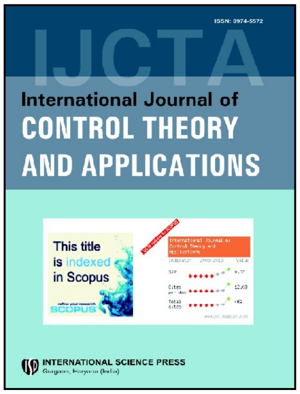

International Journal of Control Theory and Applications

ISSN : 0974-5572

Volume 10 • Number 11 • 2017

Similarity Assessment of 30 World Sign Languages and Exploring Scope for a Sign – to – Sign Translator

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Abstract: This paper proposes to find similarity between sign language finger spellings of alphabets from 30 countries with computer vision and support vector machine(SVM) classifier. A database of 30 world sign language alphabets is created in laboratory conditions with 9 test subjects per country. Binarization of sign images and subsequent feature extraction with histogram of oriented gradients (HOG) gives a feature vector. Classification with SVM provides insight into the similarity between world sign languages. The results show a similarity of 61% between Indian sign language and Bangladesh sign language belonging to the same continent. Whereas the similarity is 11% and 7% with American and French sign languages in different continents. Several feature extraction models such as SIFT, SURF, LBP, Haar, MSER etc. were tested for accuracy and speed. The overall classification rate of multi class SVM is 95% with HOG features when compared to other feature types. Cross validation of the classifier is performed by finding an image structural similarity measure with Structural Similarity Index Measure (SSIM). This study enables hearing impaired to significantly learn new sign language in less time through sign similarity and the sign-to-sign translator enables them to effectively communicate with their communities in different countries effortlessly.

Keywords: Sign Language Recognition, World Sign Languages Comparison, Feature Extraction, Support Vector Machines, Sign - to - Sign Translator

1. INTRODUCTION

Language translator form google [1] is helping 200 million people to communicate from all over the word. Although there are many such language translators [2], the primary goal is translation of words and sentences in one language to another language. The program compares language structures instead of word or sentence features in both languages. The language is modelled through vector spaces and the transformations happen by vector space mapping between different languages. The rate of accuracy for a 5-word conversion is around 90%. There are many such models for language converters in speech and text [3-5], but this paper articulates a sign language translator between multiple countries.

Vocal languages are produced by voice and basic structure is decided by the alphabets. Every language around the world is represented by a set of alphabets and their infinite combination produces words that convey information. But for hearing impaired people this is of no use. Their alternative is Sign Language. Sign Languages are produced by finger shapes, hands location with respect to head, face and body along with facial expressions. The alphabets in sign languages are finger mapped. Each English alphabet is mapped into either 5 fingers (single hand) or 10 fingers (double hand). The structural representation of fingers form alphabets for sign languages.

The Ethnologue – language encyclopaedia of the world lists 6909 living languages from which only 130 are deaf sign languages. Before exploring the possibility of a sign-to-sign translator that transforms one countries sign language into another, this work focuses on identifying a similarity between these visual languages. We have carefully chosen 30 countries whose sign languages are popular and extensive research is going on in developing machine translation of these sign languages with non – visual (Glove based) and visual (Video Camera based) techniques. The countries are American, Mexican, Indian, Bangladesh, Pakistan, Srilanka, Chinese, Philippines, Indonesia, British, French, Irish, Spanish, Czech, Estonian, Finnish, German, Hungarian, Nederland, Norwegian, Polish, Chile, Australian, New Zealand, Iceland, Brazil, Kenya, South African, Uganda and Zambian.

Hand signs for these countries are publically available from image search in google. By using them we have created a lab setup to capture the signs as shown in figure 1.

Figure 1: Lab setup for capturing hand signs of different countries with 9 test subjects

The lighting and background are carefully controlled during capture using a 12 mega pixel Sony Dslr camera. Each alphabet of a particular country is captured 9 times to test the robustness of the feature extraction algorithms and the classifier. Two samples of the database are presented in figure 2(a) and (b). Figure 2(a) shows alphabets from a test signer of Indian Sign language (ISL) and figure 2(b) shows that of a British sign language(BSL).

Figure 3 shows the alphabet 'C' from the entire set of 30 sign languages, which is found to be common in all the sign languages used for comparison. Visually the structural similarity between the letters can be decoded by the human brain with some efforts but it is quite a challenge for the computer. In an experiment at our lab even the humans who learned one sign language found it difficult to follow signs from another sign language. Their failure rate was 60% for other sign languages, but again this is a subjective evaluation. This visual decoding and

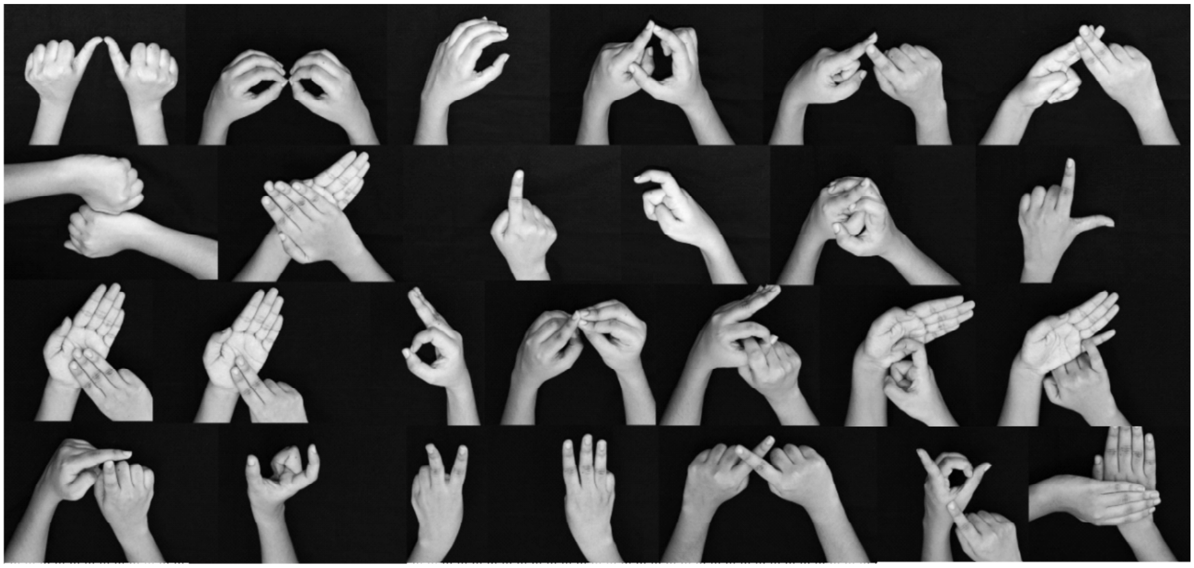

Figure 2(a): Alphabets of Indian Sign Language from 'A' to 'Z' moving horizontally

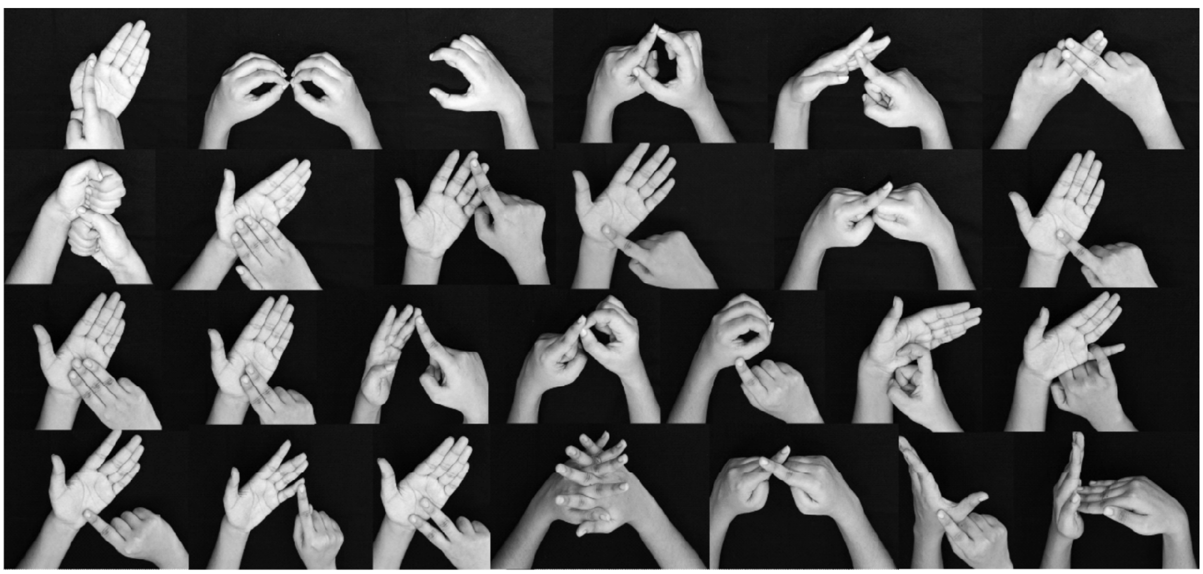

Figure 2(b): Alphabets of British Sign Language from 'A' to 'Z' moving horizontally

mapping of signs to text or speech is challenging researchers for around two and half decades. For an efficient sign – to – sign translation between countries the following are important factors for evaluation.

