Hand Gestures Detecting Using Radon and Fan Beam Projection Features

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Hand gesture recognition is one of the most effective ways of human interaction with a computer and it is also an important field in computer vision and machine learning. This theme enables many applications by allowing users to communicate the interfaces of different systems, without the need for additional hardware. That is, the primary goal of gesture recognition is to create systems in order to identify specific human gestures and use them to transmit information and signals or control various devices. There are more of research in the field of pattern recognition about gesture recognition, some of these researches focus on dimensionality reduction, others on the recognition model, on the type of feature selection and so on. In this paper, the static hand gesture is detected depending on the application of radon features and fan beam projection on hand images to calculate the projection at certain angles. The reason for adopting these techniques is to take advantage of their qualities in given features that are not related to the shape and size of the object. The decision tree model is used in the classification stage to discover five different hand gestures, and all the results are explained in the research below. With the adoption of these two projection methods in extracting the characteristics of the hand signal, the results showed high potential, where the highest success rate for classification was at the 90 theta, so the success rate with radon features was 88% and with beam projection was 91.8%.

Povzetek: *V tej raziskavi se izvajajo različne tehnike ekstrakcije zvočnih funkcij in predstavljeni so klasifikacijski pristopi za razvrščanje sedmih vrst vetra. Kjer smo uporabili tehniko funkcij, kot so Zero Crossing Rate (ZCR), Fast Fourier Transformation (FFT), Linear Prediction Coding (LPC), Perceptual Linear Prediction (PLP). Vemo, da nekatere od teh metod dobro vplivajo na človeške glasove, vendar smo jih poskušali uporabiti tukaj za označevanje zvočne vsebine vetra. Za določitev razreda vhodnega zvočnega signala vetra je uporabljena klasifikacijska metoda CNN. Eksperimentalni rezultati kažejo, da je vsaka od teh metod ekstrakcijskih lastnosti dala različne rezultate, vendar se je za klasifikacijo lastnosti PLP izkazalo, da imajo najboljše rezultat.*

1 Introduction

Gestures are one of the most natural way to interact with different people and things around us, and they include various gestures in the body, such as hand gestures, also, they represent an indication of a specific behavior or expression, where a person can make many gestures at the same time. And because human gestures can be identified and followed up, it has occupied a very wide area in the field of computer vision in terms of attention and research because of its importance and because the representation of these gestures at the level of languages and algorithms is not easy and may be complex [1] [2].

Gestures, in general, are kinetic behaviors that express the parts of the body that emits that behavior, the purpose of which is to convey a specific communication message to the party that receives these signals. Scientifically, gestures may be categorized into dynamic and static gestures. Dynamic gestures are changed during a period of time, while the static gestures change at the spurt of the moment. An example of dynamic gestures is the waving of the hand, while the static gestures can be exemplified by a stop sign. In order to understand a complete message, all kinds of the dynamic and static gestures must be understood over a period of time. Then, gesture recognition represents the process of recognition and interpretation of a stream of the continuous sequential gestures from an input data set [1] [3].

In order to build a richer bridge between machines and humans, the issue of gesture recognition may be observed as a way for the computers to start understanding signals of human body [4]. Accordingly, methods of gesture recognition are split into vision-based and glove-based data methods. In the case of Data-Glove, it uses optical or mechanical sensors that are attached to a glove, which converts the fingers flexion into electrical signals to diagnose hand position. As for the vision-based technologies, they do not require a camera, so they can achieve a natural interaction between computers and humans by requiring no additional devices. All of the systems attempt to simulate biological vision via applying systems of artificial vision in hardware and/or software. The vision-based methods may be one of the most natural methods, not just the design of a human-computer interface.

In some visual environments, we can get the visual information about the user, and then extract the required gesture, nevertheless, there are some challenges: firstly, the recognition of the moving hand from a cluttering background, secondly, the hand motions analyses, thirdly, the hand position tracking relative to the environments, and lastly, detection of the hand postures [5][6].

The processing of gesture recognition problem are a problem of a pattern recognition, where the gesture input as images, and this image can be processed by using image processing techniques. These images pass initially through the preprocessing, then, features are extracted and captured from an image, finally the video files in turn are matched to pre-defined exemplification of the gestures (i.e. patterns)[5].

