JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

State of the Art Real Time Finger Tracking System

Shivangi Yadav[1*], Sapna Yadav[2], Ms. Laxmi Yadav[3]

[1*]Scholar (B. Tech Final Year) Information Technology, B. N. College of Engineering & Technology, Lucknow
[2] Scholar (B. Tech Final Year) Computer Science & Engineering, B. N. College of Engineering & Technology, Lucknow
[3]Assistant Professor, Department of Computer Science & Engineering, B. N. College of Engineering & Technology, Lucknow

Abstract: The hands hold significant importance in virtual reality (VR) applications since they serve as the primary mode of interaction with the virtual environment. The human hand is a highly intricate biological mechanism capable of executing a wide range of tasks with remarkable precision and agility. In addition, gestures play a significant role in our daily social interactions, and humans possess a notable aptitude for discerning and comprehending intricate signals within communication. Developing realistic hand gestures for virtual characters is a significant and complex undertaking. This research presents a methodology for the detection of human finger motion and gestures via a dual-camera system. The identification of the target on a flat monitor or screen is achieved by the utilization of image processing techniques and the intersection of lines. This is achieved through the analysis of photos captured from above and from the side of the hand. The device possesses the capability to monitor and record the motion of the finger without the need to construct a three-dimensional representation of the hand. The extraction of finger coordinates and movement from a real-time video feed can be utilized to determine the corresponding coordinates and movement of the mouse pointer, thereby facilitating human-computer interaction.

Keywords: Hand Gesture, Recognition, Computer Vision, Human Computer Interaction (HCI), Hand Posture.

1. Introduction

Nonverbal communication can be effectively utilized as a means of transmitting and receiving messages among individuals. Nonverbal communication encompasses various forms, including gestures and touch, body language or posture, physical distance, face expression, and eye contact. Hand gestures serve as a viable and effective means of interaction between individuals and computer systems [1]. The advent of recent advancements in computer software and associated hardware technology has facilitated the provision of value-added services to users. Physical gestures have a significant role in interpersonal communication in various contexts of daily life. They possess the ability to effectively communicate a diverse range of information and emotions in a cost-efficient manner. The recognition of hand gestures is a significant and fundamental problem within the field of computer vision. In light of current advancements in information technology and media, there has been a development of automated systems for human interactions that require various manual processing tasks such as hand detection, hand recognition, and hand tracking [2]. This occurrence sparked my curiosity, leading me to devise a software system capable of detecting and interpreting human movements [3] using computer vision, a specialized domain within the subject of artificial intelligence [4]. The objective of the software developed with computer vision techniques was to enable the computer to effectively interpret and comprehend the contents of a given scene or identify certain aspects within an image.

The initial stage in any manual processing system involves the identification and spatial determination of a hand inside an image. The issue of detecting hands was a significant challenge because to the inherent variety in factors such as stance, orientation, location, and scale. Moreover, the presence of various lighting conditions introduces additional levels of variability. In recent years, there has been significant advancement and cost reduction in high technology. The increasing accessibility of high-speed CPUs and affordable cameras has sparked a growing interest among individuals in real-time applications pertaining to image processing. The challenge of hand tracking using vision-based techniques holds significant importance within the domain of human-computer interaction [8]. This is due to the possible utilization of hand motions and gestures as a means to interface with computers in a more intuitive manner. Several proposed solutions have been documented in the existing academic literature. However, it is important to note that the topic at hand remains unresolved, as interactive applications necessitate real-time hand tracking capabilities.

