Journal of King Saud University – Computer and Information Sciences (2015) 27, 68–76

King Saud University

Journal of King Saud University – Computer and Information Sciences

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SignsWorld Atlas; a benchmark Arabic Sign Language database

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Received 22 April 2013; revised 26 February 2014; accepted 13 March 2014
Available online 29 December 2014

KEYWORDS

Sign language recognition;
Manual signs;
Non-manual signs;
Arabic Sign Language;
Database

Abstract Research has increased notably in vision-based automatic sign language recognition (ASLR). However, there has been little attention given to building a uniform platform for these purposes. Sign language (SL) includes not only static hand gestures, finger spelling, hand motions (which are called manual signs "MS") but also facial expressions, lip reading, and body language (which are called non-manual signs "NMS"). Building up a database (DB) that includes both MS and NMS is the main first step for any SL recognition task. In addition to this, the Arabic Sign Language (ArSL) has no standard database. For this purpose, this paper presents a DB developed for the ArSL MS and NM signs which we call SignsWorld Atlas. The postures, gestures, and motions included in this DB are collected in lighting and background laboratory conditions. Individual facial expression recognition and static hand gestures recognition tasks were tested by the authors using the SignsWorld Atlas, achieving a recognition rate of 97% and 95.28%, respectively.

1. Introduction

SL is a powerful means of communication among humans. However, Gesturing is rooted deeply in human communication that people often continue gesturing even during a telephone conversation. Vision based hand gesture recognition is the exemplary case in computer vision and has all along attracted researcher's attention (Ong and Ranganath, 2005).

SL recognition has many important applications. It is used in the natural human computer interactions like virtual environments (Berry, 1998). In addition, SL became powerful enough to fulfill the needs of the deaf people in their day to day life. SL is also a subset of the gestured communication used in deaf-mute society (Khan et al., 2009 and Riad et al., 2012). ASLR systems are being developed for daily communication between the deaf and the hearing persons (Wang and Wang, 2006 and Malima et al., 2006).

With Toshiba's media center software (Toshiba Company, 2008) users can pause or play videos and music by holding an

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Peer review under responsibility of King Saud University.

Production and hosting by Elsevier

http://dx.doi.org/10.1016/j.jksuci.2014.03.011
1319-1578

open palm up to the screen. Make a fist and your hand works as a mouse, by making a cursor move around the screen.

Also Hongmo Je et al. (Jiman et al., 2007) proposed a vision based hand gesture recognition system to understand musical time pattern and tempo which is presented by a human conductor.

Two different approaches for recognizing the MS and NM signs are device based approaches and the vision based approach. In the device based approach, sensors are worn by the signer and they often include positional sensors, trackers and displacement sensors. When a signer makes signing, articulator's data is captured on a designed rate and inputted to the recognition stage (Yang et al., 2009). On the other side, the vision-based SL recognition approaches utilize hand or face detection and tracking algorithms to extract their characteristics (Alon, 2006).

With the increase of research in vision-based SLR, new algorithms are being developed (Tsai and Huang, 2010 and Theodorakis et al., 2009). But there is a low attention paid for developing a standard platform for these purposes (Dadgostar et al., 2005) Building up a database of MS and NM gesture images is an important first step for standardizing the research on hand gesture recognition. The contribution of this paper is presenting a developed DB for the ArSL MS and NM signs which we called the SignsWorld Atlas. To form our Atlas content we used the Unified Arabic Sign Language Dictionary (The Arabic Dictionary of Gestures For The Deaf, 2005). This dictionary was built by more than 100 fluent ArSL signers and specialists from different deaf organizations allover the Arabic countries to unify the different versions of ArSLs.

This paper is organized as follows. Section 2 describes the available existing SL databases. Section 3 describes the developed SignsWorld Atlas. Also some experimental results are presented in Section 4. How to extend the SignsWorld Atlas are presented in Section 5. Finally, the conclusion is presented.

2. Related Work

According to the literature, and to the best of our knowledge, there are few available comprehensive hand gesture databases that provide a range of signed material under controlled lighting conditions.

