Robust Gesture Recognition Using Gaussian Distribution for Features Fitting

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***Abstract*—Hand gesture became second language that complements almost many speeches, encounters, lectures, as well as friends chatting even in computer chatting they may gesturing to each other since it is a rotted habit in our behavior, we can notice that even if someone was sitting alone and thinking; he will continue gesturing during his meditation, however, the imitating of this natural behavior is an important issue for transferring this behavior to the human made machines and the intuitive interface will not be changed as compared to human-human communication, in this paper, we have applied a novel approach for recognizing the hand gesture and to maximize the level of unrestricted communication by solving the problem of rotation invariance that matters, we have employed a Gaussian bivariate likelihood function for hand modeling and features fitting and to produce uniform features that can be a reference for gesture database, we have achieved remarkable recognition percentages using 20 different gestures with a high speed recognition time, our system can be used for real time applications in which the time factor is important issue for the success of such systems, we have made a comparative study with some other known gesture algorithms as well.**

***Index Terms*—Gesture recognition, gaussian mulivariate function, gaussian bivariate funciotn, template matching, orientation histogram, elastic graph, fuzzy C-mean, euclidian distance.**

I. Introduction

A human gesture is a form of non-spoken interaction in which human bodily actions are employed to explain a meaning; it takes the form of speech or spoken words or together [WikiPedia]. Gestures can originate from any bodily pose but commonly initiate from the face or hand [WikiPedia]. The gestures are used along with spoken words for human speaking [WikiPedia].

Computer recognition of hand gestures may provide a more natural human-computer interface, allowing people to point at, or rotate a graphical model by rotating their hands. Interactive computer games would be enhanced and developed if the computer vision could understand and carry on players' hand gestures. Gesture recognition may even be useful to control household appliances [2]. Robots and human made machines of the future time should communicate with humans in a natural way [3]. However, many challenges can be addresses when the human interact with the robot using hand gestures or face expression, these challenges can mislead the robot, in [2] and [3], they address these problems as complex backgrounds, dynamic lighting conditions and a deformable human hand shape. The gesture recognition problem employed pattern representation and decision making [4], and can be connected with computer vision and image processing and artificial intelligence. Fig. 1 [1] shows the hand gesture that done by the underwater divers since it is their only communication way available.

Fig. 1. Divers gesture to deliver the message "I am cold" [1]

There are two types for gestures, we can call them as static and dynamic, static gesture is a particular hand pose which represented by a single image. The latter type is a moving gesture represented by a sequence of images [5].

The aim of the gesture recognition is to enable humans to interact with the human made machines in natural way without any mechanical devices and without using the normal input devices which are the keyboard and mouse and the mathematical equations will be the translator that translates the poses between the gestures and the telerobotic.

II. Used Strategies

We have studied four gesture recognition methods which are template matching [6], orientation histogram [2], elastic graph matching [5] and fuzzy c-means [3]. The input picture is taken from a computer camera and then we have applied sequencing processing steps including segmentation, and we have applied the slope-based normalization operation to reduce the number of gesture samples taken for each gesture type, and then we have applied our recognition technique for getting the features for each distinct input gesture image.

The extracted features are stored in a database as a the final step for the training operation, the same processing sequence are applied in testing phase to get the final features of the input picture and then use some techniques to find the corresponding gesture from the database which represents the final step of the recognition operation.

III. Gestures Features Representation

Gestures are usually represented by various features, which are templates, transformations [4], geometric features, and non-geometric features. Templates are the easiest features to compute; they are simply the input gesture in its

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raw form without any extra calculations. Transformations, such as rotation, translation, or scaling can be applied to reduce the number of feature vectors in templates and then reduce the database size which may speed up the recognition time. Geometric features are the features that calculated somehow directly from the gesture skeleton or contour before or after applying some preprocessing operation; these features includes the width of the gesture, the height of the gesture; the number of fingers, the distance between the hand fingers, etc. The non-geometric features include all the features that are extracted from applying some mathematical equations on a preprocessed hand gestures in order to obtain more refined and distinguishable features for accurate recognition. Fig. 2 shows an example of geometric features.

