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New Method for Optimization of Static Hand Gesture Recognition

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***Abstract*—The main objective of this effort is to explore two of the methods of extracting features of interest, a contour hand and complex Alhzat to solve the problem of identifying the hand gestures by placing the main advantages and disadvantages of each method . The establishment of artificial neural network for the purpose of classification using the background learning algorithm.**

***Keywords*—Gesture recognition; Hand gestures; Artificial neural network; Human-computer interaction; Computer vision**

I. Introduction

computers have become a key element in the social club since the first screen in the second half of last century. Browsing the web or writing a message or playing a video game or data storage and retrieval are some of the tasks that require the use of information processing systems models. Computers will increasingly determine our daily lives due to the continued decline in the price and size of personal computers and the advancement of advanced engineering. Today, widespread use of nomadic devices such as smartphones and tablet devices, whether for work or communication has allowed the masses to easily access applications in different areas, including navigation in GPS applications and learning the language and so on. Effective use of most current computer applications requires user interaction. Therefore, it became the interaction between human and computer (HIC) an area of active research in recent years [1]. On the other hand, input devices for large changes have not been revealed from the most common information processing system in the 1980s perhaps because the devices are the same. The integration of information processing systems is closely related to everyday life, and new applications and devices are always presented to the demands of society to be responses to speak [2]. It is based on most current HSI devices in mechanical devices, such as keyboards, mice, sticks, or game pads. However, a growing interest arose in a class of applications that use hand gestures, intended for the natural interaction between the human computer screens and several controlled by [3]. The role of human impulses have become, especially hand gestures, an important element in the intelligent interaction between human and computer (HIC) in recent years, which helps as a driving force for research in The modeling, analysis and gesture recognition hand [4]. You can extend the various technologies that have been developed in Hsaia to other countries, such as surveillance, robot control, remote trading [4]. Sensor and understanding of the hand and body has become an important and difficult task gestures in computer vision. This can be illustrated by indicating the problem either by using natural movements that apply to verbal and non-verbal communication[5].

II. Methodology

General description of the hand gesture recognition system (as shown in Figure 1), and consists of the following steps. The first point is the step of taking a manual Nod image where the icons are set with a digital camera under different conditions such as scale, translation and rotation. The second stage is the pre-processor stage where processes for edge detection, homogeneity, and other filtering operations are produced. In the next stage, the lines are extracted from the hand gesture images by using two methods, namely the complex hand contour and Alhzat.The last point is classification using the artificial neural network (Ann), where the input rate is calculated for each of the which based on manual subsistence, and which depends that moments and complex based comparison . The search is a description of these stages.

A. Pre-processing stage

The main destination for the pre-treatment stage is to ensure a unified entry for the classification of the network. This phase includes segmenting the hand to provide insulated (hand movement) ground and employ special filters to eliminate any interference caused by the splitting process. This level also includes edge detection to determine the final shape of the hand.

1) Training Phase: In this stage, the composite feature vectors computed earlier and stored in a feature image database are applied as inputs to develop the neural networks. The learning process for the five multilayer neural networks is accomplished by using the parameters shown in Table 1.

TABLE I. Parameters for the Five Neural Networks

Parameters	Values
input patterns	1055 intersection
Convolution patterns	99 intersection
Classic patterns	6
factual error	0.03
discrimination learning	0.7

2) Training Phase: Later features vector counts, each (vector features) contains a 6 translation, scaled, fixed and rotating elements distinguish the complex moments of gestures with hands. And five are similar compilations of neural network formation with a data set containing 25 different bearing (data set formation). This has been a set of vector personal grooming account, which includes five lessons for each hand gesture performed by a discipline. Scholarships made of neural networks with new propagation process by using the parameters listed in Table 2. equal to the number of nodes in the input patterns for the vector element while equal to the number of nodes in the Classic patterns a Number of patterns proposed hand. In combination, the choice of the number of nodes in the hidden layer on the basis of trial and error, ie many experiments with a different number of nodes and form, which gives the best decision to be chosen.

TABLE II. PARAMETERS OF BACK-PROPAGATION NEURAL NETWORKS

Parameters	Values
input patterns	9 intersection
Convolution patterns	6 intersection
Classic patterns	6
factual error	0.03
discrimination learning	0.7

3) Testing Phase: After the development of five neural networks using training data consisting of 25 images, the process was evaluated using a group input network test and then work on the incorrect classification. Testing process of each bit is done in the same way the old way. At this stage, 90 is applied to the image of the gesture with the hand to try to leave the system. Each of the six hand gestures have a number of samples in different lighting conditions and the effects of scale, translation and rotation.