Athitsos and Sclaroff (2003) published a database for hands posed in different gestures. The database contains about 107,000 images. But the database covers 26 gestures and the images actually present only the edges of the hands.

Wilbur and Kak (2006) developed an American Sign Language (ASL) database that provides a range of signed material that contained 2576 videos from 14 different signers.

Also Cambridge University developed the Hand Gesture Data set(Kim et al., 2007) that consists of 900 image sequences of 9 gesture classes, which are defined by 3 primitives and the image quality is high. But it can only be used for very small set of gesture recognitions.

Dadgostar et al. (2005) developed an image database that includes about 1500 images of hand posture and gesture images. But they didnot use formal gestures from any known SL but all were random ones. Recently an Irish SL database has been released (Dreuw et al., 2007). Dreuw et al. (2008) presented a video database for automatic SL recognition which consists of 843 sentences from the ASL and can be used also for testing the automatic recognition techniques of the SL.

As new hand detection and gesture recognition algorithms are being developed,the use of features such as color, and shape of the favorite object are more likely to be used and also colors have great importance in the body tracking (Mohandes et al., 2007).

Development of automatic recognition systems for ArSL needs a comprehensive SL database. There are no common DBs available for researchers in this field and the available few ones have very few gestures (Youssif et al., 2011 and Assaleh et al., 2011), they have problems in the image quality and the lighting conditions (Avenue, 2010), and they donot include both the MS and NM signs. Consequently, we tried to build a comprehensive SL DB considering the ArSL. Our DB is prepared to adequate the vision based hand and face gesture recognition researches, for both training and testing purposes.

3. The SignsWorld ArSL DB

The SignsWorld ArSL DB is an image and video DB that has been developed by the authors to evaluate their methods and algorithms for real-time ArSL gesture and posture recognition. Our DB, as in Fig. 1, has been created to contain (a) hand shapes in isolation and in single signs, (b) the Arabic finger spelling alphabet, (c) numbers, (d) movement in single signs, (e) movement in continuous sentences, (f) lip movement in Arabic sentences, and (g) facial expressions. All of these are produced by 10 signers under controlled lighting conditions. Our DB contains about 500 MS and NMS elements.

3.1. Different condition considerations

3.1.1. Lighting and background conditions

All the hand images in our DB are with a black background and with a direct light on the object. This will give the flexibility for the researchers to make any further processing on the images such as background subtraction, like in Fig. 2. Or any other processing as researchers can add their own background images to the dataset like in Fig. 3. This can be used in challenging the background conditions.

3.1.2. Data organization

The data are organized as follows:

1. Alphabet: The hand shapes in Arabic fingerspelling that correspond to each letter of the written alphabet. This particular set of finger spelled hand shapes is unique to the Arabic people.
2. Numbers 0–10: The hand shapes for the Arabic numbers from zero (pronounced Sefr in Arabic) to ten (pronounced Ashra in Arabic).
3. Hand-shapes with 2 example signs for each.
4. Signs in isolation to show different motions.
5. Movement in continuous sentences.
6. Lip movement in Arabic sentences
7. Facial expression

Figure 1 SignsWorld ArSL atlas snapshots.

Figure 2 Cropped image.

3.1.3. Filenames code

Table 1 includes the coding technique for the files in our DB with two examples of the used naming technique.

3.1.4. Signer independence

To achieve the signer independence we chose 10 different signers with different ages ranging from 3 to 30 years.

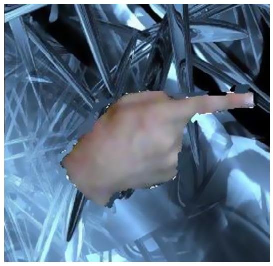


Figure 3 Cropped image with different BGs.

3.1.5. Image quality

The DB gestures are acquired by a Canon Power Shot A490 digital camera in an image quality of 1024*768 pixels and video quality of 10 MB.

3.2. Entity-relationship diagram

This section will describe the Entity–Relationship diagram (ERD) of the SignsWorld Atlas. Our Atlas contains seven DBs which have simple design. These DBs are Hand_Shapes, Ar_Finger_Spelling, Ar_Numbers, Individual_Signs, Cont_Sentences, Lip_Motions, Faces.