The hand gestures recognition (HGR) has become in recent few years widespread and interesting for the purpose of increasing the interaction between humans and machines [7]. It is known that hand gestures give more important information compared to the other gesture types like the arm, hand, face and others. Hand gestures are represented by certain movements of the fingers and hand depicting a specific message in the nonverbal communications. Now, hand gesture recognition can be considered as perceptual computing that provides the machines with the ability to recognize gestures of the hand and implement the relevant actions. The current situation of the (COVID19) pandemic has caused a great necessity for HGR in different areas of the life like: consumer electronics market, transportation sector, gaming, defence, non-touch smart-phones, home automation, robotics, sign language machine translations, and so on. This means that we need to integrate HGR with the AI in order to evolve and design custom touch interfaces for everyday activities at the same time as maintaining the physical distance. Here, we say that we need a powerful HGR system, which can work on the memory-limited devices in the real-world applications and with high efficiency. Examples of these systems are: color-marking approach, vision-based approach, glove-based method and depth-based method [8][9]. This paper shows new processing method of hand gesture recognition, we applied radon features and fan beam projection on hand images, to extract the important characteristics from hand gestures, and then enter these features to decision tree model for decision-making. The details of the work are explained in the paragraphs below.

2 Literature review

Gesture recognition systems have been increasing, as they become an important aspect of the human - computer interactions. The gestures are created by movement of an individual. Hands and/or Face are the gesture sources. The body movement mirrors the feeling / information through the gestures. “Saying Hi” can be considered gesture but "Typing anything" on keyboard is not considered gesture. It is due to the fact that the movements of the typing fingers are not noticeable. The utilization of the hand gestures in various applications of software has participated in improving computer and human interaction [10], and there are more studies which have been conducted in the pattern recognition field. (Mohamed et al., 2010) In this search, Gaussian Mixture Model (GMM) was utilized in order to excavate the hand from the video series. Extremed points have been obtained from the splited hand utilizing star skeletonization and recognition has been implemented through the distance signature. The results of the proposed way have been experienced on the set of data which has been taken in the locked environment with the hypothesis that the user must be in Field Of View (FOV). This search was applied for 5 various data-sets in different lighting conditions. The conclusion of this search had suggested a system real time vision for gesture of hand basis computer interactions for controlling an event such as Power Point Presentation slides navigation [11]. (Sauvik et al, 2012), have presented a study to deal with the detection of several hand gestures through ML techniques and prime component analyses. An amplifier of biomedical signal is created after applying a simulation software with the aid of NI Multisim. At the beginning, two pairs of surface electrodes that are utilized to get the (EMG) signals of the hands. By using the surfaced electrodes, these signals are amplified through an amplifier of BioMedical Signal. An amplifier of BioMedical signal that was utilized has been essentially an amplifier device made with the aid of IC AD 620. The output of an amplifier device was filtered by the aid of an appropriate Filter, such as the Band-Pass. The output of this filter is inputted to an Analog to Digital converter (ADC). After that, the data of ADC is fed to appropriate technique to detect various gestures of the hand. [12]. (Pavlo Molchanov et al., 2015) proposed a recognition algorithm of drivers’ hand gestures from challenging depth and intensity data utilizing 3-D convolutional neural networks (CNN).The information is merged from multi scales of spatial domain for ultimate predictions. It also employed spatiotemporal data augmentation for more efficient training and in order to minimize the possibility overfitting. This technique realized 77.5% rate of classification on the database of VIVA challenge [13]. (Feng et al., 2015) in this work, a new proposed method of multiple-layered gesture recognition technique that was depending on Kinect. It explored the fundamental linguistic codes of gestures that represent the combinations concurrent and the sequential organization codes, in this multi-layered framework, features are extracted of both the units of segmented semantic and the full gesture series, and after this, the location, shape, and motion components are serially classified. At the 1st layer, an enhanced foundation motion has been performed for modeling the motion combinations. In the 2nd layer, a descriptor of particle-based and a weighted dynamic time warping have been suggested for classification of location combination. In the last layer, the spatial path warping has been further proposed for classifying the form combination that is represented via unclosed shape context. The proposed technique could obtain relatively high achievement for one-shot learning gesture detection on the ChaLearn Gesture (CG) Data-set that comprises over 50000 gesture series that have been recorded with the Kinect [14]. (Ying et al., 2014), in this study, the probabilistic detection framework dependent on the hidden Markov models (HMMs) combine the detection of the two compose of gestures. Utilizing information from the hidden (i.e. unobserved) states in the HMM, then could distinguish a variety of the stages of gestures: prestroke, nucleus and poststroke stages. This allowed the system to answer suitably to both gestures, which demand a discrete answer and those requiring a continuous answer. This system can extend: in only a few minutes, users could define their own gestures via granting a few instance rather than writing code. And as well combined a new gesture set of data which include the two shapes of gestures, and a new hybrid achievement metric has been proposed for evaluating gesture detection techniques for real-time interaction. [15]. (A. Mujahid et al.,2021) proposed a model to a tagged database of hand gestures in both YOLO format and Pascal VOC that realized best outputs via extraction of features from the hand as well as the detected hand gestures via suggested YOLOv3 based model. The training model can be utilized for real-time recognition, both for the dynamic hand images and static gestures recorded on a video [16]. (H. Huang et al.,2019) proposed a rapid and strong technique for hand gesture detection based on (Red-Green-Blue) RGB video. First, they recognize the skin according to their color, then essence the segment and contour the hand region. Lastly, they detect that gesture [17].