2. Related Work

Hand gesture detection using vision-based technologies is widely used in human-computer interaction (HCI). Keyboards and mice have become increasingly important in human-computer interaction in recent decades. However, new kinds of HCI [9] techniques have been needed due to the quick evolution of technology and software. In the realm of HCI, technologies like gesture and speech recognition are given a lot of attention. A gesture can represent an emotion or a physical behavior. Both hand and body gestures are included. Static gesture [10] and dynamic gesture [11] are the two categories into which it falls. For the former, a sign is indicated by a body position or hand gesture. For the latter, certain messages are sent through hand or body movement. A computer and a human can communicate with one other using gestures. It is very different from the conventional hardware-based approaches and uses gesture detection to enable human-computer interaction. By identifying the gesture or movement of the body or certain body parts, gesture recognition ascertains the user's intention. Numerous academics have worked to advance hand motion detection technology over the past few decades. identification of hand gestures is very useful in many applications, including robot control [13], augmented reality (virtual reality), sign language interpreters for the disabled [12], and sign language identification [13]. An algorithm for using 2D and 3D hand gestures to control a computer mouse was presented by Argyros et al. [14] in another study. This approach is susceptible to disturbances and uneven lighting in the background of clutter. Local invariant traits were the subject of some research [15]. Juan et al. [16] conducted numerous experiments to assess the effectiveness of SIFT, principal component analysis (PCA) – SIFT, and accelerated robust features (SURF). The SIFT algorithm is used to extract features from images that are independent of scale and rotation. Introduced in [17], PCASIFT uses PCA to normalize gradient patch. Robust SURF features are employed in [18] for image convolutions and the Fast-Hessian detector. Shimada et al. suggest a TV control interface that recognizes hand gestures in [19]. In order to classify hand gestures, Keskin et al. [20] partition the hand into 21 distinct regions and train a support vector machine (SVM) classifier to predict the combined distribution of these regions for a variety of hand motions. Zeng et al.'s [21] use of hand gesture recognition enhances the quality of medical services. Three compound states and five hand gestures are part of the intelligent wheelchair's HCI recognition system. Their method operates with dependability both in indoor and outdoor environments and under varying illumination conditions.

3. Hand Gesture Recognition and Detection

In order to identify a hand gesture, the initial step is the recognition of the hand. The study of hand detection and recognition has been a prominent area of research within the discipline of computer vision and image processing over the past three decades [22]. Significant advancements have been made in these respective domains, and a multitude of methodologies have been put forth. However, the conventional methodology employed in a comprehensive automated hand gesture recognition system, as depicted in Figure 1 [23], is as follows.

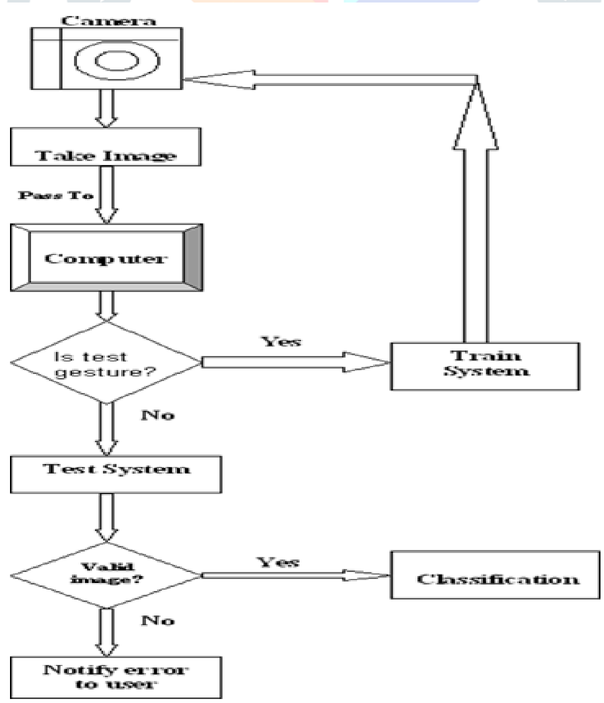

Figure 1: Flow Chart for Hand Gesture Recognition

3.1 Hand Detection

The detection of hands plays a crucial role in the accurate recognition of gestures. Various strategies were employed in an attempt to accomplish this objective. In the initial approach, maintaining a consistent background allows for the segmentation of the hand as the foreground. The aforementioned approach yields favorable outcomes; nevertheless, it also identifies the user's arm as foreground, which deviates from the desired outcome [24]. In order to address this constraint, the utilization of the HSV (Hue Saturation Value) color space is employed for the purpose of segmenting skin color and subsequently identifying the hand. The HSV color space has superior tolerance to illumination variations and enhanced potential for image segmentation in comparison to the RGB and YCrCb color spaces. The findings indicate that optimal results are achieved when the light source is positioned behind the webcam. Conversely, when the light source is situated in a different direction, particularly from above, the outcomes are subpar. The HSV color model is employed to illustrate the remaining tasks. The hand that has been segmented appears as depicted in Figure 2 when it is transformed into a binary image. To ensure optimal tracking performance, it is advisable to exclude the presence of the user's other hand and face from the frame acquired by the webcam. It is worth mentioning that the aforementioned detection method [25] exhibits robustness in the presence of faces, with the caveat that the proximity of the user's face to the camera should not be excessively close.