We intended to build each one independently that the recognition tasks for the facial expressions, static hand gestures, dynamic hand gestures, continuos ArSL, or the lip movements definitely differ in their preprocessing and feature extraction operations. Moreover, each MS and NMS, differ from each other in their physical representation. Finally, the independency makes it faster in processing and easier in retrieving, updating and deleting processes.

Each DB, except the Hand_Shapes and Faces, contains a relation with the following fields. "ID" referring to the coding technique described in Table 1. Also it is the primary key for each relation. The second field is "Arabic_Meaning", this field contains the Arabic meaning of each content. The third field is "English_Meaning", this field contains the English meaning for each content."File_Content" this contains image files or the relative path for the video file on the hard disk. The Hand_Shapes and Faces DBs donot contain the "Arabic_Meaning" and "English_Meaning" fields. In the faces

Table 1 Filenames coding.

Signer code	aa	1–10
Type	b	A (for alphabet), M (for motion), H (for handshapes), N (for number), S (for sentence), L (for lip) and F (for faces)
Gesture number	ccc	1–100 (for motion), 1–100(for handshapes), 1–28 (for alphabets), 1–11(for numbers including zero), 1–5 (for sentences), and 1–5(for lip movement), and 1–8 (for faces)
File number	d	1–5 This indicates the file number for different images for the same gesture by the same signer
Example 1	1-A-1	Signer 1, Alphabet 1 (pronounced aleph)
Example 2	9-F-5-2	Signer 9, Facial expression 5 (surprising), file number 2 that contains the same gesture by signer 9