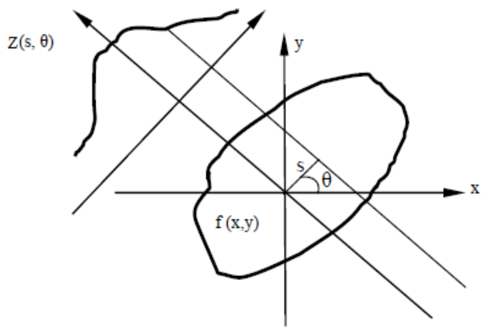


Figure 1: Geometry of Radon transform.

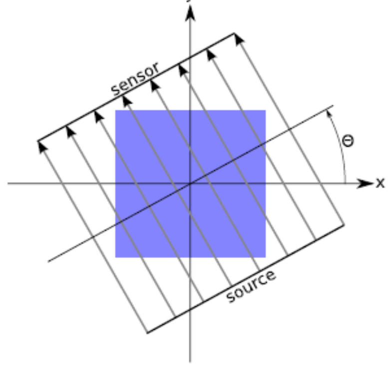


Figure 2: Parallel Beam Projection of the RT at Rotation Angle θ.

3 Hand feature extraction

Each raw of data has low-level information, which is analyzed to produce semantic information in higher-level that are used for recognizing the postures and gestures, this process is called Feature Extraction and Analyses [18]. Feature-extraction approaches are used to collect the data about the gesture position, posture, orientation, and temporal progression. In this section, radon and fan beam projection is the feature extracted from each image, because these features can give different information about the curves and angles of the hand then, the sign of the hand can be determined.

Radon transform (RT) is the mapping from function onto projections. In image analysis area, RT is mainly known due to its role in computed tomography [19], which is used to model the acquiring projections process of the original object by using X-rays, and also used to detect shape. The function f(x, y) used to defined the Radon transform, and denoted as Z(s, θ), has been characterized as its line integral along a line which had inclined at θ angle and at distance s to the origin. The Radon transform geometry is shown in figure (1) and may be expressed as:

$$Z(s,\theta) = \int f(x,y)du = \iint_{-\infty}^{\infty} f(x,y)\delta(x\cos\theta + y\sin\theta - s)dxdy \quad (1)$$

where δ(x) represents Dirac's delta function[20][21].

There are 2 distinct RTs, the source may either be a single point or it may be an array of sources. Figure2 illustrates the parallel beam projection at certain angle of rotation θ. The source and sensor contrapment has been rotated around the object's center. For every one of the angles q, density of matter the rays from source passes through accumulates at sensor. Which is repeated for a certain group of angels, typically from q ∈ [0;180). The angle 180 isn't included due to the fact that the result would be similar to angle 0. For any input images I the radon (image, θ) returns RT of intensity image for the angle θ degrees. Radon transform gives linear features, and it is a useful to fine the directional features of images, then it is computed with respect to this axis, tendering robust features.