Figure 2: Hand Detection

Hand detection pertains to the determination of the spatial coordinates of a hand inside a static image or a series of images, such as those in motion. When dealing with moving sequences [26], it is possible to subsequently track the hand throughout the scene. However, this particular application is more pertinent to domains such as sign language. The fundamental principle of hand detection is rooted in the disparity between human visual perception and machine-based object identification. Human eyes possess a superior ability to discern items that machines struggle to identify with comparable precision. From a mechanistic perspective, the process can be likened to a human clumsily utilizing their senses to locate an object.

3.2 Lighting

The process of distinguishing the pixels corresponding to the skin from those belonging to the backdrop can be significantly facilitated with a meticulous selection of lighting conditions. According to Ray Lockton, the mitigation of self-shadowing effects can be achieved to a significant extent when the lighting remains consistent throughout the camera's field of view, as depicted in figure 3.

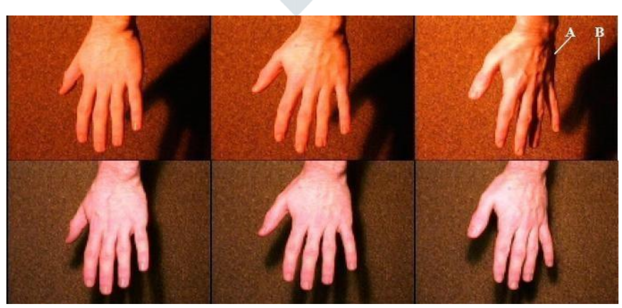

Figure 3: Lightning

The three highest-ranking photos were illuminated by a solitary light source positioned to the left. A self-shadowing phenomenon is observable in all three images, with particularly pronounced effects evident in the right image, when the hand is positioned at an angle away from the light source. The three photos located at the bottom exhibit a higher degree of homogeneous lighting, characterized by less presence of self-shadowing. The presence of cast shadows in the photographs does not have a detrimental impact on the detection of the skin. It is worth observing that the augmentation of illumination in the lower three photographs leads to a heightened disparity between the skin and backdrop, so enhancing the contrast.

3.3 Background Subtraction

The tracking system's initial step is to distinguish between possible hand pixels and non-hand pixels. A straightforward background subtraction approach is employed to separate any possible foreground hand information from the static backdrop scene depicted in figure 4 because the cameras are positioned above a stationary [27] workplace.

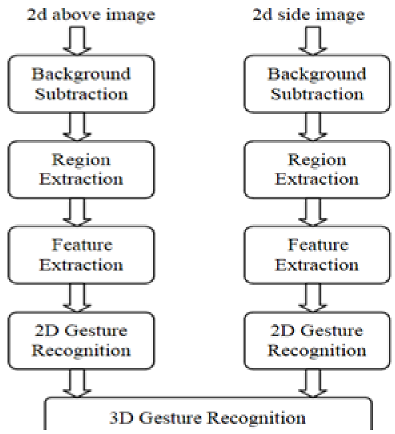

Figure 4: Background Selection

3.4 Finger Tracking

The finger tracking system is designed for user-data interaction, in which the user manipulates the dimensions of a desired 3D object [28] with their fingers in order to engage with the virtual data. Based on the issue of human-computer interaction, the system was created. The aim is to facilitate communication between them by utilizing intuitive gestures and hand movements. A technique called Finger Tracking has been developed. These systems use natural hand gestures and movements to communicate while tracking in real time the orientation and 3D and 2D position of each marker's fingers. We created the two-dimensional finger tracking interface as a preliminary step toward complete hand tracking in three dimensions. The interface's primary goal was to facilitate research into strategies for enhancing lost feature reacquisition and, thus, the tracking system's resilience. A thorough, methodical search of the full video frame is not a practical solution since it takes too long. Furthermore, a systematic search may not locate the object entirely because the system is dynamic and there is no guarantee that the object (hand) will stop moving simply because tracking [29] has been lost. We require intelligent search algorithms. The position where the feature was last identified and the movement vector at that moment are the two fundamental pieces of information provided by the tracking system. Our approach employs a dynamic search pattern, expanding the search region over time as the feature goes undiscovered while initially concentrating on locations where the feature is most likely to be found.

