Driving Aid for Rotator Cuff Injured Patients using Hand Gesture Recognition

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Abstract: - Gesture recognition is a way for computers to understand how humans move and express themselves without using traditional methods like typing or clicking. Instead of relying on text or graphics, gesture recognition focuses on reading body movements, such as those made by the hands or face. Currently, there is a specific interest in recognizing hand gestures by analyzing the veins on the back of the hand. Scientists have found that each person has a unique arrangement of veins beneath the skin of their hand. When the hand moves, the position of these veins changes, and this change is considered a gesture. These gestures are then translated into specific actions or tasks by coding the hand movements. This technology is particularly helpful for individuals with rotator cuff injuries. The rotator cuff is a group of muscles and tendons in the shoulder that can get injured, causing pain and limiting movement. People with these injuries may have difficulty steering a car, especially if their job or sport involves repetitive overhead motions. With gesture recognition technology, a person can control the car by simply moving their wrist, eliminating the need to use the shoulder. In summary, gesture recognition technology reads the unique patterns of hand veins to interpret hand movements, making it a practical solution for individuals with rotator cuff injuries who may struggle with certain tasks, like steering a car.

Key-Words: - Rotator cuff, hand gestures, Complex Walsh transform, Sectorization, Dorsal hand vein arrangements, Kalman filter, Discrete wavelets.

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1 Introduction

A gesture is a way of showing actions or emotions visually, like using body and hand movements. There are two types of gestures: passive ones, where the body or hand position gives a clue, and active ones, where the body or hand changes to convey information. Gestures help people interact with computers in a different way than using regular tools. Instead of relying on hardware like keyboards or mice, computers can understand human intent by recognizing body movements or changes in limb positions. Scientists have been working on improving the technology to recognize hand gestures, [1], [2], [3], and it has various applications such as understanding sign language and enhancing experiences in virtual reality.

1.1 Rotator Cuff Injury

The rotator cuff as shown in Figure 1 is like a bunch of muscles and tendons around your shoulder joint. It keeps the upper arm bone in place in the shoulder. If your shoulder hurts, it might be because of a rotator cuff injury. The pain can get worse if you sleep on the sore shoulder. People who do jobs or play sports that involve a lot of overhead movements, like carpenters, painters, tennis players, and baseball players, are more likely to get rotator cuff injuries. The risk of these injuries goes up as you get older. The injury could be a simple inflammation or a complete tear, [4], [5].

Having a rotator cuff problem is painful and limits your ability to move your shoulder. A big injury to the shoulder or the slow wearing down of tendon tissue can cause rotator cuff problems. Doing a lot of overhead movements over a long time, developing bone spurs around the shoulder, or continuous upward actions can make the tendon worse.

In these situations, people with rotator cuff injuries may find it hard to put pressure on their shoulders, like when driving a car. If a driver has a rotator cuff injury, he/she might struggle to turn the steering wheel and may even do accident because he/she can't control the car properly due to pain. However, if we design an aiding tool for people suffering from rotary cuff injuries which allows the driver to control the car by just moving the hands without putting pressure on shoulder. This way, they can steer the car effectively with less physical effort and better control.

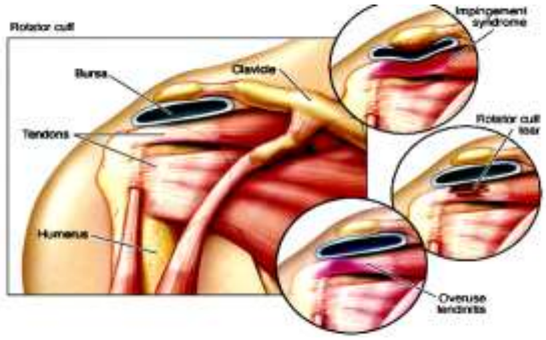

Fig. 1: Rotary cuff diagram

1.2 Dorsal Hand Veins

The dorsal hand vein is the arrangement of the blood veins beneath the dermis of the hand. This pattern is exclusive to every person and cannot be tampered with or forged by anybody. Due to this sturdy nature of characteristics, this is used as a Biometrics in recent days. This arrangement is used as the representation of the hand gesture and utilized for detecting the rotation of the hand, [6], [7].