1. The first part is to find a similarity between 30 world sign languages using Histogram of oriented gradients (HOG) features and Support vector machine (SVM).
2. To draw a confusion matrix for these 30 countries and to evaluate the performance of the classifier.
3. The third part we used various feature extractors to test the robustness of the HOG as it maps 9 bin gradient orientations into histograms making it rotation and scale invariant for small variations.
4. Lastly, we plot the conversion efficiency of one sign language into another and also measure the relativity between sign languages geographically.

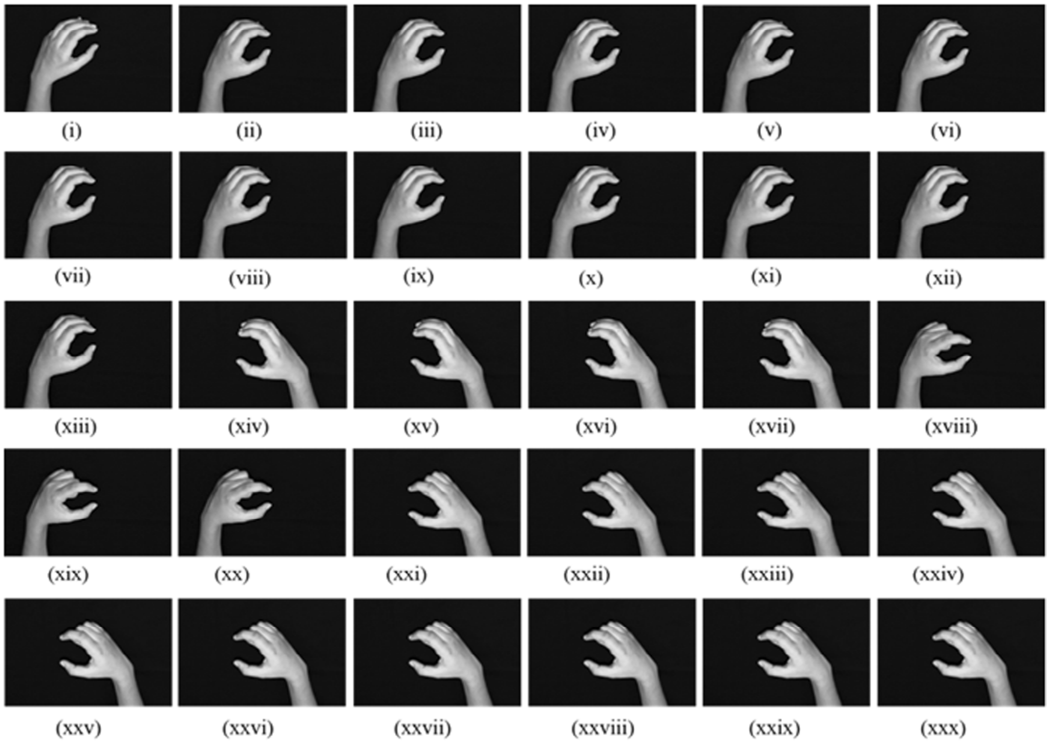

Figure 3: Sign for alphabet 'C' from 30 counties ordered as mentioned in the text

2. LITERATURE: SIGN LANGUAGE RECOGNITION

Two models of sign language recognition are commonly explored in every continent of the world. Non-visual external hardware based gloves which decode the finger movements with 90% efficiency [6, 7]. Here the problem is based in signal domain. The solutions are one dimensional time series data analysis models [8]or frequency domain analysis to extract features from the moving fingers [9]. Researches also used time – frequency analysis to represent finger movements into features [10]. Costly hardware is an issue in this model along with the basic flaw, that is sign language is visual. Sumaira[11] developed Pakistani sign language recognition system by using Fuzzy Classifier. In this method, colored gloves are used to identify each fingertip and joint. The position features to fuzzy classifier calculate the angle between finger-tip and finger-joint. The proposed system recognition accuracy rate is quite high.Rudy Hartanto [12] researched to recognize hand gestures based on hue saturation value (HSV) and SURF feature algorithm. The system is capable to eliminate the background and it can recognize hand gestures without using glove. The recognizing under complex backgrounds for an alphabet sign language is low.Peter Matetelki[13] describes an Interpreter Glove for deaf and dumb people. This paper introduces automatic sign language gesture recognition. The automatic sign language interpreter consists of two algorithms: sign descriptor stream segmentation and text auto correction. The architecture works in complex applications and focus on developing hand gestures descriptors.

Visual models are most widely researched in literature. Visual models are more accurate because of the fact that sign language is visual. It has been decoded visually by hearing impaired people.But the capturing and processing power of human eye and brain is far superior to portable digital cameras and mobile computers. But with today's state of the art cameras and mobiles it is not far, behind Some of the recent visual models in literature related to different countries sign language recognition are presented here.

Derpanis G [14] proposed a unique method to vision based gesture recognition of single hand movements in American Sign Language (ASL). The proposed Collections of characteristic signatures were reached at by evaluating the perfect mappings among the phonemic actions and the kinematic explanation of the visual motion field on the image plane. Thismethod has been simulated and tested using 592 gesture structures and is found capable of generating a recognition accuracy of 86% for totally computerized handling and 97% for physically modified operation.

Nguyen [15] proposed sign language video tracking using facial features along with facial expression recognition in ASL. The proposed recognition framework analyzed time-based visual signs achieved tracking and classification using nine HMMs (Hidden Markov Model)and an SVM (Support Vector Machine). The tracking results are input to recognition model comprising HMM and SVM. The ASL facial expressions achieved 91.76% recognition.

The Australian sign language automatic recognition classifier developed by Holden Eun-Jung [16]uses face and hand tracks as features for recognition of the gesture expressions. The method effectively deals with the obstruction of face by identifying the contour of the foreground moving hands. The recognition of expressions is performed using HMM's with 163 test samples. The proposed method recognize 97% of the expressions.

Angur[17] proposed a new fingertip finder algorithm for recognizing Bengali sign language by using hand gestures. This method uses feed forward neural networks and centroid of the hand region from 2300 sign images of which 70% images are used for training, 15% images for testing and 15% images for validating, respectively. The proposed method averaged a recognizing rate of 88.69%.

Bastos[18] presented his study of sign language using Histogram of oriented gradients (HOG) and Zernike invariant moments (ZIM) to recognize 40 different signs from Brazilian sign language. This method shows high recognition rates, achieving a recognition rate of 96.77%.

The Chinese sign language (CSL) Synthesis method on mobile devices for the hearing imparied is discussed in [19]. The authors mainly discuss five key techniques like motion capture, static editor, motion interpolations, frame selection and animation render on mobile devices. The system is built under some assumptions for instance and words. They successfully implemented on windows mobiles to get a faster render effects with fairly good recognition rates.

The fingerspelling gestures for recognizing multiple sign languages by using HMM is proposed in[20]. The system converts finger spelled words to speech and vice versa using fingerspelling recognition in Czech, Russian and Turkish languages. This method is experimented on 88 different signs by five signers giving good conversion efficiency.

Paper [21]employs a real time gesture tracking and hand posture extraction by using markless recognition systemNew Zealand sign language. In this work 13 plus markless tracking gestures are used in unknown category during testing. The markless recognition of hand gestures is a more challenging area when compared to other models.

According to reference [22] the sign language gestures are converted to text and speech. The main objective of this paper is to build a low cost recognition system using different methods like hu moments, contour, histograms, convex and defects computation for recognition. The author identify hu moments combined with digital image processing techniques is the best approach for low cost recognition of sign language when compared to other methods.

Michael [23] proposed a mobile application for South African sign language recognition. The application connects to local server via Bluetooth to access database and other routires. Torecognize 31 static signs the system uses two networks based on log-sigmoid and symmetric Elliott activation functions.The paper also discusses support vector machines as classifier that has an recognition efficiency of 99%. The application works will in low end smartphones with execution times below 45ms, by using 15 system memory.

Mariusz [24] proposed polish sign language recognition with kinect sensor. Twotypes of features from primary data produced by Kinect sensor are used for hand tracking and shape representation. The dynamic time warping technique is used to recognize gestures from Kinect sensor data with an accuracy of 89%. In the second phase the accuracy jumped to 98% by adding hand shapes to the tracking data.

A Mexican sign language recognition system is being formulated in [25]. This system uses a movement sensor for capturing depth images and the skeleton of the human hand for tracking movements. The system uses as random forests, decision trees and ANN during recognition process. Resulting in an average recognition rate of 76.19%.

large vocabulary continuous sign language recognition across different signers is discussed in [26]. Which is evolving from artificial lab generated data to real life data. The system uses tracking & shape features to model signer dependent and independent large vocabulary SLR. The system was tested using 25 signers, 455 sign vocabulary, 19k sentence representing lab data and real life data from 9 signers, 1081 sign vocabulary, 7k sentences.Word error rates of 10% / 16.4% for lab data and 34.3% / 53% for real life data were reported.

In [27]analysis Finnish sign language head movements are tracked in motion captured data. The paper describes and analyzes the grammatical and textual function of nodes, nodding, head thrusts and head pulls in Finnish sign language data with 3D motion capture technology.