III. SPECIFICITY AND REACTIVITY FOR HAND CONTOUR

As shown in Table 3. The reactivity and precision values of the gesture categories are the same, since they are calculated in the same way. For the values of privacy, we observed that Euopean and the cat reached the highest value and the lowest, respectively. For Euopean, the privacy value is as high as 0.7553, which means that the probability of any image taken from other categories (ie close, cut, paste, max, min) to identify them correctly is 0, 7551, or simply the average credit rating and other categories is (75.51%), which means that Fatah has contributed negatively to the public recognition rate. For reactivity, which reflects the annual recognition rate, we noticed that the cut open has the highest lowest value of 0.8 0.4, which means that cut Open has the worst worst Recognition between the rate of six proposals.

IV. SCALING AND TRANSLATION IN HAND CONTOUR

Table 4, note that most of the error recognition resulting from the images associated with the translation(74%) , while errors Amlrttbh result ratio images in which the proportion of forms down (18.79%) And less than those resulting from industrial lighting (6.28%). To evaluate image recognition with scaling and innovation in hand contour showing results of image recognition of measured and experimental effects, respectively, the contour of the hand was able to cover cases of relatively good scaling Rate (27 valid cases out of 28), or(89.29 %). The only problem was related to translation cases, especially for some gestures such as opening, pasting, and Maine (0 %), (33.33 %) and (27

TABLE III. SPECIFICITY AND REACTIVITY VALUES FOR HAND GESTURES (HAND CONTOUR)

genuflection	Specificity	precision
Open	0.7553	0.4
Close	0.7082	0.77
Cut	0.6806	0.8
Paste	0.7447	0.50
Max	0.7022	0.90
Min	0.7237	0.60

TABLE IV. RECOGNITION ERRORS OF GENUFLECTION WITH SCALING, TRANSLATION AND ARTIFICIAL ILLUMINATION EFFECTS

genuflection	Scaling	Translation	Artificial	Total
Open	1 (27 %)	3 (79 %)	0 (0 %)	4
Close	0 (0 %)	2 (99 %)	0 (0 %)	2
Cut	1 (98 %)	0 (0 %)	0 (0 %)	1
Paste	1 (28 %)	2 (55 %)	1 (27 %)	4
Max	0 (0 %)	2 (99 %)	0 (0 %)	2
Min	0 (0 %)	3 (99 %)	0 (0 %)	3
Total	3	12	1	16
Recognition rate (%)	18.79 %	74 %	6.28 %	100

1) Specificity and sensitivity for Complex Moments : As shown in Table 5, the sensitivity and accuracy values of the gesture categories are the same, since they are calculated in the same way. This shows that maximum and minimum privacy is achieved with a paste (0.8899) and open, respectively. As for the aperture, the privacy value is 0.8407, the lowest value while the sensitivity is 1.00, the higher value means that the probability of having selected an image of an open gesture class is recognized Correctly is the highest (probability of 1) the probability of the other average years (probability is 0.8407). This also means that the open class contributes positively to the public recognition rate.

TABLE V. SPECIFICITY AND SENSITIVITY VALUES FOR GENUFLECTIONS (COMPLEX MOMENTSR)

genuflection	Specificity	Sensitivity
Open	0.8407	1.00
Close	0.886	0.7
Cut	0.876	0.834
Paste	0.8899	0.77
Max	0.8575	0.936
Min	0.8698	0.868

2) Rotation, Scaling and Translation for Complex Moments : Table 6 clearly shows that most of the vehicle errors identified errors due to cases having a turnover (82.2%).

TABLE VI. ERROR OF GESTURE WITH (COMPLEX MOMENTS) TRANSLATION

genuflection	Scaling	Translation	Rotation	Total
Open	0 (0 %)	0 (0 %)	0 (0 %)	0
Close	1 (34. %)	0 (0 %)	2 (70.6 %)	3
Cut	0 (0 %)	0 (0 %)	2 (99 %)	2
Paste	0 (0 %)	0 (0 %)	3 (98 %)	3
Max	0 (0 %)	0 (0 %)	1 (99 %)	1
Min	1 (55 %)	0 (0 %)	1 (55 %)	2
Total	2	0	9	11
Recognition rate (%)	19.1 %	0 %	82.2 %	100

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