4. Method Used

For the purpose of human-computer interaction, gestures are typically interpreted using one of two methods, which are described below.

4.1 Data Gloves based Method

In this particular approach, it is necessary for the user to don gloves, a helmet, and other cumbersome equipment. In order to detect hand gestures, various optical or mechanical sensors, an actuator, and an accelerometer are affixed to the glove [30]. The aforementioned apparatus facilitates the transformation of finger flexions into electrical impulses, hence enabling the determination of hand posture. In this particular methodology, the user was required to handle a significant quantity of cables, posing challenges in effectively managing them within a real-time setting. The maintenance requirements of this technology are increased as a result of the intricate wired structures, as illustrated in figure 5.

Figure 5: Data Gloves Based Hand Gesture Recognition

4.2 Vision Based Method

The current advances in computer vision techniques are characterized by their simplicity, naturalness, and cost-effectiveness in comparison. The proposed methodology involves the extraction of features from the frames of the video. Currently, the majority of laptops are equipped with an embedded webcam, rendering it a readily accessible gadget [31]. In our research project, we are currently developing a hand gesture recognition system that is capable of accurately detecting and identifying the movements of a hand based on its gestures. In this experiment, we utilized the inbuilt web camera of a laptop to capture an image frame, as depicted in figure 6.

Figure 6: Hand Postures Captured by Web Camera

5. Methodology

Hand gesture recognition system can be divided into following modules first preprocessing, second feature extraction of the processed image and third real time classification shown in figure 7.

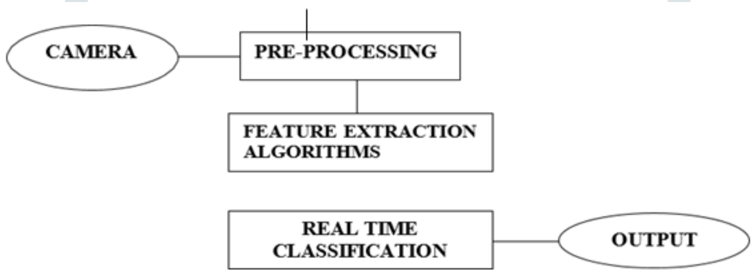

Figure 7: The Proposed Methodology

5.1 Pre-Processing

Similar to numerous other jobs involving pattern recognition, the procedure of pre-processing is necessary in order to improve the resilience and accuracy of recognition. The initial phase in the image recognition process involves preprocessing the image sequence. This step is necessary to provide the suitable image required for real-time classification, prior to doing calculations such as the diagonal sum and other algorithms. The process comprises a series of sequential steps. The primary outcome of this processing operation is the isolation of the hand from the provided input. Once the hand has been successfully detected within the input, it becomes readily identifiable.

5.2 Feature Extraction

We are investigated and implemented four distinct methods, which are as follows: the row vector algorithm, the edging and row vector passing algorithm, the mean and standard deviation of the edged image algorithm, and the diagonal sum algorithm.

5.2.1 Row Vector Algorithm

It is well acknowledged that within the realm of computer vision, each image is accompanied by a matrix of numerical values that undergo various transformations in order to extract meaningful insights. An illustration of a computation involves the determination of a row vector from a given matrix. A row vector is defined as a one-dimensional array of numbers arranged in a single row, with a resolution of 1 by Y, where Y is the total number of columns in the picture matrix.