Merilian[28]worked on a number in Estonian sign language recognition tool based on morphological operations. That model language in a cross-linguistic perspective. The idea of number in sign language separates from the more straightforward versions of a number in spoken language.

Liwicki Stephan [29]researched extensively in British sign language automatic recognition system. Their system consists of three steps: hand shape recognition, without motion cells, hand shape recognition with robust visual features, and scalability to lexicon recognition with no re training. The system is tested using 100 words and capable of recognizing up to 98.9%.

Chung-wei[30] proposed moving object classification likes: cars, motorcycles, pedestrians and bicycle by using local shape from wavelet transform and HOG features with hierarchical SVM classification. The proposed method is tested on six video sequences for classification. The average computer processing times of the object segmentation is 79ms, object tracking is 211ms, and classification is 0.01ms respectively.

In Recent years support vector machine (SVM) classifier with Histogram of oriented gradients (HOG) features are the most popular techniques for vehicle detection [31]. In real time implementation this is important for advanced driver assistance system applications. To reduce the complexity of the SVM is to reduce the dimensions of HOG features. The proposed method in [31] using SVM classifies for vehicle detection is three times faster than other algorithm in the area.

The rest of the paper is organized as: section 3 describes the followed methodology in determining the sign similarity. Results and discussion is presented in section 4 with conclusions in section 5.

3. METHODOLOGY: INTER COUNTRY SIGN LANGUAGE CLASSIFICATION

Figure 4 show the procedure followed in this paper to investigate the similarity between basic structures of world sign languages. The experiment involves only alphabets as they are the basic structures for formation of any language. Methodology involves two phases: Training phase and Testing phase.

3.1. Database Creation

Sign language databases of only a few countries are publically available for research[32, 33]. But the images of alphabets do not match our requirement. Hence we searched for the alphabet images in google and created the database in controlled lab setup. Figure 1 shows the setup installed in the lab with a signer. A set of 9 signers helped us create alphabets of 30 countries. The sign language database for Indian Sign Language is having

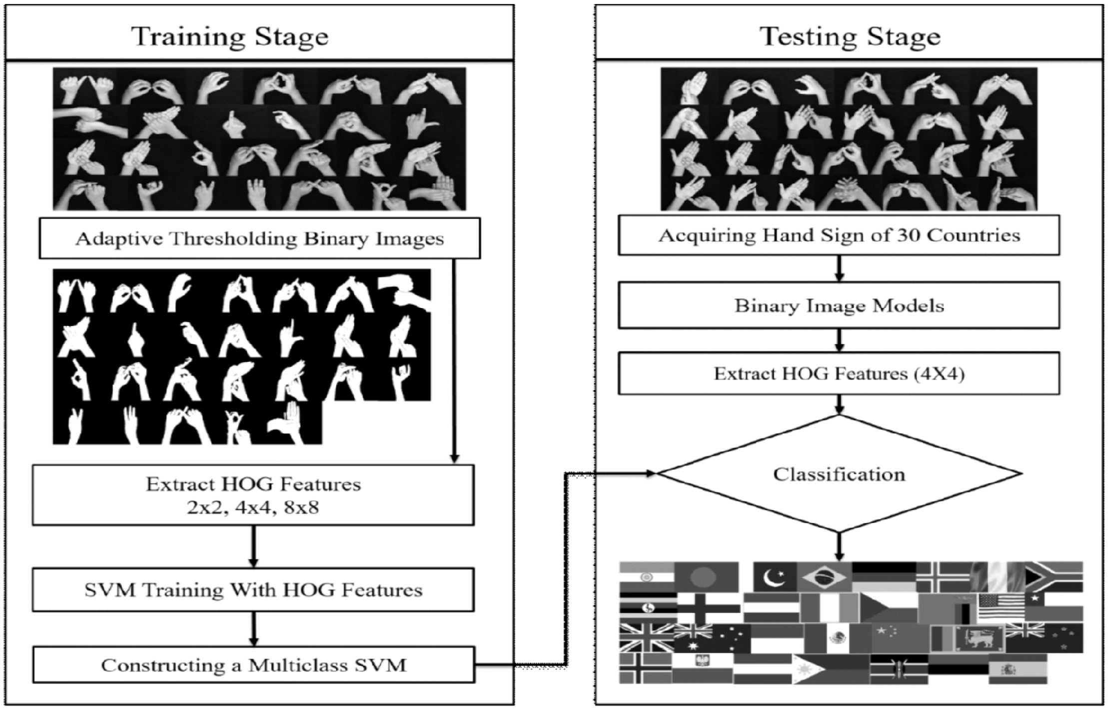

Figure 4: Algorithm for decoding relativity among world sign languages

$9 \times 26 = 234$ images. Each alphabet is photographed from 9 different signers. For 30 countries the database is having $9 \times 26 \times 30 = 7020$ sign alphabet images per language per country. Labelling each sign using a unique code such as *InA*1, *InA*2,....., *InA*9 represents alphabet 'A' from Indian Sign Language and the numbers represent signing subjects. Similarly, for ASL the labelling for alphabet '*Z*' is *AmZ*1, *AmZ*2, ..., *AmZ*9. Figure 2(a) and (b) shows sign images used in experimentation. The images are subjected to various processing methods to extract useful features for recognition.

3.2. Binarization of Images

Processing easiness for feature extraction calls for this step. The dimensionality is reduced to red plane and local maxima are computed. The local maxima in a 16×16 block is used as a threshold for that particular block making the process invariant to brightness and contrast. A set of binary sign images are coupled in figure 4 on the training side of the algorithm. Shape features are modelled from these binary images.

3.3. Low Level Features – Shape Indicators

A number of methods in literature help in determining shape features. This paper tests 10 such feature extraction models and tests on the sign – to – sign translator algorithm for best model. A two-decadelong challenge for producing animaging feature that is immune to illumination, noise, scale, orientation, partial occlusions giving good classificationaccuracy and computationspeed is coming good. The literature has Scale Invariant Feature Transform (SIFT) [34], Haar (HW) [35], Features from Accelerated Segment Test (FAST) [36], Speeded Up Robust Features (SURF) [37], Histogram of Oriented Gradients (HOG) [38], Harris Corners (HC) [39], Local Binary Patterns (LBP) [40], Local Self Similarities (LSS) [41], Binary Robust Invariant Scalable Key points (BRISK) [42], Maximally Stable External Regions (MSER) [43] and many more. A formal comparison of these methods indicate that each one has got their pros and cons. Table 1 characterizes these features based on the parameters required for good feature descriptor[44].

Table 1
Feature Descriptor Characterization for Sign Language Application

Methods	*Timing*	*Transformation*	*Scaling*	*Rotation*	*Blurring*	*Illumination*
FAST	*Common*	*Common*	*Common*	*Bad*	*Bad*	*Bad*
SIFT	*Bad*	*Good*	*Good*	*Best*	*Best*	*Best*
SURF	*Good*	*Best*	*Best*	*Good*	*Good*	*Good*
HOG	*Good*	*Best*	*Best*	*Best*	*Best*	*Best*
MESR	*good*	*Good*	*Good*	*Good*	*Common*	*Good*
Harris	*Common*	*Common*	*Good*	*Good*	*Common*	*Good*
Hessian	*Common*	*Common*	*Bad*	*Good*	*Bad*	*Some good*
LBP	*good*	*Good*	*Good*	*Good*	*Common*	*Good*
LSS	*Common*	*Common*	*Good*	*Good*	*Common*	*Good*
Brisk	*Common*	*Common*	*Bad*	*Good*	*Bad*	*Some good*

From table 1 it can be understood that the best feature descriptor is HOG. There are many variations for HOG such as HOG-LBP, HOG-LSS, LG-HOG and so on. In this paper we tried with all of them and results match to that indicated in table 1. Please refer the corresponding literature for additional information regarding low level image feature descriptors in the references provided adjacent to them in the previous paragraph.

3.4. Support Vector Machines

SVM's analyze data and produces binary responses for classification problem, which come under a class of supervised learning classifier models. The basic SVM, classifies a two class problem by projecting a hyper plane between data during training phase. The hyper plane is characterized by a subset of data points acting as support vectors. During training the SVM is presented with example vectors $\boldsymbol{x_i} \in \Re^n, \boldsymbol{i} = 1....\boldsymbol{l};$ $\boldsymbol{l}$ training samples, to label each data sample as either +1 or -1 class label which forms the indicator vector $\boldsymbol{y_i} \in \{+1, -1\}$. SVM formulates the optimization problem as a decision boundary $\boldsymbol{D}(\boldsymbol{x})$ such that

$$\boldsymbol{D}(\boldsymbol{x}) = \min_{\boldsymbol{w},\boldsymbol{b}.\lambda}\left(\frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + \boldsymbol{C}\sum_{\boldsymbol{i}=1}^{\boldsymbol{l}}\lambda_{\boldsymbol{i}}\right)$$

Subjected to $$\boldsymbol{y_i}\left\{\boldsymbol{w}^T\phi\left(\boldsymbol{x_i}\right) + \boldsymbol{b}\right\} \geq 1 - \lambda_{\boldsymbol{i}} \text{ with } \lambda_{\boldsymbol{i}} \geq 0, \boldsymbol{i} = 1, 2, ..., \boldsymbol{l}; \tag{1}$$

Where C is a positive constant defining regularization. The terms $\boldsymbol{w}$ and $\boldsymbol{b}$ are weight and bias. λ is the misclassification handler.The function $\boldsymbol{m}(\boldsymbol{x}): \boldsymbol{x} \to \phi(\boldsymbol{x})$ maps feature vector $\boldsymbol{x}$ to a higher dimensional space. The mapping function $\boldsymbol{m}(x)$ maps $\boldsymbol{x}$ into a dot product of feature space that satisfies $\boldsymbol{m}\left(\boldsymbol{x_{i-1}}, \boldsymbol{x_i}\right) = \phi^T\left(\boldsymbol{x_{i-1}}\right)\phi\left(\boldsymbol{x_i}\right)$.