In fan beams, the projection of data has been gathered rather than the parallel beams. This method allows rapid collection of the projections in comparison with the parallel beam scanning. Those diverging beams are similar to the shape of a fan, which is why, it has been referred to as fan-beam geometry, see the Figure 3, where the source S emits a thin X-rays divergent beam, and shows the detector to receive the beam. The source position is characterized by the angle β that represents source position, and (σ, β) represents each projection ray:

$-\pi/2 \leq \sigma \leq \pi/2$, $0 \leq \beta < 2\pi$. Equations (2) and (3), are indicated to the rays of the parallel beam coordinates (s, θ). [20].

$$S = D\ sin\ \sin\sigma \tag{2}$$

$$\theta = \sigma + \beta \tag{3}$$

D represents distance from the source to the origin of the object. The Fan-beam geometry is showed in Figure (4). The distance D (from the fan-beam source to the center of rotation) is firstly determined and it must be large enough to ensure that the source of fan-beam is outside of the image at all rotation angles. The Radon and Fan beam are applied the projections at a variety of angles by rotating source around the pixel of center at θ degree intervals. Then the data of the projection are features vectors [22].

4 Gestures classification part

After extract the effective features of hand image, the gesture classification method is implemented to recognize the type of hand gesture. There are different recognition models that can be used in this problem, such as Euclidean distance, HMM, SVM, KNN…etc.

Decision tree can be applied for such problems, then it is used in this system to classify five hand gestures, widely used in classification problem. The structure of the tree classifier is a decision rule that is performed through recursive partitioning of subsets of the measurement space A into disjoint regions (i.e. nodes), beginning with A itself, (i.e. the root node). The conditions that splits have to fulfil is that descendant nodes are more homogeneous as to class content than their parent. The actual construction of the classifier is based on a learning sample B consisting of the measurement data (x1,j1), ……., (xN,jN) on N cases, where xn ϵA and jn ϵB={1 …J} is a class identity, n=1,…,N, figure 5 shows an example of this structure [23], where each level splits the data according to different attributes.

Usually, a tree is constructed from the top to bottom, where the tests maximizing information gain about classification are chosen first, then the goal here is achieving perfect classification with minimal number of decisions [24].

5 The work system

This work is developed to hand gestures recognition as show in Figure 6, that shows the all the parts of the Model of this system. At every time, this system captures one frame (an image) at a time. The next steps is the preprocessing and feature extraction, where the Radon and fan-beam projections are used to compute feature vectors of hand image. The recognition rates are compared for both of these features using decision tree method. The following section includes the explanation of main steps of this work.

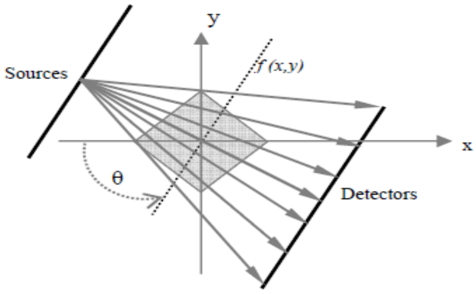


Figure 3: Fan-beam projection at rotation angle θ.

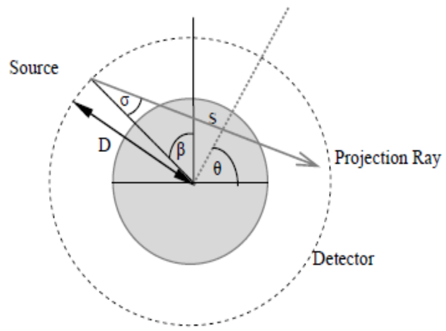


Figure 4: Fan-beam geometry.

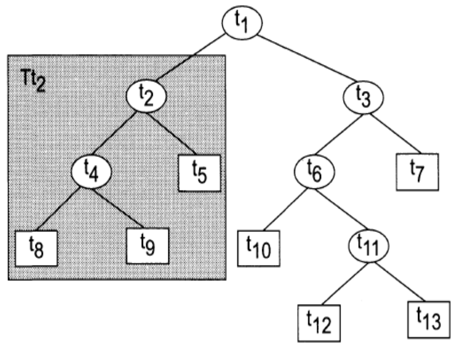


Figure 5: Example of tree structure.

