 and A3 were predicted as 1, 1, and 1, respectively, each with posterior probability greater than 0.8, whereas that for attribute A4 was predicted with a lower probability, the signs contained in both categories C5 and C6 (as stated in Table 1) were considered in the final classification of

Table 2
MLC and MC related features.

MLC-related features (no signal segmentation)	MC-related features (evaluated over 500ms signal segments)	
p^f_{kl}, p^ω_{kl}, for $k\in\{3, 4\}$, $l\in\{x, y, z\}$	MAV $= \frac{1}{N}\sum_{n=1}^{N} \lvert e_k(n)\rvert,\ k \in \{1, \cdots, 6\}$	AR coefficients, a_q, q $= 1, \dots 3$ $e_k(n) = \sum_{q=1}^{Q} a_q e_k(n-q) + w(n)$
$\overline{\sigma}^f_{kl}$, $\overline{\sigma}^\omega_{kl}$, $\overline{\sigma}^e_{kl}$, for $k\in\{3, 4\}$, $l\in\{x, y, z\}$	VAR $= \frac{1}{N}\sum_{i=1}^{N} (e_k(n) - \overline{e_k})^2$	SkewT $= \frac{\mu_3}{\mu_2^{3/2}}$, SkewF $= \frac{\tilde{\mu}_3}{\tilde{\mu}_2^{3/2}}$
$d(f_{1l}, f_{3l})$, $d(f_{2l}, f_{4l})$, $l\in\{x, y, z\}$	ZCR $= \sum_{i=1}^{N-1} [sgn(e_k(n) \times e_k(n+1)) \cap \lvert e_k(n) - e_k(n+1)\rvert] \geq \mu$	KurtT $= \frac{\mu_4}{\mu_2^2}$, KurtF $= \frac{\tilde{\mu}_4}{\tilde{\mu}_2^2}$
Mean($\lVert \omega_k(n) \rVert$), Median($\lVert \omega_{\mathbf{k}}(n) \rVert$), $n \in$ signing duration	MNF $= \sum_{m=1}^{M} f_m P_m / \sum_{m=1}^{M} P_m$, M=number of frequency bins	Mean($f_k(n)$),STD($f_k(n)$), for $k\in\{1, 2, 3, 4\}$, $d\in\{x, y, z\}$, $n\in$activity duration
std($f_{kl}(n)$),std($\omega_{kl}(n)$), for $k\in\{1, 2, 3, 4\}$, $l\in\{x, y, z\}$, $n\in$ signing duration	MDF $= \sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j$	Mean($\omega_k(n)$),STD($\omega_k(n)$), for $k\in\{1, 2, 3, 4\}$, $d\in\{x, y, z\}$, $n\in$ signing duration

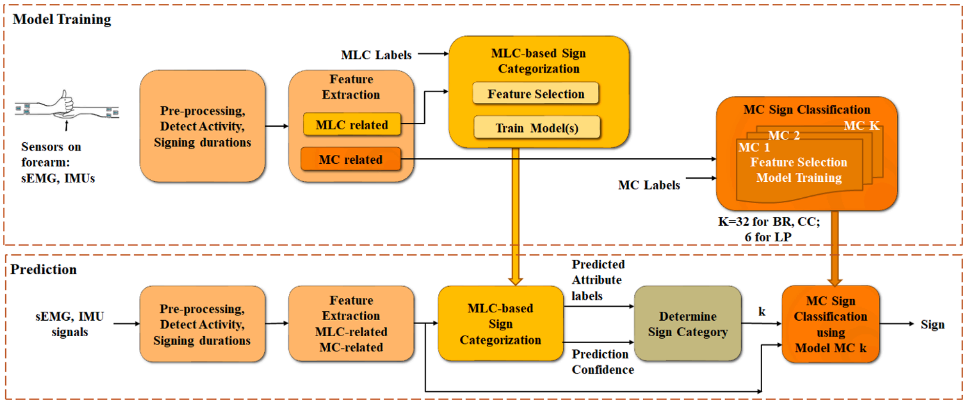


Fig. 5. The proposed MLC-aided SLR for Indian sign language recognition.