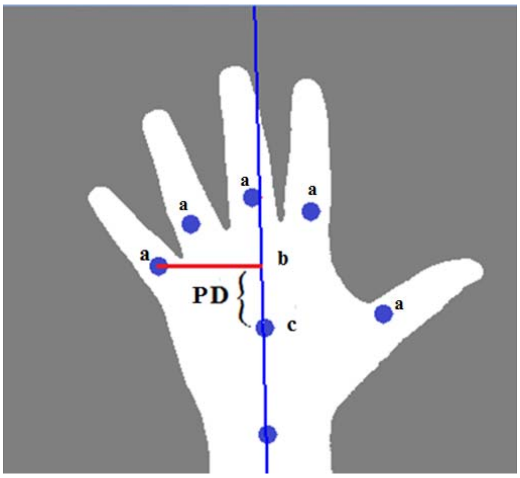


Fig. 2. Geometric features example

IV. GESTURES CATEGORIES

K. Symeonidis, Jiong J. Phu, and Yong H. Tay, classified the hand gestures into three categories in [7][8], which are:

A. Glove Based Analysis

This employs sensors (mechanical or optical) attached to a glove; those transducers finger flexions converted into electrical signals for detecting the current hand pose. The relative position of the hand is determined by an additional sensor. This sensor is normally a magnetic or an acoustic sensor attached to the glove [7][8].

B. Vision Based Analysis

This is based on the way that how human beings perceive information about their surroundings via his eyes; it is a subfield of artificial intelligence, which deals with images and understanding of images in which specific information is being extracted from the image gesture for a specific purpose [8]. Vision Based Methods use the colors information extracted from the images by using image processing techniques and then attempt to simulate the acting of human vision. This category considered to be the most natural way of constructing a human-machine interaction [9].

C. Drawing Gestures Based Analysis

This represents a simple gesture for recognition, the gestures are drawn and prepared for some commands and the human made machine may be programmed by showing of these drawn as teleoperators, and a teleoperated machine can understand this command and carry out the action specified by it. The drawing commands also used for recognition of written text [10].

V. BASIC OPERATIONS FOR GESTURE SYSTEM

We can totalize the basic operations for gesture recognition system into four main operations, Fig. 3 show a sketch for these main operations:

A. Collecting the Inputs

In this stage, the meaningful gestures that will be used as an input for the gesture recognition system must be predisposed and decided, these input images may have a background and this background may be variant or invariant, all these factors must be considered in depending on the system usage, in case of a simple usage, a non-background gesture is far enough, for moving robot usage, the background is an important factor for gesture recognition. Furthermore, the selection of the gestures should subject to discrimination of its features in the feature space that will represent, these gestures should not be overlapped during the selection, this impact on the recognition percentage since overlapped gestures will drop down the recognition accuracy.

B. Image Preprocessing

Segmentation and tracking are the most essential in order to extract useful information from raw gesture images [8]. Thus, it is necessary to be able to recognize the region of foreground and split it from the background in a given gesture image. The foreground consists of target objects which may be tracked (in our case hand gesture), while background consists of irrelevant pixels which are to be discarded. Many techniques can be used to separate foreground and background of an image, for example Binary Thresholding, Connected Components Labeling, Image Differencing and etc.

C. Feature Vector Extracting

In this stage, the features must be extracted; these features will be used at the time of testing operation, many features may be extracted for the same input gesture as mentioned above in geometric and non-geometric.

D. Efficient Classification Algorithm

The main job of the classifier is to identify which trained class the current presented testing gesture belongs to. The classifier has to score those trained classed according to the presented testing gesture and the maximum matching score is the corresponding trained gesture class.

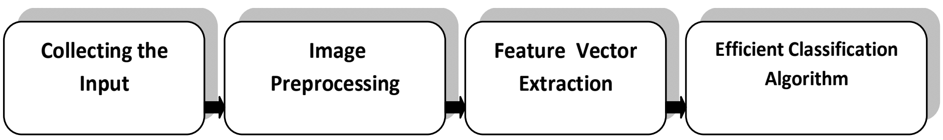


Fig. 3. Overview of gesture recognition system

VI. Challenges

There are some challenges that are facing the process of gesture recognition and these challenges can be found in preprocessing step and these are common for almost all the gesture recognition application, and if the gesture is not well obtained then this will affect all the latter pending process, however, the challenges can be summarized by the Fig. 4.