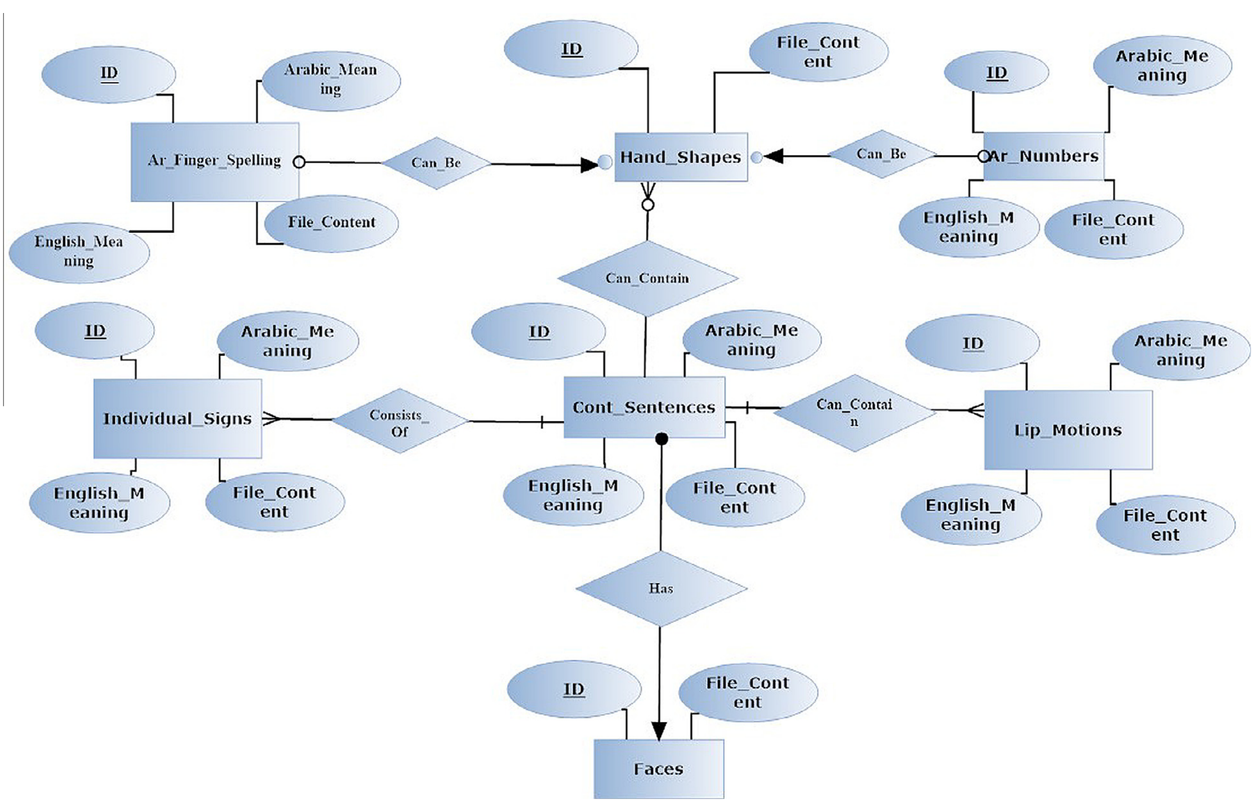


Figure 4 Full ERD for the seven DBs.

Table 2 Facial expression DB.

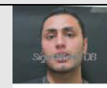
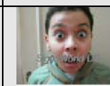
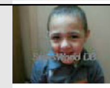
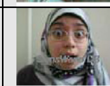
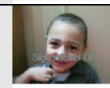
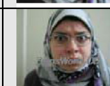
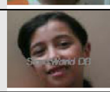
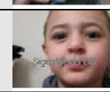
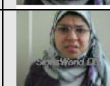
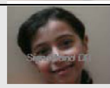
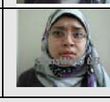
File Code	File Content	File Code	File Content	File Code	File Content
6_F_7		1_F_1		7_F_1_1	
8_F_3		9_F_6_1		5_F_1_1	
8_F_5		9_F_6_3		5_F_2	
8_F_6_1		9_F_7		5_F_3	
8_F_6_2		10_F_6		5_F_4	

Table 3 Hand shapes DB.

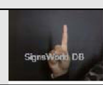
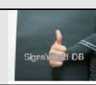
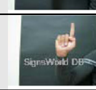
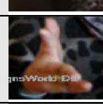
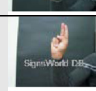
File Code	File Content	File Code	File Content
2_H_51		1_H_1	
2_H_51_2		1_H_2	
2_H_51_1		1_H_3	
2_H_52		1_H_4	
2_H_53		1_H_5	

Table 4 ArSL numbers DB.

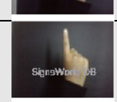
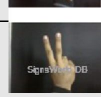
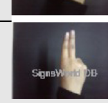
File Code	File Content	File Code	File Content
1_N_1		2_N_1	
1_N_2		2_N_2	
1_N_3		2_N_3_1	

Table 5 Arabic finger spelling alphabet.

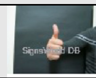
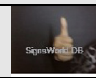
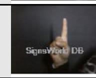
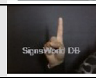
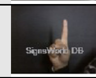
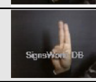
File Code	*File Content*	*File Code*	*File Content*
1_A_1		2_A_1	
1_A_2_1		2_A_2_1	
1_A_2_2		2_A_2_2	
1_A_3		2_A_3	

Table 6 ArSL individual words.

Motion code	Motion meaning in Arabic & English language	Motion code	Motion meaning in Arabic language	Motion code	Motion meaning in Arabic & English language
4_M_1_2	اثر -Affect	4_M_33_1	بطئ-Slow	4_M_64	ثوره المعلومات
3_M_1	اثر-Affect	4_M_33_2	بطئ-Slow	4_M_65	حالا _الان Now
3_M_2	اجهاد-Fatigue	4_M_34_2	خارطه-a Map	3_M_65	حالا _الان-Now
4_M_2	اجهاد-Fatigue	3_M_34	خارطه-a Map	4_M_66_1	خط عربي-Arabic handwriting
4_M_3	استغاثه-Appeal	4_M_34_1	خارطه-a Map	3_M_66	خط عربي- Arabic handwriting
3_M_3	استغاثة -Appeal	2_M_35	خلال-Through	4_M_66_2	خط عربي- Arabic handwriting

Table 7 ArSL continuous sentences.