1.3 Detection and Recognition of Hand Gesture

The objective of this research is to develop a novel technique to recognize the gestures of the hand. It is proposed a completely new algorithm for the detection of the angle of rotation through a hand gesture recognition algorithm. The techniques or methods of recognition of gestures of hand need to be satisfied for various parameters, [8], [9]:

- Flexibility: (can be applicable to any requirements), [10].

Practicality: The approach shall be practically precise enough to be used and perfectly detect the required gestures.

- Reliability it should be reliable

Robustness: The system should be robust such that it can identify the gestures even though the light is bad, the background is not clear and the position of the object is rotated.

Scalability: It should be scalable.

Versatility: The algorithm should work on different hands uniformly without any variation in the performance even if the sizes of the hands are different or the color of the hands is different.

1.4 Tracking of Dorsal Hand Veins

Dorsal hand veins are one such feature that is user independent and satisfies all the conditions mentioned. Hence, in our work, the orientation of dorsal hand veins is detected and is used to steer the car accordingly.

1.5 Related Work

Hand gesture recognition is carried out using

- Neural networks and Perceptron convergence algorithm provide noise rejection and more processing speed, [11].
- Maximum likelihood recognition, [12].
- Kalman filter approach and Bayesian framework, [13].
- With Haar Classifier and adaboost Algorithm, [14].
- A Kalman filter and hand blobs analysis. Markov models are used for gesture recognition and are robust for ASL gestures and background clusters and recognition accuracy of up to 98% has been achieved, [15]
- PCA, Pruning, and ANN, [16].
- Via LAN & Wireless Hardware control using mathematical algorithm, [17].
- With Eigen dynamics analysis by modeling hand dynamics with EDA and likelihood edge. It combines histograms of color and features of edges, [18].
- Haar Cascade, Adaboost Algorithm, Hidden Markov Model and Douglas Peucker Algorithms achieved average recognition rate of 91% on data set of 16 gestures, [19].
- Kalman filter using a 3D depth sensor. They identified the probable images of hands with the help of clusters of motion, and predefined wave motion, and tracked the positions of the hand using the Kalman filter, [20].
- Boundary lines of palms and vein patterns were detected employing canny edge detection techniques, [21].
- Depth-based segmentation and Haarlets, [22].
- Human computer interaction using hand gesture with accuracy of 95.44%, [23], [24].
- Dynamic time warping and Histogram of oriented gradient features, [25].

2 Materials

To identify the rotation of the hand, we use images of vein patterns beneath the skin on the upper part of the hand. These vein patterns can't be seen or captured with a regular camera that uses visible light. Instead, we use NIR (Near-Infrared) capturing technology with a special camera that has a monochrome Near-Infrared CCD camera fitted with an infrared lens.

Two sources of infrared (IR) energy are directed at the upper hand, and the blood's hemoglobin absorbs this energy, making the vein patterns visible as thick lines. A CCD camera then captures the image, turns it into digital data, and stores it in a database for later analysis. You can see an example of how these vein patterns are arranged in Figure 2 and Figure 3.

Fig. 2: Dorsal hand vein image-normal

Fig. 3: Dorsal hand vein image-Near infrared

3 Method

In Figure 4, you can see the steps for tracing hand vein gestures using Kalman filtering. Figure 5 shows the algorithm for recognizing vein gestures, using methods like Histogram of Oriented Gradients, Reversible Complex Hadamard Transform, and Discrete Wavelet Transform (DWT). Here's a simple breakdown of what happens:

Image Transformation:
The initial image is turned into a gray one, and a Region of Interest (ROI) is selected.

Database Enhancement:
The database is made better by rotating input images both clockwise and counterclockwise.

Various Analysis Methods:
Three different methods (Histogram of Oriented Gradients, four-phase Reversible Hadamard Transform, and DWT) are used for image analysis.

Feature Extraction:
Important features are taken from different parts of the image and saved in the database for later correlation to understand how the image is rotated.