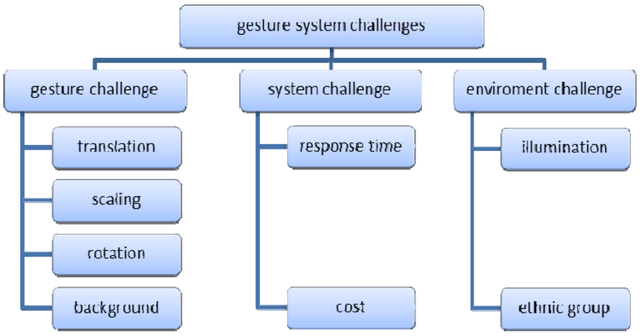


Fig. 4. Gesture challenges

A. Gesture Challenges

These kinds of challenges are embedded in the input gesture and varying from one gesture to another even in the same system some of these challenges are relatively easy to manage and some harder.

1) Translation Challenge

That is the (Δx, Δy) shift for 2D and (Δx, Δy, Δz) shift for 3D space in which just the location of the hand object may change, the computer camera or the robot should detect the change in the location of the hand object and process accordingly, usually this can be managed by trimming operation in which the whole area that the hand may appear should be considered, other remedy could provide by using the histogram technique [2] in which the histogram is immune to translation.

2) Scaling Challenge

That is the size change by the scaling factors $\left(\delta_x, \delta_y\right)$, $\left(\delta_x, \delta_y, \delta_z\right)$ for each of 2D and 3D respectively, this means the hand object may change its distance away from the capturing camera lens which reflects on overall shape scale seen by this camera, this can be solved by standardizing the detected hand object with a standard size scale to unify the size, histogram can be used as well [2] to provide fixed scale ground.

Other remedy can be done through the use of multi-scale factors to produce many images with different sales [6] and the matching will be done with all of these images sequentially.

3) Rotation Challenge

Rotation challenge plays major role in every gesture recognition system and has great impact on the final recognition accuracy; the real solution for this kind of challenge is ignored by many researchers and replaced by increasing in the number of training patterns which is the traditional approach for achieving the rotation invariant classifier.

4) Background Challenge

The main challenge and the most important one is how to extract the foreground form the background, this processing plays a vital role in any gesture system since the bare hand should be presented in the system without the accompanied background, this operation is more easy In 3D model in which the hand is modeled using one of the mentioned 3D models, however, in 2D vision based system this needs more focus and more concentration, many background have been employed from single color background [11][12][13], uniform [14][15][16], and cluttered or complex background [17][18][19].

B. System Challenges

This category covers all the challenges that should be processed by the system, these challenges have different outcome for different systems.

1) Response Time

The first and important challenge is the response time which should be fast [20]. There should be no noticeable time between user gesturing and computer response [20], this kind of challenge considered of high importance especially in real time and virtual reality systems in which the time factor is very important.

2) Cost Factor

One more challenge which is the cost challenge, the gesture system needs special hardware such as the camera and sensors as necessary [20], those special hardware will be the replacement of the existing hardware devises which may considered as low cost [20] such as the keyboard and mouse, but the gesture system with these new devices will be more worthwhile for wireless communication [20], this leads to a good selection of the system requirements according to the application used.

C. Environment Challenges

These challenges are those who affected by the surrounding environment, this factor may affect the input image or the processing time as well for the system.