3.5. Multi Class SVM

The most widely used multi class SVM models are One Vs All (OVA),One Vs One (OVO)[45], Directed Acyclic Graph (DAG)[46] and Error Correcting Output Codes (ECOC) [47]. OVA creates N binary SVM's for all categories where N is class number. For a nth SVM, only examples in that class are positive and reaming are negative. The computation time is less but at a compromised efficiency. OVO creates a pairwise 0.5N(N-1) SVM's and pairwise voting to accommodate new samples for solving multi class problems. DAG training is from OVO model and testing is from binary acyclic graph model. ECOC disambiguates output binary codes to construct a code word matrix which is compared with generated bit vectors by selecting a row as a class having minimum hamming distance. This method gives good classification rates compared to other four at the cost of execution speed. The slower speed is due to the increased length of code words to disambiguates N classes. The minimum code words in ECOC is $\log_2 N$ to a maximum of $2^{N-1}-1$ bits. Comparing the multi class SVM methods from MALAB implementation, we found ECOC performs better at optimum speeds.

The similarity measure for 30 different world sign language alphabets using computer vision model and machine learning algorithms is proposed. Experimental results show the sign language relativity between countries and continents. Validation is through human expert identification and structural similarity index measure (SSIM).

4. RESULTS AND DISCUSSION

Experimentation with the proposed methodology aims to answer the following questions.

1. How much similarityis observed between sign languages of the 30 countries.
2. Does countries of the same continent exhibit more similarity than others.
3. What is the overall similarity in Sign Language between continents of the world.
4. Can a sign – to – sign converter is possible at the image level between different sign languages of the world.

The captured sign images are large and cubic interpolations trimmed their size to 64×64. The RGB colour images have large R (red) content and hence R plane is extracted for processing. Block thresholding with in a 16-pixel block separates foreground hand regions from background. Ten features are extracted from these binary images. For each country a feature matrix is build. The size of each feature matrix is $\boldsymbol{m}^f \times \boldsymbol{n}^f$, where $\boldsymbol{m}$ = 26, i.e. the number of alphabets and $\boldsymbol{n}$ is variable column vector that captures feature values. $\boldsymbol{f}$- consists of country and test subject indicator.

The first problem encountered during feature matrix creation is the inability of our algorithm to control the length of $\boldsymbol{n}$, where n is intital length of the feature vector. For each image the length of the feature vector changes due to number of feature points detected during the feature extraction phage. For 26 different images we have 26 different feature lengths. Feature length normalization has been challenging, as it is difficult to decide on the number of features required to produce good classification rate. Figure 5 shows variational feature plots of each alphabet in Indian sign language and theaverage number $\boldsymbol{n}$ for 26 sign images of 30 countries for all the feature models is given in table 2. The plots also show that the feature variations are almost constant cross features even though the number of features per sign per country changed marginally. Normalization of $\boldsymbol{n}$ through maximum feature size is done to preserve the actuals and the remaining features are zero padded to design a constant size feature matrix. This procedure gives a fixed feature size matrix of size $\boldsymbol{m} \times \max(\boldsymbol{n})$.

The first part is to find the similarity between sign languages from 30 different countries. For this the feature matrices of all countries from all feature vector models is prepared. A multiclass SVM with ECOC model is trained with one country and tested with all other countries for each feature type.

Testing results in a classification matrix or a confusion matrix between two countries. All countries sign languages are tested against one trained country and cross verification is done by testing the multiclass SVM for all other countries. Table 3 gives values in number of matches and total percentage of matching of one country with other countries in the set. The SVM is trained with single sample and tested with a different sample form our database. Multiple testing of this kind produced more or less similar results with a deviation of ±3%.