Sentence motion code	Sentence Motion meaning in Arabic language	Sentence meaning in English
3_S_4	ذراعي يؤلمني	My arm is hurting
4_S_4	ذراعي يؤلمني	My arm is hurting
3_S_5	عملية في عيني	A surgery in my eye
4_S_5	عملية في عيني	A surgery in my eye.
4_S_2	انا احب اسرتي	I love my family
3_S_1	انا احب اسرتي	I love my family
1_S_2	جرح في جبيني	Wound in my forehead
2_S_2	جرح في جبيني	Wound in my forehead
1_S_3	خريطه المكان	A map for this place
2_S_3	خريطه المكان	A map for this place

Table 8 ArSL continuous sentences.

Lip motion code	Lip motion meaning in Arabic language	Sentence meaning in English
3_L_1_1	عمليه في عيني	A surgery in my eye
4_L_1_2	عمليه في عيني	A surgery in my eye
3_L_2_1	ذراعي يؤلمني	My arm is hurting
4_L_3_2	خريطه المكان	A map for this place
3_L_4_2	جرح في جبيني	Wound in my forehead
3_L_5_1	انا احب اسرتي	I love my family

DB, the facial expression meaning already defined properly in the ID field, as will be shown in the next section. Fig. 4 shows the full ERD of the seven DBs and the relationships between them. The opensource DB "MySQL" is used to build our DBs.

3.3. SignsWorld Atlas; full analysis

In this section we will present a full analysis for the SignsWorld Atlas. It will describe all the atlas images with its naming inside the DB. All the included images have "SignsWorld DB" watermark. For the videos, we will present each video meaning with its name only.

Table 2 includes some examples for the facial expression DB contents. The gesture numbers cell (referred to "cc" in Table 1) varies from one to eight. The gesture number 1–8 means respectively surprise, anger, disgust, fear, sadness, happiness, neutral, and profile. These facial expressions were performed by ten Egyptian persons of different ages varying from 3 to 30 years.

The following table (Table 3) includes some examples from 112 jpg original images of different hand shapes implemented by fluent two ArSL signers. The lighting and background conditions were satisfied in the hand shapes DB.

Table 4 includes some examples from original 28 images of the ArSL numbers from zero to ten (pronounced Sefr, Wahed, Ethnan, Thalatha, Arbaa, Khams, Sset, Sabaa, Thamaneya, Tesaa, and Ashra, respectively). The content for this DB was performed by two different ArSL signers.

Table 5 includes some examples from original 67 jpg images the 28 main Arabic finger spelling alphabet. The alphabets are pronounced in the Arabic language Aleph, Baa, Taa, Thaa, Gym, Hhaa, Khaa, Dal, Thal, Raa, Zay, Syn, Shen, Sad, Daad, Ttaa, Thaa, Ayn, Ghayn, Faa, KKaf, Kaf, Lam, Meem, Noon, Haa, Waaw, and Yaa, respectively. These were performed by two different ArSL signers.

Table 6 includes the motion code and its meaning of some examples from original 178 motions that were chosen to satisfy 3 different situations; medical, by the road, and learning. These motions represented about 76 ArSL words. These words were performed by 4 different ArSL fluent signers.

Table 7 includes the motion code and its meaning for ten motions for five ArSL continuous sentences. These continuous sentences were performed by 4 different ArSL fluent signers.

Table 8 includes the motion code and its meaning of some examples for original 20 lip motions for 5 sentences that were chosen to satisfy 3 different situations; medical, by the road, and learning. ArSL words in this DB were performed by 4 different ArSL fluent signers.

4. Experimental results

This section briefly clarifies that our DB is already used by the authors for many tasks and it was efficient and achieved good recognition rates. We will briefly describe the recognition tasks that our DB used in the main former processes.

4.1. Utilizing the face DB in a facial expression recognition system

- **Face detection**

Face detector is the first module in our facial expression recognition system, to localize the face in the image. This step allows an automatic labeling for facial feature points in a face image. We use a real-time face detector proposed in Viola and Jones, 2001. OpenCV library (Bradski et al., 2009) represents an adapted version of the original Viola–Jones face detector.