5.2.2 Edging and Row Vector Passing Algorithm

During the pre-processing step of this algorithm, many techniques are employed to enhance the quality of the gesture image captured. These techniques include preprocessing, skin modeling, and backdrop removal. The RGB image was transformed into grayscale format. Gray scale images are represented as matrices, where each element corresponds to the brightness or darkness of the pixel at the corresponding point [32]. There are two methods for describing the brightness of pixels. The first method involves using the Double class, which assigns floating-point numbers (decimals) ranging from 0 to 1 for each pixel. The numerical value of zero (0) signifies the color black, while the number of one (1) corresponds to the color white. The second class, referred to as "unit8," assigns integer values ranging from 0 to 255 to represent the brightness of a pixel. A value of zero (0) corresponds to black, while a value of 255 represents white. The storage capacity required for the unit8 class is approximately 1/8 of that required for double. Following the transformation of the image into grayscale, I proceeded to extract the image's edges using a predetermined threshold value of 0.5. The utilization of this threshold facilitated the elimination of extraneous elements within the image, so enhancing its clarity. The subsequent procedure involved the computation of a row vector representing the edges present in the image. The aforementioned row vector is thereafter transmitted to the neural network for the purpose of training. The classification of motions was subsequently evaluated using the neural network (NN) [33].

5.2.3 Mean and Standard Deviation of Edged Image

During the pre-processing phase, various steps are performed, including the removal of the background and the conversion of the RGB image into grayscale, as previously implemented in the method. The grayscale image is subjected to edge detection using a predetermined threshold value of 0.5. Subsequently, the mean and standard deviation of the resulting processed image are computed. The mean of a matrix is determined by summing all the pixel values within the matrix and dividing this sum by the total number of values present.

5.2.4 Diagonal Sum Algorithm

During the pre-processing phase, the following procedures outlined in the technique are performed: skin modeling, elimination of the backdrop, conversion of RGB to binary, and labeling. The binary image format represents an image as a matrix, where each pixel can only be assigned either black or white, with no intermediate shades. The system designates the numerical value of 0 to represent the color black, while assigning the numerical value of 1 to represent the color white. In the subsequent stage, the summation of all elements within each diagonal is computed. The major diagonal is denoted as k=0. Diagonals positioned below the main diagonal are denoted as k<0, while those positioned above it are denoted as k>0. The algorithm employed in the development of the gesture recognition system initially undergoes a training phase wherein it familiarizes itself with the cumulative sum of diagonal elements for each distinct gesture category, ensuring that each form of gesture is encountered at least once. Subsequently, the system's efficacy is evaluated by subjecting it to a real-time test gesture.

6. Analysis

The system operates effectively when presented with a light background and minimal visual distractions. The upper limit of the search area's dimensions is around 1.5 meters by 1 meter, although it can be readily expanded with the incorporation of further computational resources. The system is capable of functioning effectively under various lighting circumstances and possesses the ability to automatically adjust to dynamic environmental changes. The requirement for a set-up stage is unnecessary. The user has the ability to approach the system and utilize it at their convenience without any restrictions. There are no limitations imposed on the velocity of manual finger motions [34]. There is no requirement for any specialized hardware, markings, or gloves. The system operates with latencies approximately in the range of 50 milliseconds, so enabling real-time interaction. Simultaneous tracking of multiple fingers and hands is feasible. The Brainstorm system, in particular, illustrated how finger tracking may be leveraged to generate additional benefits for the user. The system's detection rate [35] is obtained through the utilization of four algorithms, as depicted in Figure 8. There exist alternative systems that facilitate the manipulation of objects projected onto a wall without the need of any tools, similar to the functionality provided by Brainstorm. Additionally, there are systems that enable the control of presentations by hand postures, akin to the capabilities offered by Freehand Present. However, it is conceivable that alternative finger tracking systems could have been utilized to develop the aforementioned applications. The efficacy of the proposed approach is heavily contingent upon the outcome of hand detection. The presence of moving objects that share a similar color to human skin can adversely affect the efficacy of finger tracking recognition by interfering with the accuracy of finger detection.