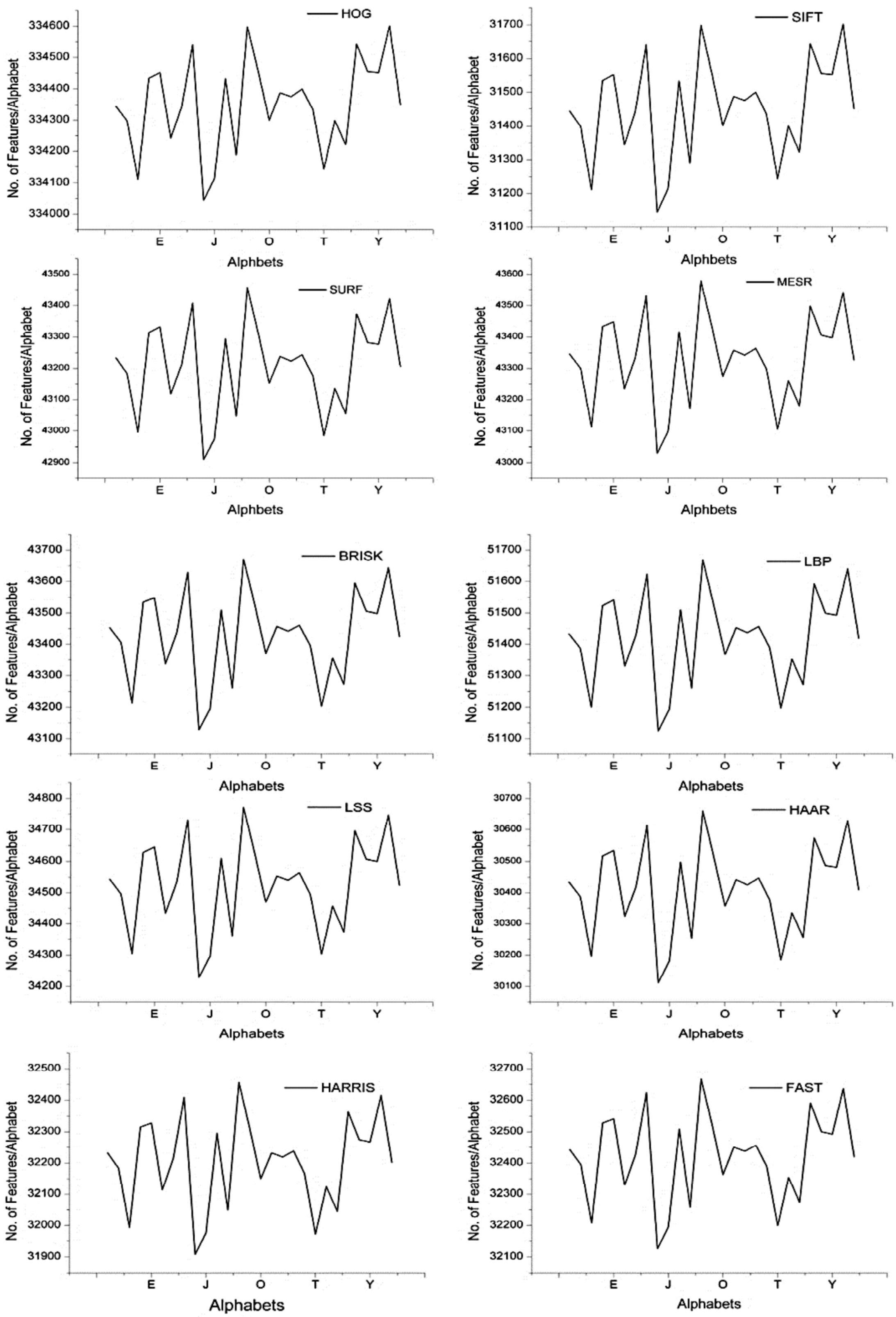

Figure 5: Feature Number variations of Alphabets from ISL

Table 2
Average Number of Features per Alphabet per country

Features/Countries	*HOG*	*SIFT*	*SURF*	*MESR*	*BRISK*	*LBP*	*LSS*	*HAAR*	*HARRIS*	*FAST*
india	334350	31451	43213	43313	43433	51417	34510	30409	32208	32426
bangala	334305	31404	43166	43266	43384	51364	34457	30354	32150	32367
french	334118	31213	42973	43068	43186	51166	34254	30148	31944	32160
irish	334441	31533	43292	43384	43499	51474	34559	30453	32244	32460
american	334459	31548	43305	43397	43512	51483	34567	30459	32246	32458
spanish	334250	31339	43094	43182	43296	51267	34347	30236	32021	32231
australian	334350	31438	43188	43272	43386	51355	34433	30320	32100	32308
pakistan	334548	31631	43376	43457	43566	51533	34611	30494	32270	32476
newzealand	334051	31131	42875	42952	43058	51021	34097	29975	31748	31954
british	334121	31201	42943	43015	43119	51081	34154	30029	31800	32002
srilanka	334440	31515	43253	43324	43424	51381	34450	30322	32090	32289
brazil	334195	31266	43002	43069	43167	51123	34189	30058	31826	32020
chinese	334605	31674	43406	43473	43570	51523	34589	30458	32226	32420
czech	334463	31530	43257	43319	43415	51364	34425	30291	32054	32243
estonian	334307	31369	43091	43153	43249	51196	34257	30118	31880	32066
finnish	334394	31454	43175	43235	43328	51275	34336	30193	31952	32134
german	334382	31439	43160	43218	43309	51252	34311	30168	31925	32104
hungarian	334406	31459	43178	43235	43326	51264	34319	30174	31931	32106
iceland	334340	31389	43103	43158	43245	51183	34235	30088	31845	32015
kenya	334150	31194	42905	42955	43039	50977	34024	29872	31629	31796
mexican	334306	31350	43058	43106	43189	51126	34171	30015	31769	31933
nederland	334228	31268	42976	43022	43100	51033	34074	29913	31666	31828
norwegin	334550	31590	43293	43339	43413	51343	34384	30221	31971	32129
polish	334462	31498	43200	43241	43314	51243	34279	30112	31857	32014
southafrican	334459	31492	43193	43230	43298	51224	34257	30085	31825	31981
uganda	334608	31639	43337	43372	43435	51356	34389	30212	31951	32107
indonesia	334650	31681	43377	43409	43467	51388	34420	30243	31981	32137
chile	334694	31723	43415	43443	43500	51421	34452	30272	32008	32162
philippnies	334741	31770	43460	43486	43542	51460	34491	30310	32044	32195
zambian	334790	31818	43504	43529	43585	51500	34526	30344	32073	32219

The table 3 gives a confusion matrix produced form HOG features that trains and tests SVM classifier for 30 sign languages of the world. There is a full matching of features from the same country with different test image vector for multiple testing. The sign matches between two countries forms the box value of intersecting country names. For example, India and Bangladesh has a sign similarity of 61.53% that is 16 signs match out of 26 alphabets. Visual cross checking between the alphabets of India and Bangladesh provides a platform for validating the multi class SVM classifier with the corresponding feature extraction technique. Figure 6 shows the results of cross checking. From figure 6 we cross verified and found the alphabets ‘E’, ‘F’, ‘G’, ‘I’, ‘K’, ‘Q’, ‘S’, ‘U’, ‘W’ and ‘Z’ are differently oriented in both countries sign languages. Multiple testing using SVM classifier using different test subjects resulted in the same result with variance of ±2.8%.

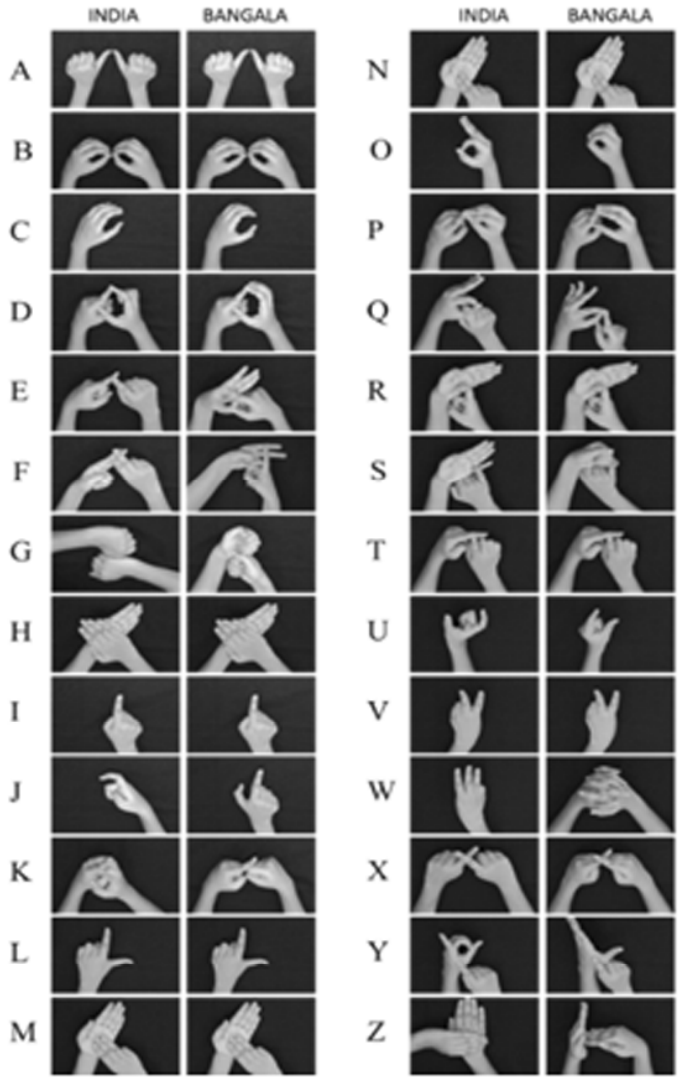

Figure 6: Showing side by side representation of Indian sign language and Bangladesh sign language for visual cross verification

Table 3
Country to Country Alphabets Matching Table

Co	*in*	*ba*	*fr*	*ir*	*am*	*sp*	*au*	*pa*	*nz*	*uk*	*sr*	*br*	*cn*	*cz*	*es*	*fi*	*ge*	*hu*	*ic*	*ke*	*me*	*ne*	*no*	*po*	*so*	*ug*	*ia*	*ch*	*ph*	*za*
in	26	16	2	5	3	5	10	4	12	10	10	5	4	10	6	5	5	5	6	5	4	3	11	6	5	5	11	4	5	6
ba	16	26	2	3	2	3	11	8	14	14	13	3	4	15	6	3	3	3	4	3	2	2	18	3	3	3	15	2	3	4
fr	4	3	26	11	9	11	2	3	1	4	3	12	7	2	3	13	12	11	9	12	10	11	2	7	12	10	2	10	10	10
ir	1	2	7	26	9	12	3	3	3	4	4	15	5	3	7	16	13	15	14	13	13	14	3	7	13	15	4	13	15	13
am	0	1	7	9	26	16	0	2	1	3	2	12	6	2	5	12	16	15	9	16	17	12	2	4	18	14	3	9	15	15
sp	2	2	10	13	16	26	2	2	2	4	1	17	10	1	6	21	25	19	14	23	24	20	2	8	22	18	2	13	22	22
au	10	9	2	2	2	2	26	10	13	14	14	1	1	7	1	2	2	2	2	3	1	0	10	1	3	2	6	1	1	3
pa	5	8	1	1	1	1	10	26	10	10	11	1	1	7	3	1	1	1	1	1	2	1	9	1	1	1	7	2	2	1

contd. table 3

Co	*in*	*ba*	*fr*	*ir*	*am*	*sp*	*au*	*pa*	*nz*	*uk*	*sr*	*br*	*cn*	*cz*	*es*	*fi*	*ge*	*hu*	*ic*	*ke*	*me*	*ne*	*no*	*po*	*so*	*ug*	*ia*	*ch*	*ph*	*za*
nz	11	14	1	3	1	1	17	11	26	23	22	1	1	10	3	1	1	1	1	1	2	1	13	1	1	1	9	2	2	1
uk	11	14	2	4	3	4	15	11	22	26	21	3	3	9	4	3	4	3	2	4	5	3	12	1	4	3	10	4	4	3
sr	10	12	0	4	1	1	15	11	20	19	26	1	2	9	4	1	1	1	1	1	2	1	12	1	1	1	9	2	2	1
br	3	1	10	16	12	18	1	1	1	3	1	26	10	3	6	21	19	19	17	17	17	17	1	9	17	19	2	18	18	16
cn	4	3	6	8	7	12	1	1	1	3	1	12	26	2	4	14	12	13	10	12	11	13	2	7	11	13	2	11	10	11
cz	9	12	2	3	1	1	9	6	9	8	9	1	1	26	5	1	1	1	2	1	2	1	15	1	1	1	13	2	3	2
es	4	4	0	5	6	6	2	2	1	3	4	7	3	6	26	7	7	7	8	7	7	5	6	5	7	7	7	6	6	7
fi	4	3	12	17	12	21	2	2	2	4	2	20	12	3	6	26	22	21	19	21	20	19	2	10	20	20	3	17	21	21
ge	2	2	10	13	16	25	1	2	2	3	1	18	10	2	6	22	26	19	15	23	24	17	1	8	22	18	2	13	23	22
hu	4	3	10	15	15	19	2	2	2	4	2	18	11	3	6	21	19	26	16	21	19	17	2	9	23	23	3	15	16	19
ic	3	3	7	13	8	13	2	2	2	2	1	15	8	4	6	18	14	15	26	14	12	13	3	13	14	15	4	14	14	14
ke	3	3	11	13	16	23	3	3	3	5	3	16	10	3	6	21	23	20	14	26	23	16	3	9	23	20	3	14	20	23
me	1	1	9	13	17	24	1	3	3	5	3	16	9	3	7	20	24	19	13	23	26	18	3	7	22	18	3	14	23	22
ne	2	1	9	13	11	17	1	1	0	2	2	16	11	2	5	19	17	16	14	15	17	26	1	7	15	15	2	13	16	15
no	11	13	1	2	2	1	11	9	11	10	12	1	2	15	5	1	1	1	2	1	2	1	26	2	1	1	13	2	2	1
po	4	1	7	7	4	8	2	1	2	2	0	11	4	1	6	9	8	8	12	8	7	7	1	26	8	7	2	10	8	8
so	3	3	11	13	18	22	3	2	3	5	3	16	9	3	6	20	22	23	15	24	22	16	3	9	26	21	3	14	19	22
ug	4	3	9	15	14	18	2	2	2	4	2	18	11	3	6	20	18	22	15	20	18	16	2	9	20	26	3	15	15	18
ia	11	13	1	4	2	2	6	6	7	8	9	2	3	12	7	2	2	2	3	2	3	2	4	2	2	2	26	3	4	3
ch	5	3	11	15	10	1	1	4	4	6	4	18	9	3	6	17	13	15	14	14	14	14	4	9	14	15	6	26	14	13
ph	2	2	10	17	15	22	1	2	4	4	3	17	8	2	7	21	23	16	15	20	23	19	3	8	19	15	3	14	26	22
za	5	7	10	14	15	22	3	3	3	4	3	15	10	4	7	21	22	19	15	23	22	16	4	9	22	18	4	13	22	26
%	23.1	24.1	26.4	38.1	35.1	45.8	21.2	18.6	23.8	27.7	24.6	42.8	27.1	22.4	23.2	48.6	48.2	45.9	39.5	47.9	47.6	41.2	23.1	25.5	47.4	44.5	23.3	37.9	46.3	46.7