- **Facial feature extraction**

To spatially sample the outline of the eyebrows, eyes, nostrils, and lips from an input frontal-view face image. We apply a simple analysis of image histograms in a combination with various filter transformations to locate six regions of interest (ROIs) in the face region segmented from an input frontal-view face image: two eyebrows, two eyes, nose, and mouth. The followed procedure is the updated version of the procedure in (Pantic and Rothkrantz, 2000 and Bouguet, 2000). We supported head rotation of −20–20 degrees of both in-plane and out-of-plane rotations. Detection speed ranges from 0.15 to 1.5 s, and the returned information of detected face based on (x, y) coordinates of face center, width and rotational angle. For facial feature extraction processes, we used the SignsWorld DB. These points figure the x and y coordinates of each extracted feature. Fig. 5 shows the extracted 66 key facial points.

- **Extracted facial points tracking**

The facial feature points detected in the first image of the sequence will be tracked using pyramidal Lucas–Kanade algorithm (Bradski and Kaebler, 2008). This algorithm supposes that the brightness of every point of a static or moving object remains stable in time. Fig. 5 illustrates all 66 adopted facial feature points. Each key point of the feature extracted from the original frame is highlighted with a point in the figure.

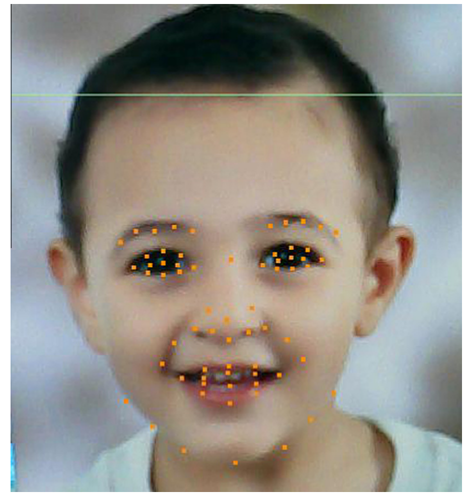


Figure 5 Facial features extracted.

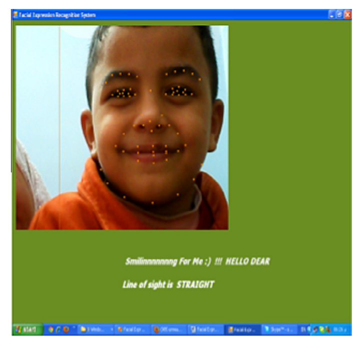


Figure 6 A snapshot for the running facial expression recognition application.

- **Facial expression recognition**

We deduced to recognize four facial expressions; smile, sadness, surprise, and neutral. We formed a simple rule-based classifier to detect the intended facial expressions. The followed rules were reached from testing the values on 10 persons with different ages, facial characteristics, and genders.

Permanent facial features are facial components such as eyebrows, eyes, and mouth. Their shape and location can alter immensely with expressions (e.g., pursed lips versus delighted smile). Consequently, we calculated some geometric distances from each image that we addressed in the calculated geometric formulas (GF). With experiments of about more than 6200 frames from online videos, we proved that the ratio (R) between two geometric features remains in the same range even if the observed object differs.

- **Testing**

Experiments show that the system works reliably under rotation angle between −20 and 20 degree. However it fails when the rotation angle is beyond this limit, or there is heavy occlusion. In the case of a tracking failure, the system will be reset and

Figure 7 A snapshot for the running static hand gesture recognition application.

resume tracking shortly. We tested 100 examples for each of (Neutral, sadness, surprise, andsmile) facial expressions. Our recognition system achieved a recognition rate of 97%.

We noted that surprising facial expression results in particularly low recognition rates (about 88%). This is due to the fact that our built (geometric formulas) GFs used for this expression may need some improvements. Fig. 6 represents a snapshot for the running facial expression recognition application.

4.2. Utilizing the hand gestures DB in static gesture recognition task

In the following paragraphs, we will briefly describe our utilized techniques for both training and testing processes.

- **Training and recognition**

To detect the hand region, the Viola–Jones classifier function is employed from OpenCV (Bradski and Kaebler, 2008). Before using the function, we should create XML file. The training samples (hand image) must be collected. There are two samples: negative and positive samples. Thenegative sample corresponds to non-object background images whereasthe positive sample corresponds to object image. For the training of the hand regions we used the SignsWorld Atlas. The output XML file is used to detect the hand region.