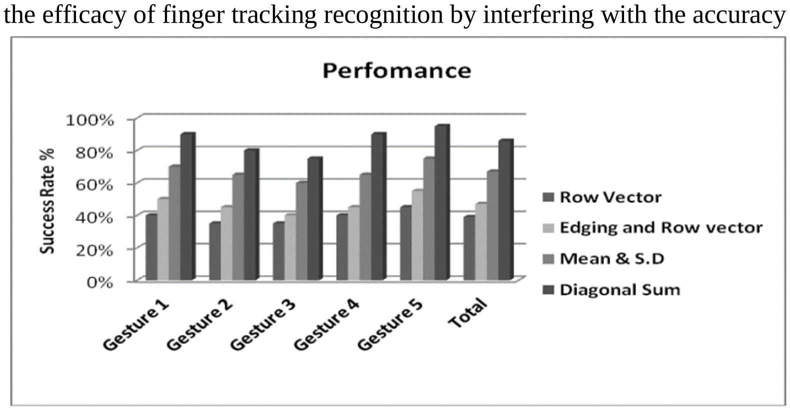

Figure 8: The Performance Chart of Algorithms

7. Conclusion

Human-Computer Interaction (HCI) has emerged as a prominent element within computer science disciplines, facilitating the interaction between humans and machines through intuitive and straightforward means. This development has opened up new avenues for research, enabling exploration of novel dimensions in the area. The identification of hand gestures holds great importance in the realm of human-computer interaction. I examined multiple methodologies for conducting my thesis research and devised four distinct techniques: the Row Vector algorithm, the Edging and Row Vector Passing algorithm, the Mean and Standard Deviation of Edged Image, and the Diagonal Sum algorithm. Each of these methods was tested with neural networks, and their performance rates were ranked in ascending order. One initial constraint observed across all algorithms employed in conjunction with neural networks was the reliance of their performance on the quantity of training data available. The efficiency of the system improved significantly when trained on a larger dataset in comparison to a smaller dataset. The early utilization of the Row vector algorithm for classification was characterized by a lack of specificity, as empirical observations revealed the possibility of two distinct images having identical row vectors. I would like to request that you rewrite the user's text to be more academic in nature. The edging and row vector-passing approach incorporates the edging parameter alongside the row vector in order to enhance the accuracy of gesture categorization. However, it has been shown that the presence of self-shadowing effects in edges hinders the desired improvement in the detection rate. The subsequent parameters that were employed for classification encompassed the measures of mean and standard deviation. Furthermore, despite their inability to yield appropriate outcomes, namely those exceeding 60%, these parameters remained among the most effective ones employed for neural network identification.

8. Future Works

The system might potentially be enhanced by implementing a specialized training process that focuses on one or two specific gestures, as opposed to attempting to recognize a wide range of gestures. This targeted training approach would then allow for more efficient testing and evaluation of the system's performance. The implementation of the necessary modifications to the existing interface code was not carried out within the allocated timeframe. The elimination of the one-time training constraint for real-time systems may be achieved by the development of an algorithm that demonstrates efficiency in accommodating various skin types and light situations. However, it is currently deemed unattainable. Utilizing the concept of the Centre of Gravity (COG) for the purpose of controlling the orientation element has the potential to enhance the efficacy of this system in practical applications. The efficiency of the preprocessing phase can potentially be enhanced by implementing the code using VC/VC.Net.

References:

[1] M. Elmezain, A. Al-Hamadi, and B. Michaelis, “A robust method for hand gesture segmentation and recognition using forward spotting scheme in conditional random fields,” in Proceedings of the 20th International Conference on Pattern Recognition (ICPR ’10), pp. 3850–3853, 2010

[2] R. Yang, S. Sarkar, and B. Loeding, “Handling movement epenthesis and hand segmentation ambiguities in continuous sign language recognition using nested dynamic program ming,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, no. 3, pp. 462–477, 2010

[3] Bhavesh Kumar Jaisawal, Dr. Yusuf Perwej, Sanjay Kumar Singh, Susheel Kumar, Jai Pratap Dixit, Niraj Kumar Singh, “An Empirical Investigation of Human Identity Verification Methods” , International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN: 2395-1990 , Online ISSN : 2394-4099, Volume 10, Issue 1, Pages 16-38, 2022, DOI: 10.32628/IJSRSET2310012

[4] D. Droeschel, J. Stuckler, and S. Behnke, “Learning to interpret ¨ pointing gestures with a time-of-flight camera,” in Proceedings of the 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI ’11), pp. 481–488, March 2011

[5] Y. Perwej, “An Evaluation of Deep Learning Miniature Concerning in Soft Computing”, International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE), ISSN (Online): 2278-1021, ISSN (Print): 2319-5940, Volume 4, Issue 2, Pages 10 - 16, 2015, DOI: 10.17148/IJARCCE.2015.4203