the sign. Hence, the probability of incorrect categorization was reduced, but the possible categories increased from 6 to 32. Consequently, in the final classification stage following the BR and CC-based categorization, 32 different models were learned. In LP-based MLC, however, an observation may only be categorized into one of the 6 categories mentioned in Table 1 and only six models were required to be learned for the final classification stage. In general, the categorization of a new observation lead to a reduced set of signs from amongst which the performed sign is to be identified. In the final stage of classification, PCA was applied on the subset of training features belonging to all the signs in a particular category, and a multiclass SVM with Gaussian kernel and one-vs-all encoding was learned. Hence, for a new observation, the MC-model for the determined category was used for classification.

The MLC-aided SLR proposed above was compared with a tree-based SLR described as follows. The order of attributes mentioned in Table 1 was used for tree splitting, which is the optimal in terms of Gini's diversity index. Starting with the entire training data, a binary classifier model was learned to classify a sign as one- or two-handed. Then, the subsets of training data corresponding to one- and two-handed signs were used to learn two more binary models that would classify the dominant hand as dynamic or static. Here, features of only the dominant hand were used while those of non-dominant hand were ignored. From the subset of data belonging to

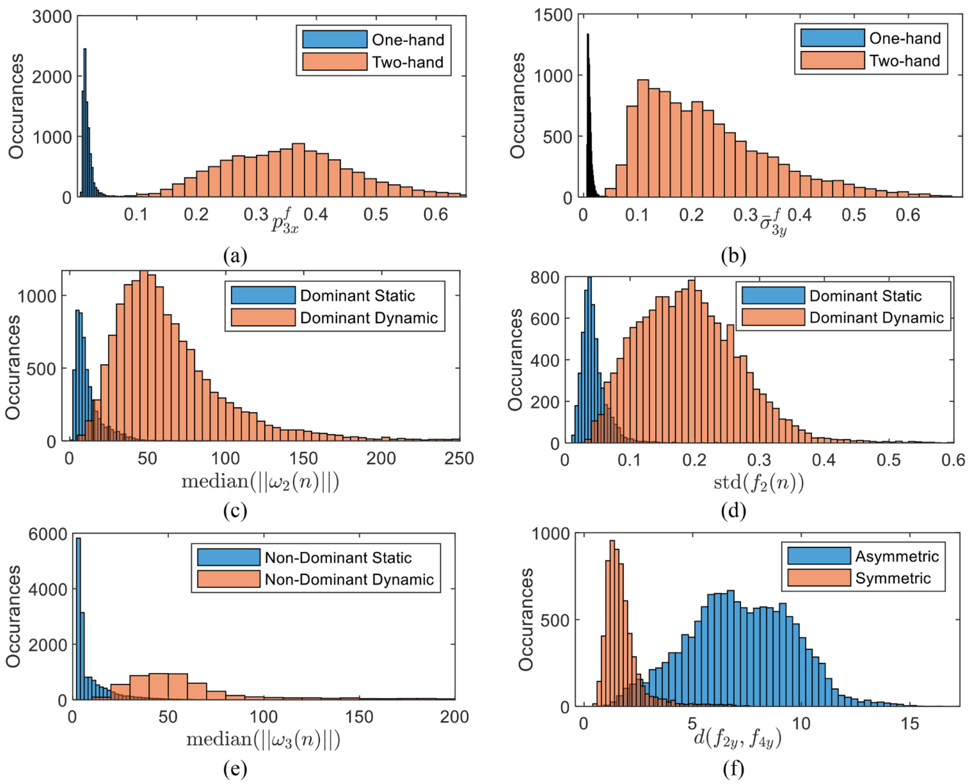


Fig. 6. MLC-related features for sign categorization.

two-hand dominant-dynamic signs, a fourth classifier was learned to determine if the non-dominant hand is dynamic, using features of only the non-dominant hand. A fifth classifier was learned from the subset of data corresponding to two hand signs with both hands in dynamic motion to classify the sign as symmetric or asymmetric using features from both the hands. For each node, MLC-features were used in SVM classifier with Gaussian kernel. Finally, six multiclass classifiers were trained using subset of data belonging to the signs in the six categories using MC features. For a new observation, the sign was categorized using the tree structure, following which the sign was classified from the set of signs in the identified category.