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
G	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
O	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
W	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Z	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 7: Confusion Matrix between Indian Sign alphabets and Bangla Sign alphabets with SVM Classifier

Misclassifications between the Indian signs (ISL) and Bangladesh signs (BanSL) is projected from the confusion matrix in figure 7. The green is Bangladesh and saffron is India. From the confusion matrix the Bangladesh 'E' is classified as Indian 'D'. From figure 6, there is some kind of structural relation between these two letters. 'F' in BanSL is classified as 'O' in ISL. A total of 10 signs are misclassified using our proposed method of classification. Total 16 signs match between the two countries.

Matching between French and Indian sign languages is only 7.6% when SVM is trained with Indian sign language and tested with French sign language but it is 15.2% for the SVM trained with French sign language and tested with Indian. The signs that passed the test in the first instance are 'C' and 'V'. In the opposite direction the signs 'C', 'V', 'D' and 'W' matched during testing with Indian. The reason for structural shape similarity can be gauged visually using the figure 8. The matching signs between Indian and French are shown in figure 8. Because of closeness of Indian SL with Bangladesh SL it also gets the same 7.6% similarity with French SL.

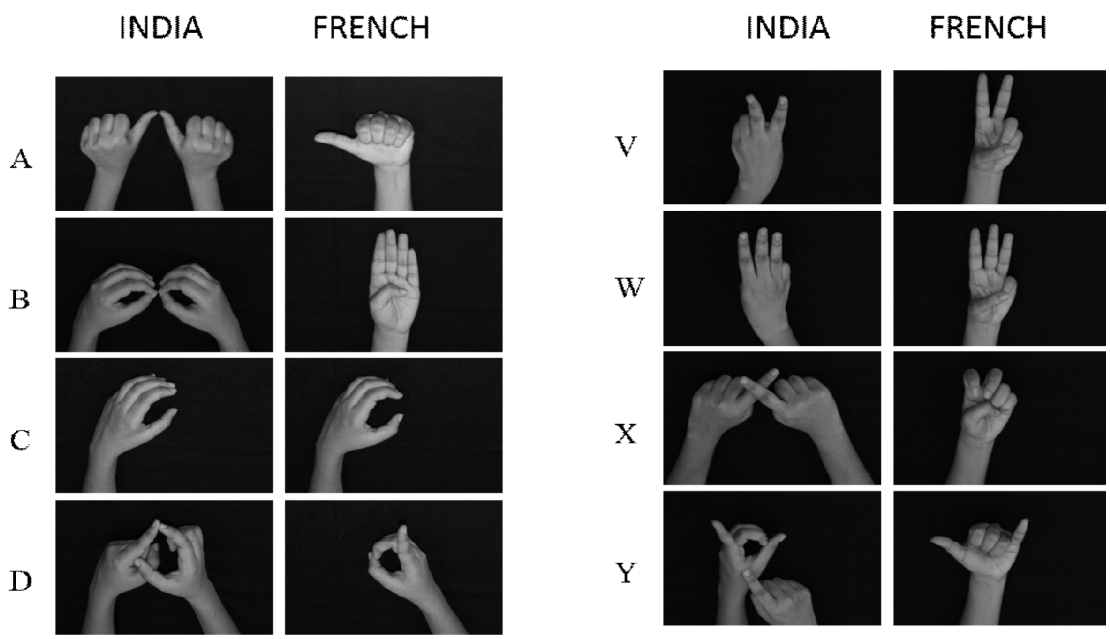

Figure 8: Indian SL with French SL matching signs

The reason for matching in letter 'D' is due to a 50% shape matching between the two signs. Multiple instances of training also classified 'W' correctly. Table 3 gives the confusion matrix between 30 countries having use their own sign languages with matching sign numbers. The last row in the table is average matching percentage of each county with the rest of the 29 countries. From table 3 the following observations on the similarity of world sign languages is formulated as

1. Spain and German Sign languages are 96% similar with 25 signs being matched intwo-way training and testing.
2. Mexican – Spain, Mexican – German and Kenya – South Africa are next with 24 sign matches having 92.3% similarity.
3. The lowest similarity set countries are (Australia, American SL), (American, Indian SL), (Netherlands, Australia SL), (Srilanka, French SL), (Estonian, French SL), (Netherlands, New Zealand SL) and (Polish, Srilanka SL) where the matching signs in both directions range between 0 to 2. Visual verification can be made using figure 9 for a set of two sign alphabets 'C' and 'N'.

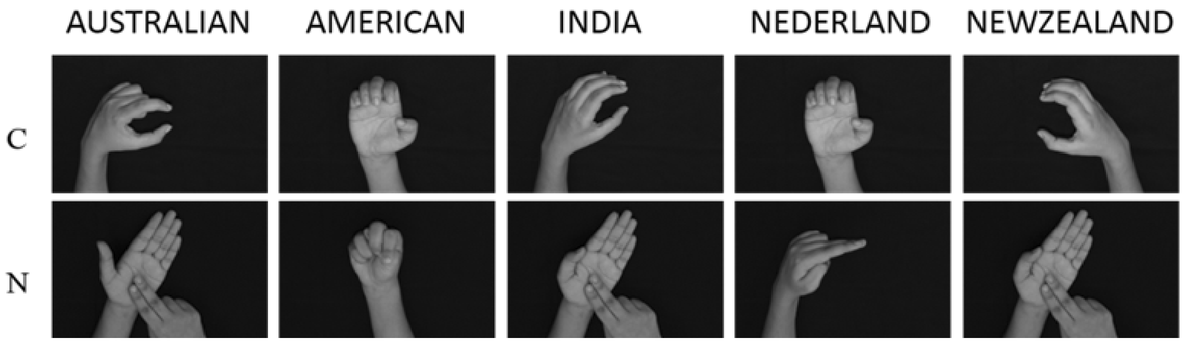

Figure 9: For Visual Verification between sign languages of 5 different countries

4. The reason interpreted by us for lowest and highest similarity match among sign languages of different countries depend on the geographical regions in which the country is located.
5. The continent wise similarity measure is checked and the results for one continent i.e. Asia is projected in the plot in figure 10.