[6] Y. Perwej, Asif Perwej, Firoj Parwej, “An Adaptive Watermarking Technique for the copyright of digital images and Digital Image Protection”, International journal of Multimedia & Its Applications (IJMA), Academy & Industry Research Collaboration Center (AIRCC) , USA , Volume 4, No.2, Pages 21- 38, April 2012, DOI: 10.5121/ijma.2012.4202

[7] Y. Perwej, “An Optimal Approach to Edge Detection Using Fuzzy Rule and Sobel Method”, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE), ISSN (Print) : 2320 – 3765, ISSN (Online): 2278 – 8875, Volume 4, Issue 11, Pages 9161-9179, November 2015, DOI: 10.15662/IJAREEIE.2015.0411054

[8] L Bretzner , I Laptev and T Lindeberg. “Hand gesture recognition using multiscale color features, hieracrchichal models and particle filtering”. Proc. Int. Conf. Autom. Face Gest

[9] Dardas NH, Georganas, Nicolas D. “Real-Time Hand Gesture Detection and Recognition Using Bag-of-Features and Support Vector Machine Techniques”. IEEE Transactions on Instrumentation and Measurement, 60(11): 3592, 3607, 2011

[10] A. D. Bagdanov, A. Del Bimbo, L. Seidenari, and L. Usai, “Real-time hand status recognition from RGB-D imagery,” in Proceedings of the 21st International Conference on Pattern Recognition (ICPR ’12), pp. 2456–2459, November 2012

[11] Y. Wang, C. Yang, X. Wu, S. Xu, and H. Li, “Kinect based dynamic hand gesture recognition algorithm research,” in Proceedings of the 4th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC ’12), pp. 274– 279, August 2012

[12] Z. Zafrulla, H. Brashear, T. Starner, H. Hamilton, and P. Presti, “American sign language recognition with the kinect,” in Proceedings of the 13th ACM International Conference on Multimodal Interfaces (ICMI '11), pp. 279–286, November 2011

[13] D. Droeschel, J. Stuckler, and S. Behnke, “Learning to interpret ¨ pointing gestures with a time-of-flight camera,” in Proceedings of the 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI ’11), pp. 481–488, March 2011

[14] A Argyros and M Lourakis. “Vision-based interpretation of hand gestures for remote control of a computer mouse”. Proc. Workshop Comput. Human Interact, 40 -51, 2006

[15] Q Chen, N Georganas and E Petriu. “Real-time vision-based hand gesture recognition using Haar-like features”. Proc. IEEE IMTC., 1-6, 2007

[16] L Juan and O Gwun. “A comparison of SIFT, PCA-SIFT and SURF”. Int. J. Image Process. (IJIP)., 3(4): 143-152, 2009

[17] Y Ke and R Sukthankar. “PCA-SIFT: A more distinctive representation for local image descriptors”. in Proc. IEEE Conf. Comput. Vis. Pattern Recog., II-506–II-513, 2004

[18] H Bay, A Ess, T Tuytelaars, and L Gool. “SURF: Speeded up robust features”. Comput. Vis. Image Understand. (CVIU)., 110(3): 346-359, 2008

[19] A. Shimada, T. Yamashita, and R.-I. Taniguchi, “Hand gesture based TV control system—towards both user & machinefriendly gesture applications,” in Proceedings of the 19th KoreaJapan Joint Workshop on Frontiers of Computer Vision (FCV ’13), pp. 121–126, February 2013
[20] C. Keskin, F. Kirac¸, Y. E. Kara, and L. Akarun, “Real time hand pose estimation using depth sensors,” in Proceedings of the IEEE International Conference on Computer Vision Workshops (ICCV ’11), pp. 1228–1234, 2011

[21] J. Zeng, Y. Sun, and F. Wang, “A natural hand gesture system for intelligent human-computer interaction and medical assistance,” in Proceedings of the 3rd Global Congress on Intelligent Systems (GCIS ’12), pp. 382–385, 2012