We utilized a simple heuristic approach to classifya set of explicit IF-THEN rules that refer to the target's features and require them to lie within a certain range that is typical of a specific gesture. The researches for automatic learning of rules are presented in (Kraiss, 2006 and Mitchell, 1997). The rule based classification is usually used as a primary step for the dynamic gesture classification algorithms. It is also an efficient technique for a small data set.

- **Testing**

Tests were done with the help of students in MeetHadar school for Hearing impairments in Mansoura City, Dakhlia Egypt. We asked the students to help in performing the static gestures and test these gestures in the real-time on our application. 95.28% of recognition rate is reached. Fig. 7 represents a snapshot for the running static hand gesture recognition application.

5. Extending the SignsWorld Atlas

SignsWorld Atlas and gesture DB could be extended in different ways. Firstly, the lighting conditions could be extended by producing more of the same type of images so that the 3D object lighting conditions could be considered. Secondly, more gesture elements could be collected. Finally, to ensure the signer independence a larger number of different hands would extend the DB with respect to the geometrical proportions of the human hand.

6. Conclusion

In this paper, we described the development of a colored ArSL DB that is called SignsWorld Atlas. We developed the SignsWorld Atlas with the intention of providing a common benchmark. It provides different types of the ArSL MS and NM signs (Arabic finger spelling, numbers, different handshakes, individual signs, continuos sentences, lip movement in Arabic sentences, and facial expressions). The developing of the DB considered the lighting and background conditions. So that it can provide flexibility for the different research purposes. Also for flexibility of the DB access we designed a unique coding for the filenames. We considered the signer independence by using the signs from 10 signers with different ages. Images were produced with a quality of 1024*768 pixels and videos with a quality of 10 MB.

Acknowledgments

Deep thanks to all who assisted us to prepare this DB Prof. Dr. A. Abu Elfetouh Saleh who provided us with a place to work in. To all of Abd Alatheem, Shaymaa, Amro, and Shereen who performed the ArSL words, sentences and lip motions that were presented in our DB. Also thanks to other persons who helped in the other facial expression images.

References

Alon, J., 2006. Spatiotemporal Gesture Segmentation (Ph.D. thesis). Computer Science Dept., Boston Univ.

Assaleh, K., Shanableh, T., Fanaswala, M., Amin, F., Bajaj, H., 2011. Continuous Arabic Sign Language recognition in user dependent mode. J. Intell. Learn. Syst. Appl. 2 (1), 19–27.

Athitsos, V., Sclaroff, S., 2003. Estimating 3d hand pose from a cluttered image. In: The IEEE Conference on Computer Vision and Pattern Recognition, Madison, Wisconsin, USA.

Avenue, Cupcake, 2010. Arabic Sign Language – Alphabet. <http://www.youtube.com/watch?v=u-x6G8lrOBQ> (Last access: 3 Oct 2013).

Berry, G., 1998. Small-wall: A Multimodal Human Computer Intelligent Interaction Test Bed with Applications (M.Sc. thesis). Dept. of ECE, University of Illinois at Urbana-Champaign.

Bouguet, J.Y., 2000. Pyramidal Implementation of the Lucas Kanade Feature Tracker. Intel corporation, Microprocessor Research Labs.

Bradski, G., Kaebler, A., 2008. Learning Computer Vision with the OpenCV Library. O'Reilly, Sebastopol, pp. 214–219.

Bradski, G., Darrell, T., Essa, I., Malik, J., Perona, P., Sclaroff, S., Tomasi, C., 2009. OpenCV Project, <http://sourceforge.net/projects/opencvlibrary/> (Last access: 3 Oct. 2013).

Dadgostar, Farhad, Barczak, Andre L.C., Sarrafzadehres, Abdolhossein, 2005. A color hand gesture database for evaluating and improving algorithms on hand gesture and posture recognition. Lett. Inf. Math. Sci. 7.