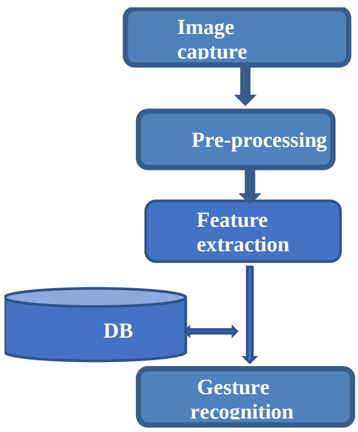


Figure 6: Vision-based hand gesture processing stages.

5.1 Preprocessing and features extraction

The main objective of this stage is the preparation of input image for the purpose of extracting features in the next stage, where the optimal result mainly depends upon the next step, due to the fact that some of the methods only require an approximate bounding box of the hand, while others require an accurately segmented region of the hand for the purpose of getting the silhouette of the hand [25] [26].

Then, in this stage some processes are applied to determine and extract the hand in image, which include:

1- background subtraction[27] [28],

2- determination of the hand boundary by finding the region where values of summation of row and column are more than1,

3- finally image resizing, Figure 7 shows an example of hand extraction.

Radon transformation: figure 8,shows the resulted Radon transformation features of one frame of image I with theta ranging from 0 to180 degrees. Initially the pixels in the image I are divided into four sub-pixels and each subpixel is projected separately.

In this research, our focus has been on the theta from 0 to 45, which means the angles (5, 10, 15, 20, 25, 30, 35, 40 and 45), because the values of theta that are greater than 45 do not give the values of hand signal differentiation, While the values of theta that are less than 45 give distinct values of RT, and this is what has been relied on here, as show in figure 9. The resulted RT feature is a vector with length 1x459 values for each angle. For any inputted image I:

The fan-beam is calculated as following:

a- The fan-beam (I, D) is computed here, where D=300. The D must be large enough to ensure that fan-beam vertex is outside of the image at all rotation angles. Figure 10 shows the fan-beam projections (FB) for rotation angles that cover the entire image I.

b- The FB projection is calculated at different direction angles, which are :30,45,90 and 180, respectively, then, the resulted feature vector for each angle are of size: 101x12, 101x8, 101x4 and 101x2 For each one of the selected angles respectively.

c- Also the fan-beam projection and its corresponding Radon transform at particular rotation angle (fan rotation angle) are computed and the final resulted size of features are 459x12, 459x8, 459x4 and 459x2 respectively radon features according to each angles.

Fig.11 shows the vector that has been generated using Fan-beam and its corresponding radon features with different angles.

5.2 Classification stage

In this stage, the decision tree model is used to be classify to five classes cues of hand images, and to learn the decision tree there are two phases, which are:

1. Learning the decision tree of a training set: tree=built-tree (training set), the output is classification tree according to the input training set, this tree is a binary Decision tree (BDT), where each branching node is split based on the values of a column of training set. Figure 12 shows the returned trees for the training set of radon transformation. In Fig 12(1) with the angle of 45 and the length of

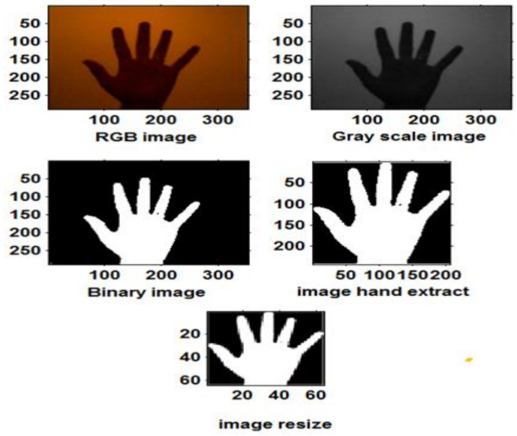


Figure 7: The processes of extraction the hand region.