[22] Y. Perwej , Firoj Parwej, Asif Perwej, “Copyright Protection of Digital Images Using Robust Watermarking Based on Joint DLT and DWT ”, International Journal of Scientific & Engineering Research (IJSER), France, ISSN 2229-5518, Volume 3, Issue 6, Pages 1- 9, 2012

[23] Z. Mo and U. Neumann, “Real-time hand pose recognition using low-resolution depth images,” in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR ’06), pp. 1499–1505, June 2006

[24] J. Zhu and G. Zhu, “Joint face detection and facial expression recognition with MTCNN,” in Proceedings of the 2017 4th International Conference on Information Science and Control Engineering (ICISCE), pp. 424–427, ICISCE), Changsha, China, July 2017

[25] N. Akhtar, Y. Perwej, Firoj Parwej, Jai Pratap Dixit, “A Review of Solving Real Domain Problems in Engineering for Computational Intelligence Using Soft Computing” Proceedings of the 11th INDIACom; INDIACom-2017; SCOPUS, IEEE Conference ID: 40353, 2017 4th International Conference on “Computing for Sustainable Global Development”, ISSN 0973-7529; ISBN 978-93-80544-24-3, Pages 706–711, Bharati Vidyapeeth's Institute of Computer Applications and Management (BVICAM), New Delhi (INDIA), 01st - 03rd March, 2017

[26] Shweta Pandey, Rohit Agarwal, Sachin Bhardwaj, Sanjay Kumar Singh, Dr. Y. Perwej, Niraj Kumar Singh, “A Review of Current Perspective and Propensity in Reinforcement Learning (RL) in an Orderly Manner” , International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), Volume 9, Issue 1, Pages 206-227, January-February-2023, DOI: 10.32628/CSEIT2390147

[27] F. Parwej, "English Sentence Recognition using Artificial Neural Network through Mouse-based Gestures", International Journal of Computer Applications, vol. 61, no. 17, pp. 33-38, 2013

[28] W. Han, Z. Huang, M. Yan, and H. Fu, “A mask detection method for shoppers under the threat of COVID-19 coronavirus,” in Proceedings of the 2020 International Conference on Computer Vision, Image and Deep Learning (CVIDL), pp. 442–447, IEEE, Chongqing, China, July 2020

[29] Y. Perwej, Nikhat Akhtar, Firoj Parwej, “The Kingdom of Saudi Arabia Vehicle License Plate Recognition using Learning Vector Quantization Artificial Neural Network”, International Journal of Computer Applications (IJCA), USA, ISSN 0975 – 8887, Volume 98, No.11, Pages 32 – 38, http://www.ijcaonline.org., 2014, DOI: 10.5120/17230-7556

[30] C.-S. Lee, S. Y. Chun, and S. W. Park, “Articulated hand configuration and rotation estimation using extended torus manifold embedding,” in Proceedings of the 21st International Conference on Pattern Recognition (ICPR ’12), pp. 441–444, 2012

[31] A. Bevilacqua, A. Gherardi and L. Carozza, "Automatic perspective camera calibration based on an incomplete set of chessboard markers", 2008 Sixth Indian Conference on Computer Vision Graphics Image Processing, pp. 126-133, 2008

[32] Y. Wang, C. Yang, X. Wu, S. Xu, and H. Li, “Kinect based dynamic hand gesture recognition algorithm research,” in Proceedings of the 4th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC ’12), pp. 274– 279, August 2012

[33] Y. Perwej, “The Bidirectional Long-Short-Term Memory Neural Network based Word Retrieval for Arabic Documents”, Transactions on Machine Learning and Artificial Intelligence (TMLAI), Society for Science and Education, United Kingdom (UK), ISSN 2054-7390, Volume 3, Issue 1, Pages 16 - 27, 2015, DOI: 10.14738/tmlai.31.863

[34] Z. Chen, T. Ellis and S.A. Velastin, "Vehicle type categorization: A comparison of classification schemes," 14th IEEE Mnual Conference on Intelligent Transportation Systems, Oct. 5-7, The George Washington University, Washington, DC, USA. pp. 74-79, 2011

[35] Z. Zivkovic and F. Heijden, "Efficient adaptive density estimation per image pixel for the task of background subtraction," Pattern Recognition Letters, 27(7): 773-780, 2006