Histogram of Oriented Gradients:
Gradients (changes in intensity) are calculated from the image database, creating a feature database that helps determine the rotated angle.

Reversible Complex Hadamard Transform:
Attributes are taken from quarters of coefficients of the reverse Hadamard transform and stored in the database for matching attributes and finding the rotated angle.

Gestures Tracking with Kalman Filtering:
Kalman filtering, Sobel, and Canny edge detectors are used to locate edges. The reference centroid is calculated, and the Kalman filter helps track coordinates.

In simple terms, these steps show how computer programs can analyze images of hand veins, understand the gestures, and figure out how the hand is rotated using advanced techniques.

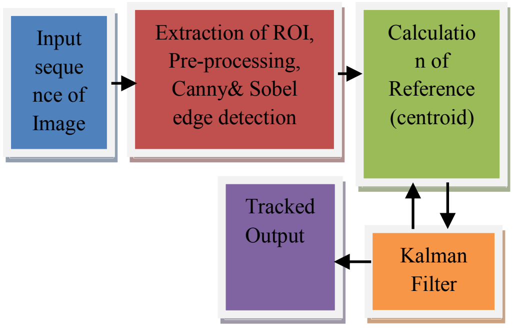

Fig. 4: Hand gestures tracing using Kalman filtering

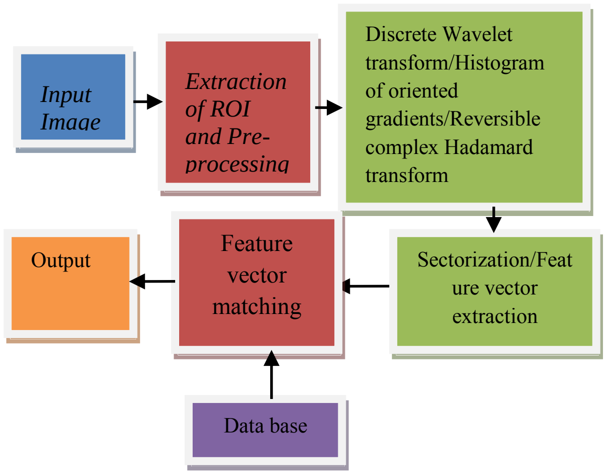

Fig. 5: The method of identifying vein patterns on the back of the hands using techniques like DWT, Histogram of Oriented Gradients, and Reversible

Complex Hadamard Transform is outlined in the algorithm

The features taken from a given image are then compared with those in the image database using Euclidean distance to find the best match. This matching process considers parameters such as standard deviation, arithmetic average, skewness, and median.

3.1 Pre-processing

To make the analysis more effective, we first cut out the part of the image where the vein arrangement is visible by cropping. We then remove the rest of the image, and apply adaptive histogram equalization to improve the image quality by making the pixel values more even . Once this processing is done, we save these improved images in a database for training purposes.

3.2 Discrete Wavelet Transform

The process of breaking down the Discrete Wavelet Transform (DWT) into a pyramid structure involves using low-pass and high pass filters on the original image. This produces four second-level coefficients: a smoothened image known as a low-low (LL) partitioned image, which holds the approximate details of the original image, and three detailed partitioned images that show the horizontal (LH), vertical (HL), and diagonal (HH) directions of the original image. First level decomposition is given in Figure 6 and second level decomposition is given in Figure 7.

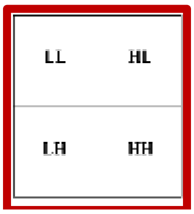

Fig. 6: First level DWT decomposition

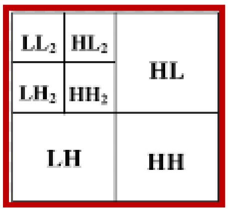

Fig. 7: Second level DWT decomposition

The decision on which class an image belongs to is made by measuring the Euclidean distance between the features of the query image and those of the training dataset.