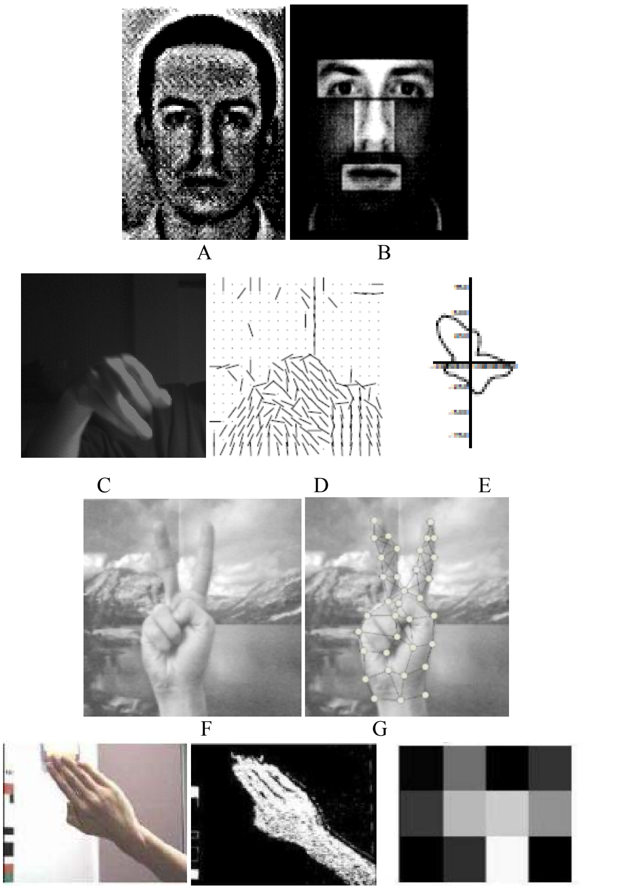
1) Illumination

Illumination is the changing in the light condition weather it is artificial light as indoor or at night, or natural lights as outdoor, this challenge should be processed by segmentation operation and can be overcome by normalization the color component or by using of other color space models such as YCbCr or HSV prior to segmentation process, other remedy can be done such as producing many normalized templates with different degree of brightness [6] or using of histogram orientation that detects orientation of the edges even was dark [2].

2) Ethnic Groups

The designed computer vision algorithms should be reliable and work for different ethnic people [20] especially when the color of human is changed comparing with white and black people, the different ethnic groups have a significant property which is the different in the skin color is represented by the pigment concentration difference that affect the saturation of the skin [3][16][21] which leaves the hue almost the same and can be modeled for gesture system generalization, however, the segmentation model can be toned with different ethnic pigment skin color for better hand object locating.

bounding box [3]. The remaining 12 features represent a rough blocking of the image, where each cell of the divided grid is the mean of the gray level in the 3 by 4 block division of image [3].



A, C, F, H: the original gestures for template matching, histogram orientation, elastic graph, and fuzzy c-means respectively.
B, E, G, J: the feature gesture for A, C, F, and H respectively, D, I represent temporary steps for orientation, c-means respectively.

Fig. 8. The feature extraction for the selected methods [6, 2, 5, and 3]

X. PROPOSED ALGORITHM

We have adopted Gaussian Multivariate pdf for features fitting and modeling and for uniform features extraction, since we are working on 2D vision based system that include (x, y) coordinates, the resulted Gaussian Function is called bivariate, however, the general form for Multivariate function can be seen in Equation (1).

$$f(x_1, x_2) = k \exp\left(-\frac{1}{2}(x-\mu)^{T_{\Sigma^{-1}}}(x-\mu)\right) \tag{1}$$

where $x=(x_1, x_2)=(x, y)$, $\mu=(\mu_x, \mu_y)$, and k=1 since we are adopting this pdf as a likelihood function which means the maximum probability is one and the minimum probability is zero, Σ^{-1} is written as (2):

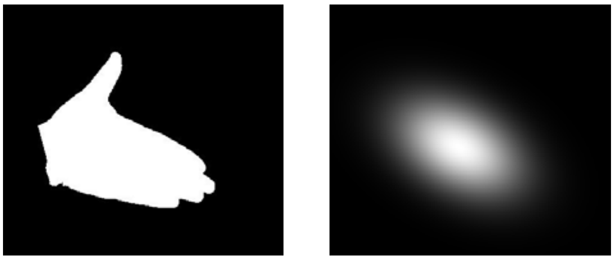
$$\Sigma^{-1} = \begin{bmatrix} \Sigma_{xx} \, \Sigma_{xy} \\ \Sigma_{yx} \, \Sigma_{yy} \end{bmatrix}^{-1} \tag{2}$$

We can find the inverse of the above matrix by simple calculations as shown below as (3):

$$\Sigma^{-1} = \frac{1}{\det(\Sigma)} \begin{bmatrix} \Sigma_{yy} - \Sigma_{xy} \\ -\Sigma_{yx} \, \Sigma_{xx} \end{bmatrix} = \frac{1}{\Sigma_{xx}\Sigma_{yy} - \Sigma_{xy}\Sigma_{yx}} \begin{bmatrix} \Sigma_{yy} - \Sigma_{xy} \\ -\Sigma_{yx} \, \Sigma_{xx} \end{bmatrix} \tag{3}$$

XI. APPLICATION OF BIVARIATE FUNCTION

We have applied the suggested distribution using input images after segmentation operation takes place, see Fig. 9.