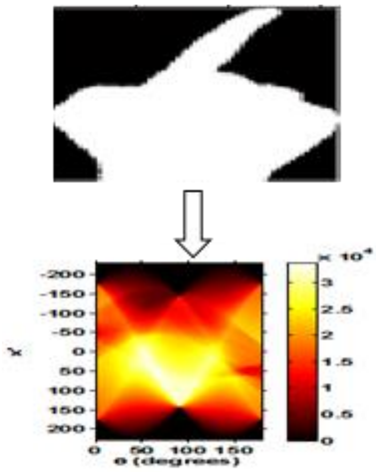


Figure 8: The image I in the upper part and its the complete radon transform is in the lower part.

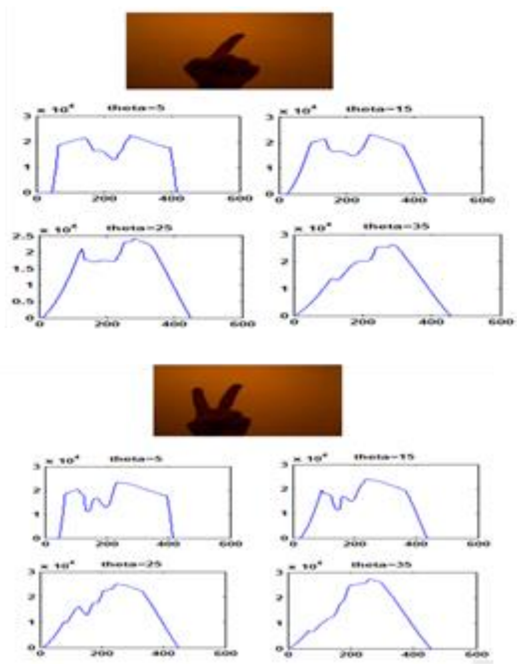


Figure 9: The image and its Radon Transformation (RT) to four different theta.

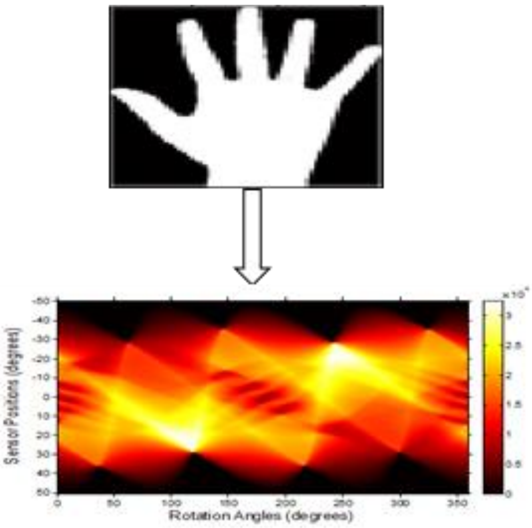


Figure 10: Fan-beam projections of image I.

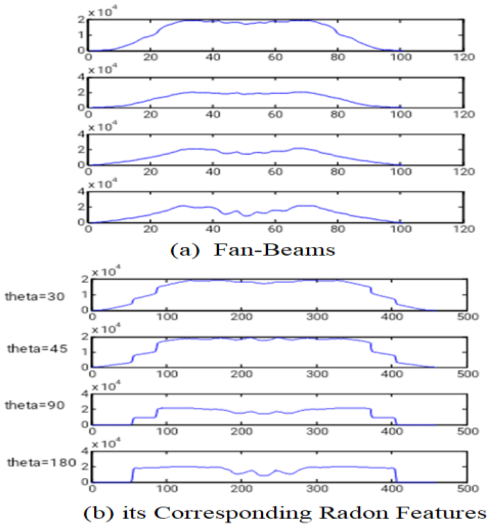
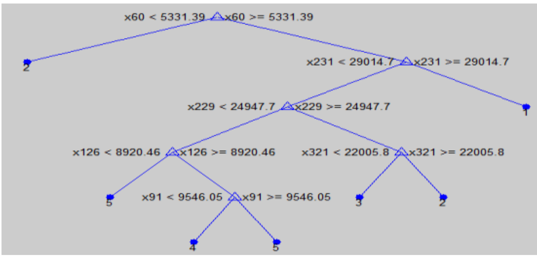
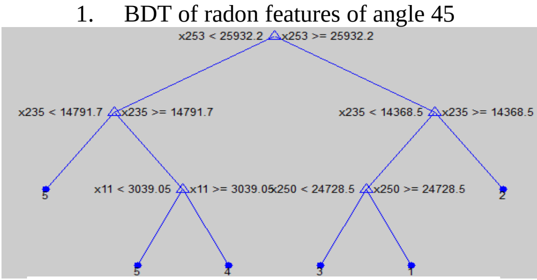


Figure 11: The feature vector generated by fan-beams and its radon features.