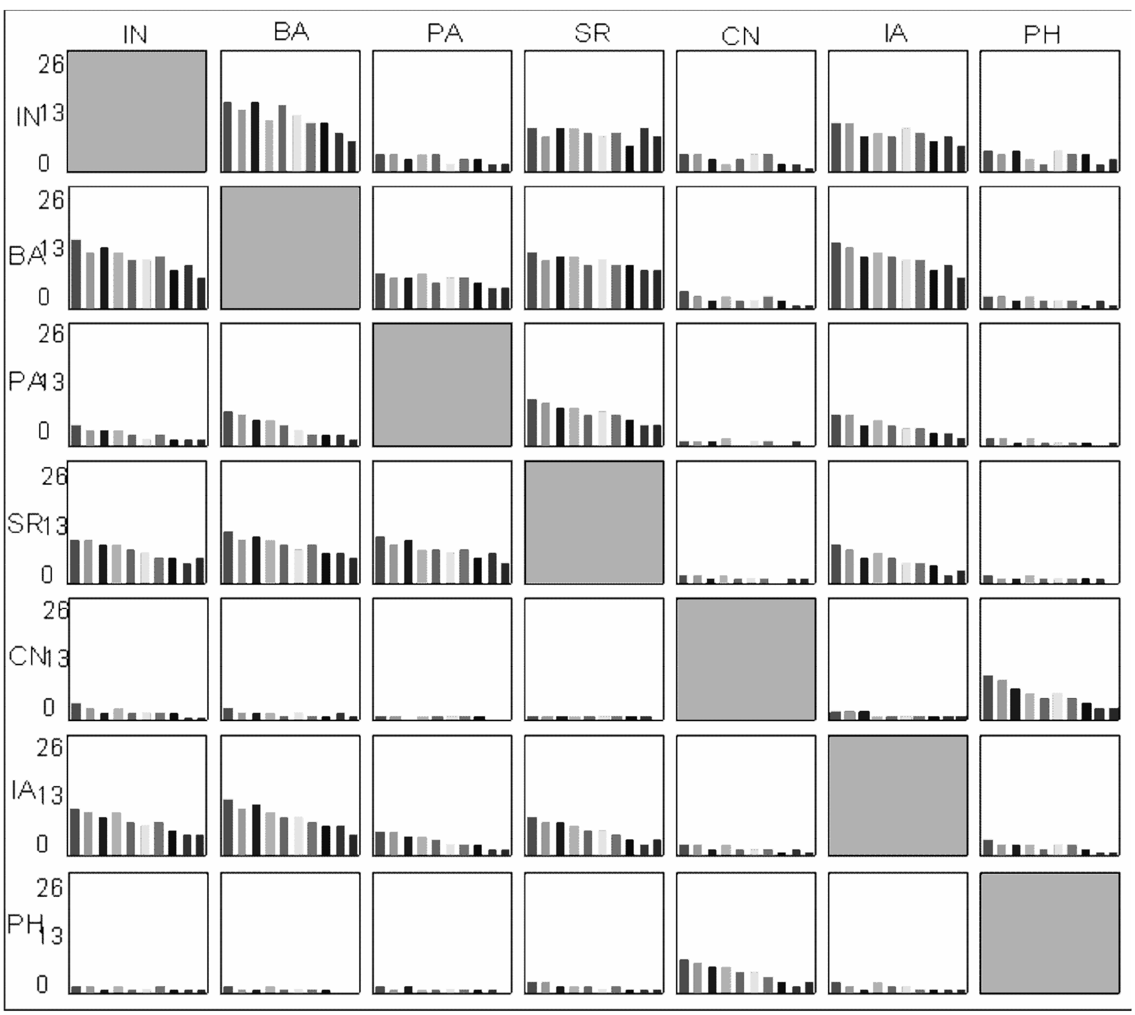

Figure 10: Sign Language Similarity measure for Asian Countries

Figure 10 has 7 Asian countries namely, India (IN), Bangladesh (BA), Pakistan (PA), Sri Lanka (SR), China (CN), Indonesia (IA) and Philippines (PH). The plots show Histogram of matching signs with 10 different types of features. Each feature representing a particular colour. Red-HOG, Green-SIFT, Blue-SURF, Cyan-MESR, Magenta-BRISK, Yellow-LBP, Dark Yellow-LSS, Navy-HAARS, Purple-HCORNERS, Wine-FAST.

Except China and Philippines all other countries sign languages show a high range of similarity of around 50-60%. China and Philippines have a high range of similarity due to their cultural influences on each other. HOG features give a high range to classifier performance compared to other features in the list during multiple instances of testing as shown in figure 10.

6. There is high similarity between countries from same continent compared to that of countries from different continents as can be analyzed from table 3.

We also explored the idea of sign – to – sign translation as in case of spoken language translators[1]. HOG features and SVM are used for training and testing. But cross verification of the feature vector is checked using a known image structure measurement parameter called Structural Similarity Index Measure (SSIM) [48, 49]. A (Graphical User Interface) GUI is built in Matlab to do the job. The user of the GUI can translate sign language alphabets between countries and check the similarity index (SSIM) value. The translator uses HOG features and SVM classifier for the recalling the corresponding signs. Snapshots of GUI testing are in figures 11 and 12.

Figure 11: Sign to Sign Translator between Bangladesh and Indonesia for sign D

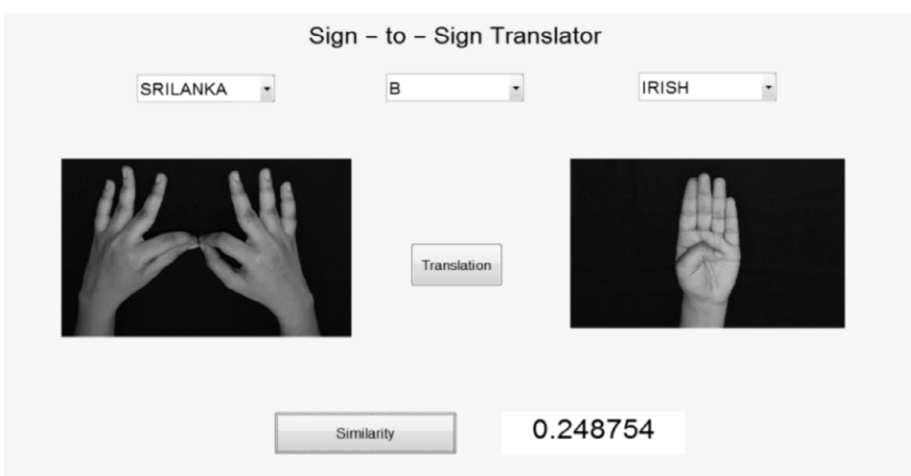

Figure 12: Sign to Sign Translator between Sri Lanka and Irish for sign B

Table 4 has SSIM percentage similarity matching values for the countries under sign language test. Matching the performance of HOG+SVM with SSIM has a deviation of ±3%. The performance of the best feature for a sign – to – sign translator with respect to structural similarity of signs is computed rigorously with 9 different sets of data from 30 different sign languages for 6 continents around the world is shown in figure 13.

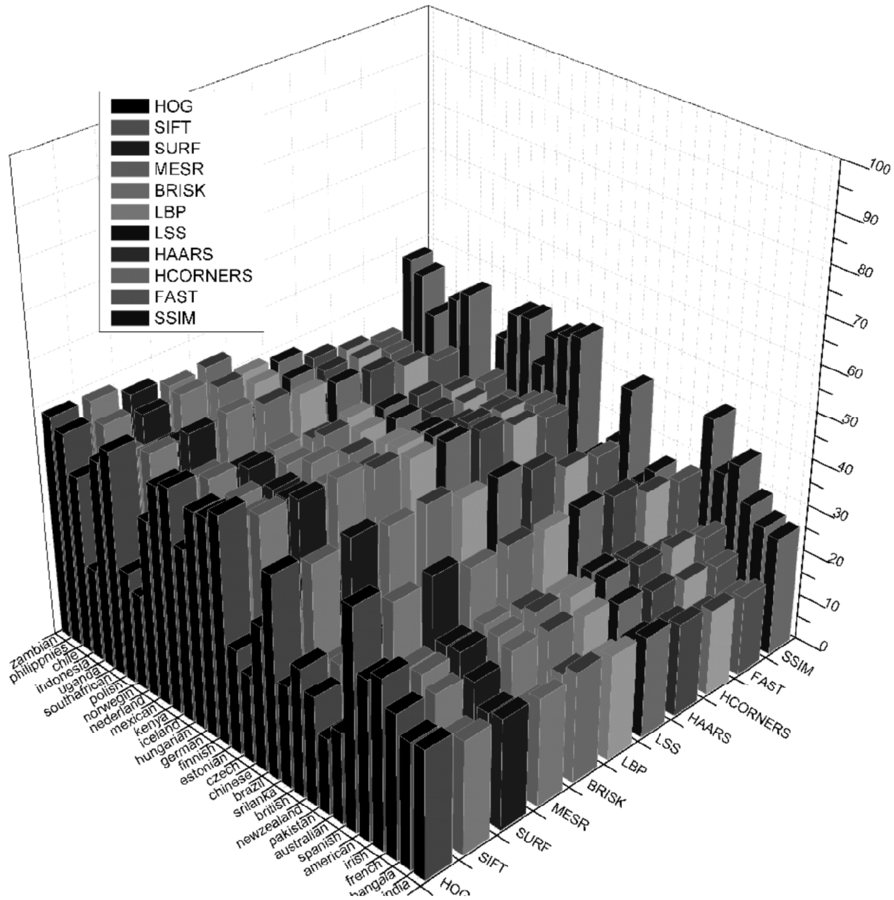

Figure 13: Performance of SVM with features used and cross verification with SSIM

5. CONCLUSION

An attempt is made to find similarity between sign languages from 30 different countries based on image processing models and pattern classifiers. Ten feature extraction techniques are compared for this work. Multi class Support vector machine classified these features and the performance of the classifier with respect to each feature is measured. Visual verification and structural verification using SSIM are preformed to validate the classifiers performance. Overall the SVM classifier registered a 95% matching with HOG feature vector and the remaining feature vectors produced less than 90% matching. A high similarity in sign languages is found in countries of same continent which are geographically close to each other. Cultural variations is also a cause for large variations in neighbouring countries having different sign languages for example India and China. A sign – to – sign translator between alphabets of 30 countries with their similarity is created and tested. This translator can be made dynamic to accept signs from various countries online and use the translator to communicate effectively by sign language users of different countries without learning other countries sign languages.