A: input image. B: corresponding Gaussian multivariate.

Fig. 9. Application of Gaussian bivariate function

XII. DIVIDING THE GAUSSIAN SURFACE

Resulted sketch has been divided into regions; the division is shaped like a terrace for reducing the effects of rotation invariance, 11 different terraces have been achieved by making this terrace its width equals to 0.1 likelihood width on the Gaussian surface, the result is 9 terraces (1-0.9, 0.9-0.8, 0.8-0.7, 0.7-0.6, 0.6, 0.5, 0.5-0.4, 0.4-0.3, 0.3-0.2, 0.2-0.1), plus one more extrapolated by non-linear regression model which has the value less than 0.1, the exterior area that lies outside the confined terraces is considered as single terrace, so, we have the total number of demanded terraces since this number ensures a high recognition accuracy as experienced from circle features divisions, Fig. 10 shows a pictorial representation for such division.

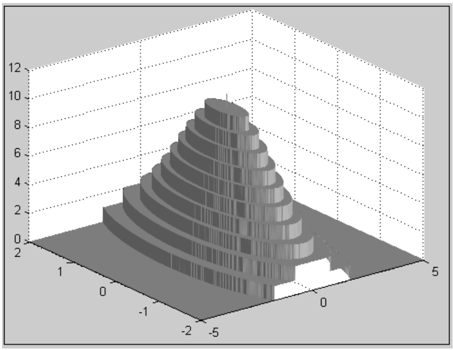
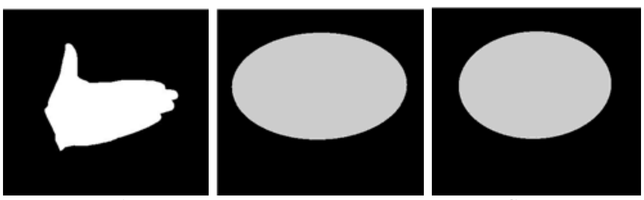


Fig. 10. Terraces division

Some modification has applied to ensure the Gaussian fits the input hand object completely and re-estimation for the above shape has been done, Fig. 11 shows this modification.



A. B. C.

A: hand object. B: initial Gaussian. C: Gaussian after parameters adjustment.

Fig. 11. Adjustment of Gaussian bivariate parameters

XIII. Feature Area Division

Feature areas is the final division for calculating the required features, the terraces are divided further into 8 portions called feature areas, number 8 has a better recognition results as seen by practical for circle features divisions, however, Fig. 12 shows the final division of the terraces areas in 2D and 3D.

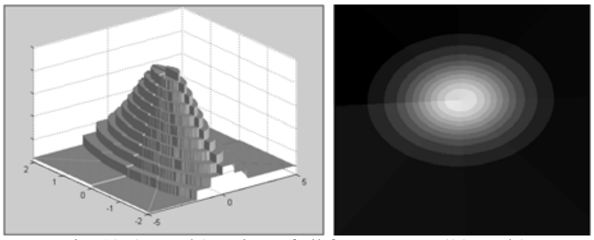
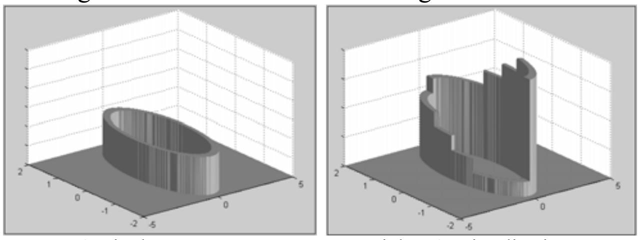


Fig. 12. 3D and 2D view of all feature areas (88 totals)

A single terrace has been shows in Fig. 13.



A: single terrace. B: eight FAs visualization.

Fig. 13. 3D subdivision visualization

As a live example applied on input image, we demonstrated Fig. 14.

Fig. 14. Image features divisions

XIV. Local Features

Feature vector has been calculated using geometric central moments since it provides a good representative for input features, we have adopted two different moments which are μ_{00} , μ_{11} as seen by Equation (4).