In the tree-based categorization, the set of possible signs at each node is a subset of the possible signs in its parent node. Hence, if at any node, the sign is incorrectly categorized, the set of signs from which classification is carried out in the final stage will not contain the actual sign. For instance, in tree-structure for a two-hand sign with both hands dynamic (category C5 or C6), if the sign is predicted as two-hand, dominant dynamic, but non-dominant static (category C4), the sign will be classified from amongst the signs in category C4, which will not contain the actual sign. Whereas, in MLC-based categorization, each attribute is determined from the data belonging to all the signs. For instance, the model used for categorization of attributes A1–A4 in BR and CC have the same set of data during training, and for a new observation, predictions for all the four attributes are combined to determine the sign category. Moreover, labels associated with low posterior probabilities are ignored. In LP, the categorization is again from the set of all signs. In the next section, the performance of proposed MLC-aided SLR is compared with the tree-based SLR.

4. Experimental results

The aim of the proposed SLR system is to determine the sign performed based on sEMG and IMU signals from both the hands. Firstly, the novel MLC-features proposed in Section 3.2 are assessed for their utility in sign categorization. Histograms of normalized peak-to-peak value and normalized standard deviation for accelerometer in IMU 3 on the non-dominant are plotted in Fig. 6a and 6b, respectively for observation belonging to one-handed and two-handed signs. As expected, their values are lower when the non-dominant hand is not used in the activity duration. Hence, they are useful in classifying a sign as one- or two-handed. Fig. 6c and 6d show the histograms of median of Euclidean norm of gyroscope signal and standard deviation of accelerometer signal from IMU 2 on the dominant hand. When evaluated over signing duration, these statistical measures provide acceptable discrimination between static and dynamic state of the dominant hand. Similarly, median of Euclidean norm of gyroscope signal from IMU 3 on the non-dominant hand provides a good distinction between static and dynamic state of the non-dominant hand, as shown in Fig. 6e. The histogram in Fig. 6f shows that the Euclidean distance between the mean-centred accelerometer signals from dominant and non-dominant hand is useful for determining whether the motion of the two hands is symmetric or asymmetric. For symmetric motion, Euclidean distance is in general lower as compared to that evaluated under asymmetric motion of hands. These MLC-related features were used with BR, CC, LP and tree-based approaches to categorize a new observation, as explained in Section 3.3.

The categorization algorithms were tested on the entire dataset using 5-fold cross validation. In Fig. 7, the 'Final' incorrect categorizations are the number of times the actual sign was not from the category determined by the categorization algorithms and subsequently the sign will be misclassified. These incorrect categorizations are out of the total number of observations, which is 20,000. In tree-based approach, once an error is made in the categorization of a sign based on an attribute, A1 to A4, the error propagates. Hence, the number of incorrect categorizations progressively increase with each stage of categorization. However, in MLC-based approaches, the number of incorrect categorizations at each stage is not dependent on that of the previous stage. In BR and CC, when the posterior probabilities provided by probabilistic SVM along with the predicted label for an attribute are not considered, the resulting numbers of incorrect categorizations are higher than the tree-based approach, as shown by the dotted lines in Fig. 7. However, when labels with low posterior probabilities are ignored, the final set of signs is more likely to consist of the actual sign and the total number of incorrect categorizations reduce. The lowest number of incorrect categorizations is provided by the LP approach. In LP approach, the categorization is not carried out in stages. Unlike in all the other methods, a single model is learned in LP approach to categorize the sign into one of the six possible categories, each represented by a pseudo-label. The predicted pseudo-label is converted into the multi-label representation shown in Table 2, to determine the incorrect categorizations of attributes, plotted in Fig. 7.