Table 4
SSIM percentages for similarity verification between countries

Co	*in*	*ba*	*fr*	*ir*	*am*	*sp*	*au*	*pa*	*nz*	*uk*	*sr*	*br*	*cn*	*cz*	*es*	*fi*	*ge*	*hu*	*ic*	*ke*	*me*	*ne*	*no*	*po*	*so*	*ug*	*ia*	*ch*	*ph*	*za*
in	100	58.8	13.5	15.4	9.6	15.4	37.3	16.2	41.2	34.6	34.6	18.1	16.2	36.9	20.4	16.9	16.9	16.9	22.3	20.0	13.5	10.8	41.2	23.1	17.3	18.1	41.5	16.5	8.5	18.1
ba	58.8	100	6.5	12.3	5.8	9.6	41.2	29.2	52.3	52.3	48.1	10.8	13.8	58.5	21.9	10.8	10.8	10.0	14.2	13.8	8.5	8.5	67.7	11.5	10.8	10.8	56.5	10.8	8.1	26.5
fr	13.5	6.5	100	40.0	33.5	39.6	7.7	10.0	9.6	13.1	10.4	41.2	25.8	11.5	10.4	48.5	41.9	40.8	33.8	43.1	37.3	40.8	6.5	25.8	41.9	39.6	7.7	41.9	37.3	38.8
ir	15.4	12.3	40.0	100	33.8	45.0	10.0	10.0	10.0	14.2	14.2	54.6	15.8	13.5	27.7	58.5	48.8	56.2	54.6	48.8	48.8	53.1	12.3	25.8	47.7	56.9	14.2	58.5	63.1	50.8
am	9.6	5.8	33.5	33.8	100	58.5	0.0	4.6	3.5	8.5	6.2	43.1	23.8	6.5	16.2	43.8	60.8	54.6	33.1	62.3	64.6	43.1	6.2	15.0	65.8	53.5	10.0	35.4	58.1	56.5
sp	15.4	9.6	39.6	45.0	58.5	100	8.5	8.5	8.5	14.2	6.5	58.5	37.7	5.0	20.8	77.7	92.7	70.0	50.8	83.5	91.2	75.4	9.2	13.8	81.5	68.1	6.2	4.6	83.1	83.5
au	37.3	41.2	7.7	10.0	0.0	8.5	100	35.0	49.6	50.8	51.2	5.8	5.8	23.8	3.5	6.5	6.5	6.5	6.5	12.3	4.6	2.3	37.3	4.6	10.0	7.3	20.0	4.6	4.6	11.2
pa	16.2	29.2	10.0	10.0	4.6	8.5	35.0	100	37.3	37.3	39.2	4.2	4.2	24.2	10.8	3.5	4.2	3.5	3.5	3.5	7.3	4.6	31.5	4.2	3.5	3.5	27.3	14.2	8.1	11.2
nz	41.2	52.3	9.6	10.0	3.5	8.5	49.6	37.3	100	85.0	85.4	3.5	3.5	37.3	10.4	3.5	3.8	4.2	3.5	3.5	6.5	3.5	50.8	3.5	3.5	4.6	33.5	14.2	12.3	11.9
uk	34.6	52.3	13.1	14.2	8.5	14.2	50.8	37.3	85.0	100	79.2	10.8	10.8	33.5	14.2	10.4	14.2	10.0	7.3	13.8	18.1	12.3	45.4	3.5	13.8	10.4	37.3	22.7	13.8	14.6
sr	34.6	48.1	10.4	14.2	6.2	6.5	51.2	39.2	85.4	79.2	100	2.3	6.5	33.1	13.8	3.5	3.5	4.2	4.2	3.5	6.5	3.1	46.9	4.2	3.5	3.5	33.1	14.6	11.2	10.0
br	18.1	10.8	41.2	54.6	43.1	58.5	5.8	4.2	3.5	10.8	2.3	100	37.3	10.0	23.8	80.0	71.9	71.9	65.0	64.2	64.2	64.2	4.6	33.5	62.7	72.7	4.2	66.9	62.3	56.2
cn	16.2	13.8	25.8	15.8	23.8	37.7	5.8	4.2	3.5	10.8	6.5	37.3	100	8.5	13.8	52.7	43.1	50.4	36.9	45.0	39.2	50.4	10.4	23.8	39.2	48.8	4.6	33.5	33.1	39.2
cz	36.9	58.5	11.5	13.5	6.5	5.0	23.8	24.2	37.3	33.5	33.1	10.0	8.5	100	16.9	4.2	4.2	3.5	6.5	3.5	7.3	3.5	54.6	4.2	4.2	3.5	48.8	9.6	6.2	13.5
es	20.4	21.9	10.4	27.7	16.2	20.8	3.5	10.8	10.4	14.2	13.8	23.8	13.8	16.9	100	25.8	25.8	23.8	30.4	23.5	26.5	20.0	23.5	19.6	25.8	25.8	23.8	22.7	23.8	26.5
fi	16.9	10.8	48.5	58.5	43.8	77.7	6.5	3.5	3.5	10.4	3.5	80.0	52.7	4.2	25.8	100	83.5	79.2	73.8	80.0	75.8	71.9	9.6	37.7	75.8	75.8	12.3	65.8	79.6	81.5
ge	16.9	10.8	41.9	48.8	60.8	92.7	6.5	4.2	3.8	14.2	3.5	71.9	43.1	4.2	25.8	83.5	100	71.5	55.0	86.9	91.2	64.6	3.5	29.2	85.4	67.7	7.3	48.8	86.5	83.8
hu	16.9	10.0	40.8	56.2	54.6	70.0	6.5	3.5	4.2	10.0	4.2	71.9	50.4	3.5	23.8	79.2	71.5	100	60.0	79.2	71.2	64.2	6.9	34.2	86.9	88.8	8.8	55.0	61.2	70.0
ic	22.3	14.2	33.8	54.6	33.1	50.8	6.5	3.5	3.5	7.3	4.2	65.0	36.9	6.5	30.4	73.8	55.0	60.0	100	50.8	44.6	48.5	10.4	48.5	51.9	54.6	13.8	52.3	56.2	55.8
ke	20.0	13.8	43.1	48.8	62.3	83.5	12.3	3.5	3.5	13.8	3.5	64.2	45.0	3.5	23.5	80.0	86.9	79.2	50.8	100	86.5	58.1	11.2	35.0	85.0	72.7	14.2	52.3	75.8	86.5
me	13.5	8.5	37.3	48.8	64.6	91.2	4.6	7.3	6.5	18.1	6.5	64.2	39.2	7.3	26.5	75.8	91.2	71.2	44.6	86.5	100	67.7	8.1	28.1	84.2	67.7	11.2	53.1	87.7	81.2
ne	10.8	8.5	40.8	53.1	43.1	75.4	2.3	4.6	3.5	12.3	3.1	64.2	50.4	3.5	20.0	71.9	64.6	64.2	48.5	58.1	67.7	100	4.6	24.2	56.5	56.5	8.1	52.3	73.5	61.2
no	41.2	67.7	6.5	12.3	6.2	9.2	37.3	31.5	50.8	45.4	46.9	4.6	10.4	54.6	23.5	9.6	3.5	6.9	10.4	11.2	8.1	4.6	100	10.0	3.5	3.5	45.8	16.2	12.3	16.5
po	23.1	11.5	25.8	25.8	15.0	13.8	4.6	4.2	3.5	3.5	4.2	33.5	23.8	4.2	19.6	37.7	29.2	34.2	48.5	35.0	28.1	24.2	10.0	100	29.2	27.3	6.2	32.3	28.1	33.5
so	17.3	10.8	41.9	47.7	65.8	81.5	10.0	3.5	3.5	13.8	3.5	62.7	39.2	4.2	25.8	75.8	85.4	86.9	51.9	85.0	84.2	56.5	3.5	29.2	100	80.0	10.4	51.2	71.9	82.3
ug	18.1	10.8	39.6	56.9	53.5	68.1	7.3	3.5	4.6	10.4	3.5	72.7	48.8	3.5	25.8	75.8	67.7	88.8	54.6	72.7	67.7	56.5	3.5	27.3	80.0	100	10.4	56.2	55.8	69.6
ia	41.5	56.5	7.7	14.2	10.0	6.2	20.0	27.3	33.5	37.3	33.1	4.2	4.6	48.8	23.8	12.3	7.3	8.8	13.8	14.2	11.2	8.1	45.8	6.2	10.4	10.4	100	22.3	8.1	15.8
ch	16.5	10.8	41.9	58.5	35.4	4.6	4.6	14.2	14.2	22.7	14.6	66.9	33.5	9.6	22.7	65.8	48.8	55.0	52.3	52.3	53.1	52.3	16.2	32.3	51.2	56.2	22.3	100	53.1	50.4
ph	8.5	8.1	37.3	63.1	58.1	83.1	4.6	8.1	12.3	13.8	11.2	62.3	33.1	6.2	23.8	79.6	86.5	61.2	56.2	75.8	87.7	73.5	12.3	28.1	71.9	55.8	8.1	55.0	100	83.5
za	18.1	26.5	38.8	50.8	56.5	83.5	11.2	11.2	11.9	14.6	10.0	56.2	39.2	13.5	26.5	81.5	83.8	70.0	55.8	86.5	81.2	61.2	16.5	33.5	82.3	69.6	15.8	48.1	84.2	100

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