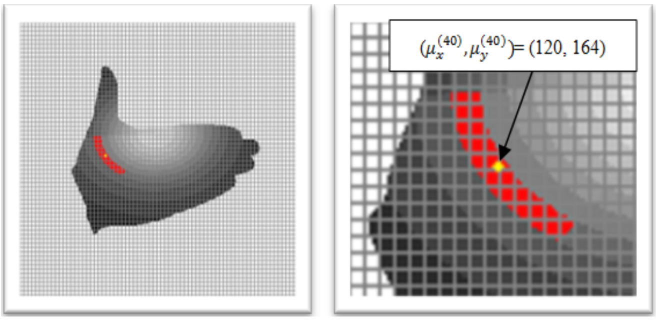
$$\mu_{pp} = \sum_{x}\sum_{y}(x-\mu_x)^p(y-\mu_y)^p\ f(x,y) \qquad (4)$$

The above μ_x and μ_y represent the mean value for each input feature area, which means 88*2 features will represent the input image, a more specific equation can be seen in(5).

$$\mu_{pp}^{(k)} = \sum_{y}\sum_{x}\left(x^{(k)}-\mu_x^{(k)}\right)^p\left(y^{(k)}-\mu_y^{(k)}\right)^p f\left(x^{(k)},y^{(k)}\right)$$

$$\forall\ k \in \{1, 2, 3, \ldots, 88\}\ \&\ \forall\ p \in \{0, 1\} \qquad (5)$$

As an example for how the mean will be calculated, consider Fig. 15.



A: partitioned image. B: centeriod of selected feature area.

Fig. 15. Centeriod of the feature area

XV. Global Features

The global features are two features that represents the first and second moments of the overall feature areas which are 88 area, each feature area is represented by the multiplication of its intensity besides its map location of the feature areas, Fig. 16 shows an example of how these features are calculated.

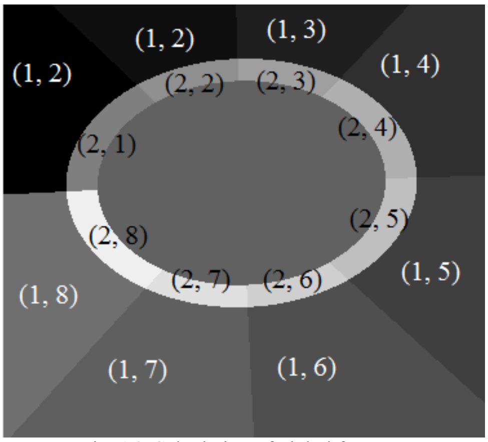


Fig. 16. Calculation of global features

After that, the total features are 178 features, 88*2 for local features =176 plus two for global features, these features show a good robust for increasing the number of gestures in the database.

XVI. Experimental Results

We have applied 20 different gestures, 5 training for each and 5 testing as well; we have achieved remarkable recognition percentages as shown in Fig. 17.

As seen by Fig. 17, we have achieved 90 % recognition percentage in case of 20 different classes are trained by the system, this percentage in increased gradually by reducing the number of trained gesture classes, at 14 class downward the recognition percentage fixed at 100 % which means full recognition, on the other hand, the time required for tested single gesture is approximately 121 milliseconds (0.121second) which is remarkable.

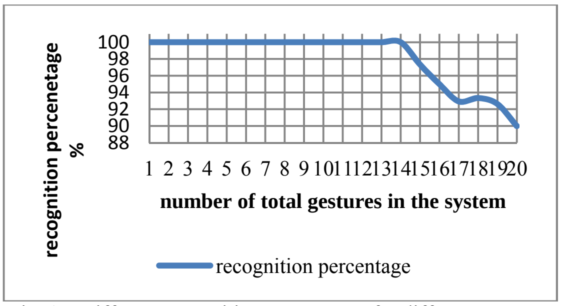


Fig. 17. Different recognition percentages for different gestures

Furthermore, the feature vector also discriminant which reflects the selection of the features used, see Fig. 18.