1. BDT of radon features of angle 45



2. BDT of fan beam features of angle 45

Figure 12: The Binary Decision Tree (BDT).

feature vector for each frame of images is 459 values. And in (b) FB features with angle 45.

2. Predict classes for novel testing example: L= predict(tree, testing samples), Where L is the predicted class, based on the resulted tree. For the trees, the classification score of the leaf node represents posterior probability of the classification at this node, which represents the number of the training sequences leading to that node with classification, divided by number of the training sequences leading to that node.

6 Results and discussion

Based on the phases of this system, our experiments have been based on a data set downloaded from the Internet. The number of input training sets is 100 examples with five classes of hand gestures. For the value of the system, the testing dataset included 100 examples.

When we get the projection of image space, the reshape of feature size is applied n:

- For the Fan beam features with size 459xN,the size vector becomes 101.N,example 101x2 features is became after the reshape size is 1x202,
- and for corresponding radon features with 459x2 is reshaped to 1x918.

For Radon features: Table 1 presents the accuracy obtained by using RT features. From the information in this, it can be seen that the sign of hand is more accurate with the theta more than 35,because with these theta degrees>= 35 are gave appropriate projections of hand image intensity along a radial line which can be help in classify the gesture of hand.

Table 2 shows the classification results, and it can be see that the gesture with the best accuracy recognized at the 40 and 50 degrees, and the fifth class that represents the gesture of five, is the best for all theta degrees. According to these results, Figure 13 and figure 14 show that, in general, the accuracy results with theta 40 and 45 were best, but with θ={15, 20, 25, 30} they were not that good, and also it has been noted the class 5 gives the best result.

In fan-beam transform features: The resulted FB features contain the fan-beam sensor data for each increment rotation angle (the rotation angles where the fan-beam projections are calculated). The features Fan-beam with 101xn, the average of the projections is taken

Theta=	Accuracy%
5◦	56
10◦	66
15◦	42
20◦	44
25◦	56
30◦	46
35◦	62
40◦	74
45◦	74

Table 1: The Accuracy of Classification Method with RT.

Theta=	Class1 %	Class2 %	Class3 %	Class4 %	Class 5 %
5°	80	40	30	30	100
10°	65	40	50	65	100
15°	20	10	40	30	100
20°	30	10	30	50	100
25°	40	20	60	60	100
30°	40	40	20	30	100
35°	40	45	80	45	100
40°	50	70	90	50	100
45°	60	90	70	50	100

Table 4: The Accuracy Results of Each Class with RT Features.

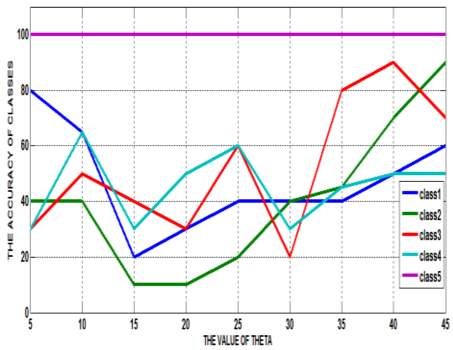


Figure 15: Chart of the Accuracy Result Compare with Theta Degrees.