The error in final classification of new observations from the set of signs in the categories determined by one of the considered approaches is shown in Fig. 8. The error in final classification of signs has been evaluated over all observations using 5-fold cross-

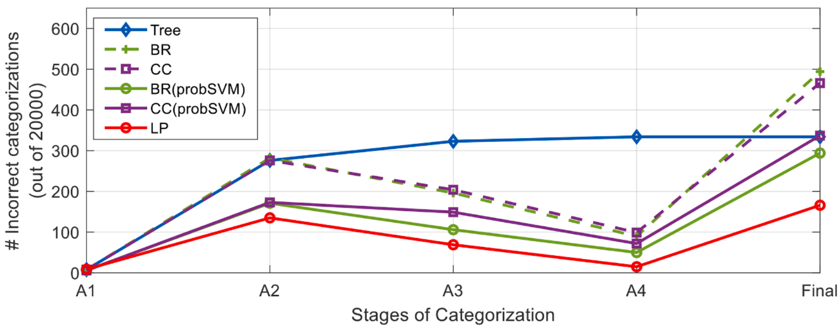


Fig. 7. Result of sign categorization.

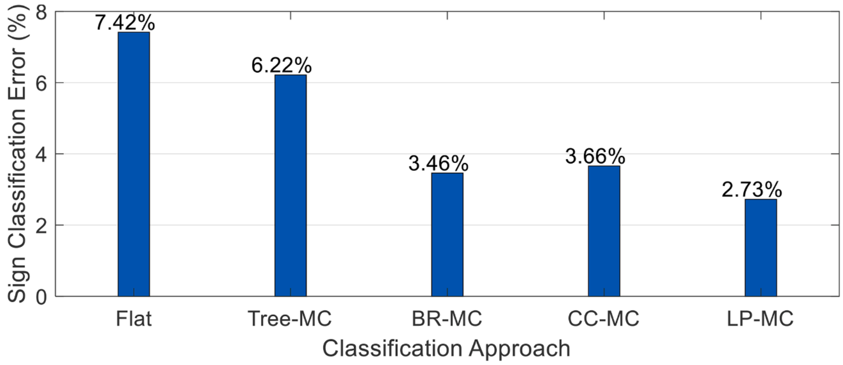


Fig. 8. Result of final sign classification.

validation, as the ratio of sum of incorrect predictions of signs and the total number of observations, which is 20,000. When flat classification approach is used and a single model learned from labelled data of all the 100 signs is used to predict the sign corresponding to a new observation, the error is maximum at 7.42%. When a new sign is first categorized using the tree-approach explained in Section 3.3, and then multiclass classification is carried out from the subset of signs in the identified category, the error is classification reduces to 6.22%. The classification error is even lower when MLC-based SLR is used. The classification errors obtained using BR and CC-based sign categorization (considering posterior probabilities to determine the reliability of the predicted label) followed by final multiclass classification are 3.46% and 3.66%. The lowest classification error of 2.73% is obtained with LP-based SLR.

Fig. 9 shows the boxplot of the classification accuracies of all the 100 signs, when different techniques are used for classification. The red-line inside the box indicates the median of the classification accuracies obtained for the 100 signs while the upper and lower edges indicate the 75th and 25th percentiles, respectively. The extreme values are indicated by whiskers and the outliers are marked with '+' symbol. As seen in Fig. 9a, MLC-aided SLR performs better as compared to flat classification and tree-based classification. The classification accuracies of all the 100 signs for different classification approaches was also tested using one-way analysis of variance (ANOVA). A highest p-value of 1.2327×10^{-7} between the groups for tree-based and MLC-based SLR indicates that the improvement in the classification accuracies is statistically significant. LP-based SLR provides the best overall classification across all the considered signs.