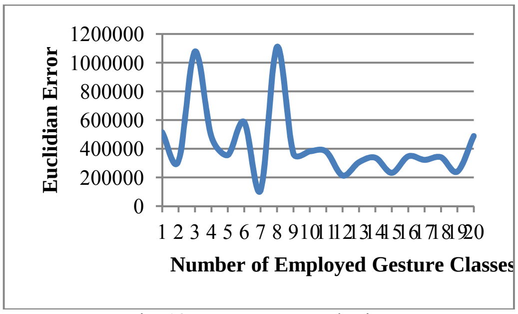


Fig. 18. Feature vector plotting

This is the class number 7 and hence has minimum difference produced by the Euclidian classifier, and other Euclidian error's correspond to other classes are far away from that class.

XVII. Efficient Classification Algorithm

The existence of an efficient classification algorithm plays a major role toward the success of the gesture recognition system, this leads toward hard algorithms which means time consuming and then will conflict with the real time applications which the speed is very important, in other hand, gesture recognition algorithm should be fast to compute, this abates the accurateness of the recognition, so, depending on the application of the system; one has to choose the classification algorithm that meets the demand.

We can say that the template matching method is the simplest approach for gesture recognition and variants to lighting change and transformation operations unless many gesture will be taken in different directions and scales which causes the time consuming, histogram orientation is more reliable than template matching and invariants to lighting and some percentage of transformation but the main disadvantage is that the hand must be the main object in the picture or else the recognition will be misled, the elastic graph matching good for background and lighting change and the scaling of 12 % and shifting the graph up 12 pixels [5] give a good flexibility for recognizing the gestures . The fuzzy c-means effected by the rotation operation and the recognition will be failed in case of the new presented gesture is rotated comparing with trained gestures.

XVIII. Disadvantages

In this section; we illustrated some disadvantages of the selected methods as follows:

A. Template Matching

As concluded by the authors in [4], the size of the feature vector increases with the size of the input [4], since they need different and more templates for different transformation to overcome the transformation problem. Moreover, this problem also addressed in rotation variance, so, they have to present more features to overcome this problem and this leads to time consuming which lead to disqualification for real time applications.

B. Orientation Histogram

As the authors in [2] practice their input gestures, they address the problem as some same gestures produce different orientation histogram and in other side, same orientation histogram can be obtained from different gestures [2] . In their present system, this problem can only be solved by providing multiple training samples for the same gesture [2]. Some different gestures have very similar orientation histograms. Fig. 19 shows this case where A and B are two different gestures, with the histograms plotted in C. They comment for the proper selection of database gesture vocabulary. The hand must be the main object in the image [2].

A B C

Fig. 19. Classification problem in histogram orientation method [2]

C. Elastic Graph

The current approach needs large geometric variations between different initiations of the same posture [5].

Another weakness is the high computation complexity required for this algorithm, this method requires several seconds to analyze a single image if no special hardware is used [5].

D. Fuzzy C-Means

When the lighting is too high, the classification is not very clear as shown in Fig. 20 which will produce different feature vector. Also the median filtering that is used to reduce the noise in this method induces blur at the edge of the hand shape [3]. And also the recognition rate goes down as the distance between the user and the camera is greater than 1.5 meters as concluded by the authors in [3] or when the lighting is too high. The system cannot recognize the image that has two or more similar size skin objects like face and hand [3], there is no special consideration for the arm [3] and treated as a part of the hand.

A B

Fig. 20. Lighting problem [3]

The fuzzy c-means algorithm minimizes intra-cluster variance as well [24], but has the same problems as k-means, the minimum is a local minimum, and the results depend on the initial choice of weights [24]. Assumptions are made for the distribution of the features within classified classes, when such assumption not satisfied, this resulting the poor performance of such systems [4].

XIX. Conclusion

In this paper, we presented four different methods for gesture recognition, the user can selects the methods according to his application, in real time application and when the speed is needed template matching is more reliable but in turns, the gestures have to be almost fixed, in robotic application the accuracy is needed and elastic graph or fuzzy c-means can be applied for this reason, elastic graph needs special hardware for processing the input image or else the software application will be not useful in real time applications, in case of background problem you can use elastic graph or you can solve the background problem by a good segmentation and then use fuzzy c-means which is very fast with good accuracy, our selected method is faster than other methods and good recognition percentages with different gestures that have different transformation variance.