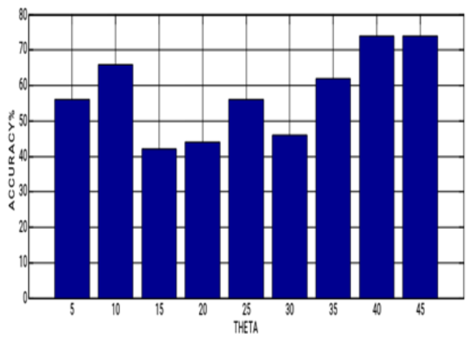


Figure 16: The Accuracy of each Class According to each Angle.

to it, Hence, the size of feature vector for one numeral becomes 1×101.Then the corresponding Radon features are calculated, according to the rotation angles that are depended in the projection of fan-beam. Table 3 shows a comparison between FB and RT, and Table 4 shows the overall comparson results of each class according to the features FB and TR and by implementing the decision tree classification models. In figures 15 and 16 it is shown that with the theta 90 the results were the best but with 180 in general they were not good, and class 5 gave the best results with the FB and corresponding RT, thus it is concluded that with the degree 90 the results were always the best.

Theta	**Fan-beam**	**Corresponding Radon**
θ =30	80%	78%
θ =45	86%	88%
θ =90	88%	92%
θ =180	52%	58%

Table 2: The result of FB and RT.

	FB features			
Classes:	***Theta =30***	***Theta =45***	***Theta =90***	***Theta =180***
Class1	*67*	*75*	*75*	*50*
Class2	*76*	*88*	*88*	*35*
Class3	*80*	*97*	*97*	*20*
Class4	*77*	*70*	*80*	*55*
Class5	*100*	*100*	*100*	*100*
	RT features			
Classes:	***Theta =30***	***Theta =45***	***Theta =90***	***Theta =180***
Class1	*67*	*75*	*77*	*95*
Class2	*66*	*97*	*100*	*50*
Class3	*97*	*88*	*88*	*15*
Class4	*60*	*80*	*94*	*30*
Class5	*100*	*100*	*100*	*100*

Table 3: Overall Classification Accuracy Results.

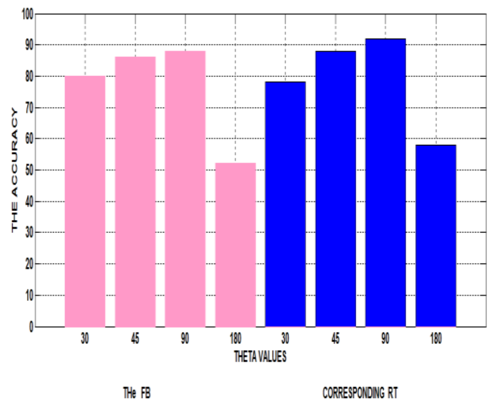


Figure 13: Accuracy Result Theta Degrees for FB and Corresponding RT.

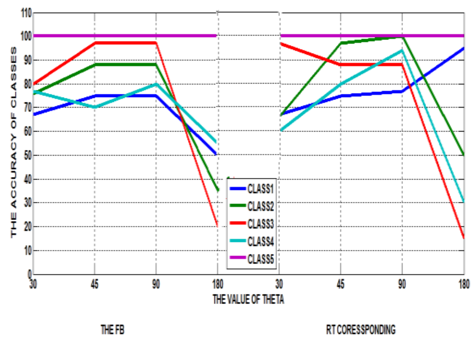


Figure 14: The Accuracy Results of each Class According to each Angle.

At the end of this paragraph, we can summarize the results that have been obtained from those experiments in the following final table

Projction	30◦	45◦	90◦	180◦
FB	80%	86%	88%	52.5%
RT	78%	87.8%	91.8%	58%

Table 5: The final accuracy.

7 Conclusions

In this work the radon transformation and fan-beam with corresponding radon features are extracted of hand images, where the experiment was done on five different types hand gestures. The Radon and its inverse use fan-beam geometry to project for each geometry, and then use their projections to provide sufficient information to classify the image. The results of the space projection are very efficient in determining the classes of hand gestures, and the following conclusion can be derived: The RT features gave the best recognition with the theta rotation that are greater than or equal to 35 degrees and the most important results were with class 5 that represents the hand sign with all fingers. With the fan beam and its corresponding radon features the best results are with theta 45 and 90 degrees and the class 5 is the best, the overall results here are important and can be relied in the problem of activity recognition. The corresponding RT features have shown more consisted results especially with 45 and 90 degrees and class 5 is the more accuracy.We can conclude that with the increasing projection degree and with images that have more details, the result may be increasing. It can also be said that the results with these two transform methods are similar, and there is a slightly better improvement with the RT features.

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