The considered approaches are compared in terms of computation time in Table 3. While flat classification uses only one model to classify 100 signs, it requires the most amount of time for training as well as testing. Tree-based categorization reduces the complexity of the classifier and hence, requires the least amount of time for learning the classifier models as well as for classifying new observations. When BR and CC are used for sign categorization using probabilistic SVM, the number of models required to be trained for final classification increase, hence increasing the time required for learning all the models, as compared to tree-based approach. LP-based SLR requires relatively smaller number of models for sign categorization and final classification as compared with BR and CC-based approaches. Hence, the computation time required to train LP-based SLR is also less as compared to the other two MLC approaches, however it is higher than the tree-based SLR. The time required for categorization and final classification of new observations using BR, CC and LP-based SLRs is higher than that of tree-based SLR. However, the average time required for testing mentioned in Table 3 is for 4000 new observations. This indicates that the signs will be classified within a millisecond making the SLR system feasible for real-time operation. In future, the work will be extended to allow classification of continuously signed sentences using sEMG and IMU sensors.

5. Conclusion

In this work, isolated signs from the Indian sign language are classified by processing signals from multiple sEMG and IMUs placed on both the forearm of signers in an integrated manner. Multiple labels are assigned to the observations in the recorded database according to four attributes of the sign being performed, making the database one of its kind in the domain of SLR. Signing duration is determined from the detected activity duration and its utility is demonstrated in extracting features that may classify the sign as static or dynamic. Euclidean distance between mean-centred accelerometer signals recorded from corresponding sensors on the two hands is shown to be useful for determining the symmetric motion between two hands. Multi-label classification approaches, namely BR, CC and LP are compared for their performance in categorizing a sign according to its lexical attributes. Then, the sign is classified from the set of signs belonging to the identified category using multiclass classification. Sign language recognition is also carried out using flat classification and tree-based approach. Flat classification shows highest classification error of 7.42% and requires more time for learning the models and classifying new observations as compared to all the other approaches. The tree-based approach results in a classification error of 6.22% in least amount of time. The MLC-based SLRs provide even lower classification errors and LP-based SLR yields the best performance with minimum categorization error of 2.73% and computation time comparable with the tree-based approach.

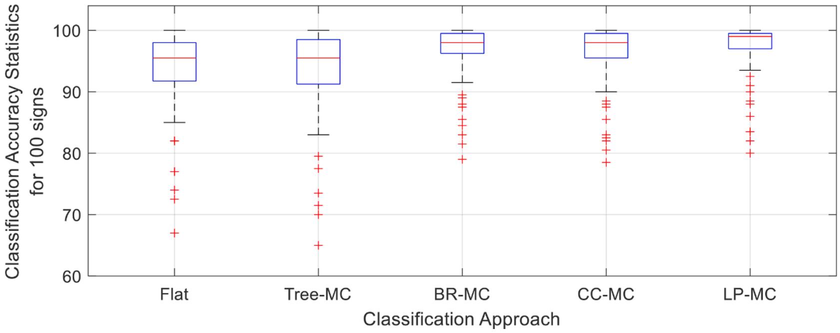


Fig. 9. Box-plot of classification accuracies for 100 signs.

Table 3
Comparison of computation time for SLR techniques.

SLR Technique	Number of Classifier Models Trained	Training Time in sec (sum over all 16000 observations in a fold and average over 5 folds of cross validation)	Test Time in sec (sum over all 4000 observations in a fold and average over 5 folds of cross validation)
Flat Classification	1	139.44	10.24
Tree-based categorization+ final MC	5+6=11	9.25+19.83=29.08	0.48+1.65=2.13
BR-based categorization+ final MC	4+32=36	26.42+109.50=135.92	1.32+2.09=3.41
CC-based categorization+ final MC	4+32=36	20.37+102.08=122.45	1.06+1.89=2.95
LP-based categorization+ final MC	1+6=7	34.87+18.31=53.18	3.08+1.50=4.58

CRediT authorship contribution statement

Rinki Gupta: Conceptualization, Methodology, Software, Investigation, Visualization, Writing - original draft, Funding acquisition, Writing - review & editing. **Arun Kumar:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compeleceng.2020.106898.

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