We have employed Gaussian bivariate pdf for fitting and capturing the segmented hand gesture, this step helps to reduce the rotation perturbation affection that is cured normally by increasing the number of trained gestures in each gesture class in order to increase the probability of matching the input tested gesture with the already trained classes in feature space, this pdf also cure the translation as well as scaling perturbations since it captures the data as aforesaid.

For more details for interested readers about the proposed algorithm please refer to [25] that have a detailed implementation of Gaussian bivariate pdf for features fitting, extraction, and gesture recognition.

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Exploiting Hierarchal Structure of XML Data Using Association Rule Analysis

Gurpreet Kaur and Naveen Aggarwal

Abstract—**Data mining is the process of extracting useful information from the huge amount of data stored in the databases. Data mining tools and techniques help to predict business trends those can occur in near future. Association rule mining is an important technique to discover hidden relationships among items in the transaction. Association rules is a popular and well researched method for finding interesting relation between variables in large databases. For generating strong association rules, it depends on the association rule extraction by any algorithm for example Apriori algorithm or FP-growth etc and the evolution of the rules by different interestingness measure for example support/confidence, lift/interest, Correlation Coefficient, Statistical Correlation, Leverage, Conviction etc. The classical model of association rules mining is support-confidence. The goal is to experimentally evaluate association rule mining approaches in the context of XML databases. Algorithms are implemented using Java. For experimental evaluation different XML datasets are used. Apriori and FP Tree algorithm have been implemented and their performance is evaluated extensively.**

Index terms—**Data mining, association rule analysis, XML.**

I. Introduction

Data mining or Knowledge discovery in databases (KDD) is the process of discovering previously unknown and "useful" patterns form the huge amount of data stored in flat files, databases, data warehouses or any other type of information repository. Database mining deals with the data stored in database management systems. Data mining tools can answer business questions that traditionally were too time consuming to resolve. There are basically two most important reasons that data mining has attracted a great deal of attention in the recent years [2]. First, our capability to collect and store the huge amount of data is rapidly increasing day by day. Due to the decrease in the cost of storage devices and increase in the processing power of computers, now a days it is possible to store huge amount of organizational data and process it. The second but the more important reason is the need to turn such data into useful information and knowledge.

If we are rich in data then we may or may not be rich in information, because the useful information is often hidden in the data. Data mining tools and techniques are used to generate information from the data that we have stored in our database repositories over the years. To take advantage in the market over the competitors, decision makers, administrators or managers need to mine the knowledge hidden in the data collected over the years and use that information in an effective and systematic way [2].

Data mining scans the databases for hidden patterns, finding predictive information that experts may miss because it lies outside their expectations. It consists of an iterative sequence of the following steps such as Data Cleaning, Data Integration, Data Selection, Data Transformation, Data Mining, Pattern Evaluation, Knowledge Extraction. The data mining step may interact with the user or a knowledge base. The interesting patterns are presented to the user and may be stored as new knowledge in the knowledge base.

A. *Evolution of Data Mining*

Evolution of data mining techniques began when business data was first stored on computers.

Improvements in data access techniques continued and technologies that allow users to navigate through their data in real time are also available. Data mining takes this process to a new dimension of data access and navigation to information delivery. Data mining is used as an application in the business community because it is supported by three technologies that are following [3]: Data collection, Multiprocessor computers, Data mining techniques and algorithms. Commercial databases are growing at unprecedented rates at different industries; market places etc. In the evolution from business data to information, each new step has built upon the previous one. Following are the four steps that allow business queries to be answered correctly [3]: Data Collection (1960s), Data Access (1980s), Data Warehousing & Decision Support (1990s) and Data Mining (Emerging Today).

B. *Application Area of Data Mining*

Some application areas are as follows:

- A pharmaceutical company [3] can analyze its recent sales and their results to improve targeting of high-value physicians and determine which marketing activities will have the greatest impact in the next few months.
- A credit card company [3] can access its large warehouse of customer transaction data to identify customers most likely to be interested in a new credit product etc

II. Association Rule Analysis: Apriori and FP-Tree Algorithm

Association rule mining is an interesting data mining technique that is used to find out interesting patterns or associations among the data items stored in the database. Support and confidence are two measures of the interestingness for the mined patterns. These are user supplied parameters and differ from user to user. Association rule mining is mainly used in market basket analysis, retail

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