Dreuw, P., Stein, D., Ney, H., 2007. Enhancing a sign language translation system with vision-based features. In: International Workshop on Gesture in Human-Computer Interaction and Simulation. Lisbon, Portugal. pp. 18–20.

Dreuw, P., Neidle, C., Athitsos, V., Sclaroff, S., Ney, H., 2008. Benchmark databases for video-based automatic sign language recognition. In: International Conference on Language Resources and Evaluation (LREC).

Jiman, Je, H., Daijin, K., 2007. Hand gesture recognition to understand musical conducting action. In: 16th IEEE International Symposium on Robot and Human Interactive Communication. Roman. pp. 163–168.

Khan, S., Gupta, G.S., Bailey, D., Demidenko, S., Messom, C., 2009. Sign language analysis and recognition: a preliminary investigation. In: 24th International Conference Image and Vision Computing New Zealand, IVCNZ 2009.

Kim, T-K., Wong, S-F., Cipolla, R., 2007. Tensor canonical correlation analysis for action classification. In: Proc. of IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Minneapolis, MN.

Kraiss, K., 2006. Advanced Man–Machine Interaction Fundamentals and Implementation. Springer, Berlin, pp. 16–54.

Malima, Ozgur, E., Cetin, M., 2006. A fast algorithm for vision based hand gesture recognition for robot control. In: 14th IEEE Conference on Signal Processing and Communications Applications.

Mitchell, T.M., 1997. Machine Learning. McGraw-Hill.

Mohandes, M., Quadri, S.I., Deriche, M., 2007. Arabic Sign Language recognition an image-based approach. In: 21st International Conference on Advanced Information Networking and Applications Workshops (AINAW'07).

Ong, Sylvie C.W., Ranganath, Surendra, 2005. Automatic sign language analysis: a survey and the future beyond lexical meaning. IEEE Trans. Pattern Anal. Mach. Intell. 27 (6), 873–891.

Pantic, M., Rothkrantz, L.J.M., 2000. Expert system for automatic analysis of facial expression. Image Vis. Comput. J. 18 (11), 881–905.

Riad, A.M., Elmonier, Hamdy K., Shohieb, Samaa M., Asem, A.S., 2012. SignsWorld; deeping into the silence world and hearing its signs (state of the art). Int. J. Comput. Sci. Inform. Technol. (IJCSIT) 4 (1), 189–208.

The Arabic Dictionary of Gestures for the Deaf, 2005. Supreme Council for Family Affairs, Qatar.

Theodorakis, S., Katsamanis, A., Maragos, P., 2009. Product-HMMs for automatic sign language recognition. In: International Conf. on Acoustics, Speech and Signal Processing (ICASSP-09).

Toshiba Formally Unveils Notebooks with SpursEngine Chip., 2008. <http://www.xbitlabs.com/news/mobile/display/20080624203611_Toshiba_Formally_Unveils_Notebooks_with_SpursEngine_Chip.html> (Last access: 3 Oct 2013).

Tsai, B.-L., Huang, C.-L., 2010. A vision-based Taiwanese sign language recognition system. In: 2010 International Conference on Pattern Recognition.

Viola, P., Jones, M., 2001. Robust real-time object detection. In: 2nd International Workshop on Statistical and Computational Theories of Vision Modeling, Learning, Computing, and Sampling. Vancouver, Canada.

Wang, C.C., Wang, K.C., 2006. In: Hand Posture Recognition using Adaboost with SIFT for Human Robot Interaction, Vol. 3. Springer, Berlin.

Wilbur, R., Kak, A.C., 2006. Purdue RVL-SLLL American sign language database. ECE Technical Reports. <http://docs.lib.purdue.edu/ecetr/338338> (Last access: 3 Oct. 2013).

Yang, H.-D., Lee, S.W., 2009. Sign language spotting with a threshold model based on conditional random fields. IEEE Trans. Pattern Anal. Mach. Intell. 31 (7).

Youssif, Aliaa A.A., Aboutabl, Amal Elsayed, Ali, Heba Hamdy, 2011. Arabic Sign Language (ArSL) recognition system using HMM. Int. J. Adv. Comput. Sci. Appl. (IJACSA) 2 (11).