Various types of wave filters are part of families like Daubechies, Coiflets, Symlets, and Fejer-Korovkin. In this case, Haar wavelet from the Daubechies family is used. Haar Wavelet is a combination of rescaled "square-shaped" functions called "basis" functions, each with different scales. Using Haar wavelets provides four coefficients of Discrete Wavelet Transform (DWT): approximation, horizontal, vertical, and diagonal. These coefficients are important for extracting features from the image.

3.3 Reversible Complex Hadamard Transform

The complex Hadamard matrix H of order N, (and H*complex conjugate transpose) is a unitary matrix with symbols ±1, ± j, where j = $\sqrt{-1}$, is shown in equation (1)

$$HH^* = H^*H = NI_N \quad (1)$$

The matrix $[CH]_2 = \begin{pmatrix} 1 & j \\ -j & 1 \end{pmatrix}$ is an illustration of a 2nd order complex Hadamard matrix. Complex, [26], [27] of The Hadamard higher order matrices are computed coercively by using Kronecker product is given in equation (2)

$$[CH]_{2^n} = H_2 * [CH]_{2^{n-1}} \quad (2)$$

The direct and inverse reversible complex Hadamard matrices are given by equation (3), (4). Basic 2x2 matrix is given by equation (5)

$$[RC]_{2^n} = (\prod_{m=1}^{n-1} I_{2^{m-1}} * Q * I_{2^{n-m}})(I_{2^{m-1}} * [CH]_2) \quad (3)$$

$$[RC]_{2^n}^{-1} = (I_{2^{n-1}} * [CH]_2^{-1})[\prod_{m=n-1}^{1} (I_{2^{m-1}} * Q^{-1} * I_{2^{n-m}})] \quad (4)$$

$$\text{Where,} \quad [CH]_2^{-1} = \begin{pmatrix} 1/2 & j/2 \\ -j/2 & -1/2 \end{pmatrix} \quad (5)$$

The direct and forward reversible complex Hadamard matrices of eighth order are given in equations (6) and (7).

$$[cs]_8^{-1} = \begin{bmatrix} \frac{1}{4} & \frac{j}{4} & \frac{1}{4} & \frac{j}{4} & \frac{1}{4} & \frac{j}{4} & \frac{1}{8} & \frac{j}{8} \\ \frac{-j}{2} & \frac{-1}{2} & \frac{-j}{4} & \frac{-1}{4} & \frac{-j}{4} & \frac{-1}{4} & \frac{-j}{8} & \frac{-1}{8} \\ \frac{1}{2} & \frac{j}{2} & \frac{-1}{4} & \frac{-j}{4} & \frac{1}{4} & \frac{j}{4} & \frac{-1}{8} & \frac{-j}{8} \\ \frac{-j}{2} & \frac{-1}{2} & \frac{j}{4} & \frac{1}{4} & \frac{-j}{4} & \frac{-1}{4} & \frac{j}{8} & \frac{1}{8} \\ \frac{1}{2} & \frac{j}{2} & \frac{1}{4} & \frac{j}{4} & \frac{-1}{4} & \frac{-j}{4} & \frac{-1}{8} & \frac{-j}{8} \\ \frac{-j}{2} & \frac{-1}{2} & \frac{-j}{4} & \frac{-1}{4} & \frac{j}{4} & \frac{1}{4} & \frac{j}{8} & \frac{1}{8} \\ \frac{1}{2} & \frac{j}{2} & \frac{-1}{4} & \frac{-j}{4} & \frac{-1}{4} & \frac{-j}{4} & \frac{1}{8} & \frac{j}{8} \\ \frac{-j}{2} & \frac{-1}{2} & \frac{j}{4} & \frac{1}{4} & \frac{j}{4} & \frac{1}{4} & \frac{-j}{8} & \frac{-1}{8} \end{bmatrix} \quad (6)$$

$$[cs]_8^1 = \begin{bmatrix} \frac{1}{4} & \frac{j}{4} & \frac{1}{4} & \frac{j}{4} & \frac{1}{4} & \frac{j}{4} & \frac{1}{4} & \frac{j}{4} \\ \frac{-j}{4} & \frac{-1}{4} & \frac{-j}{4} & \frac{-1}{4} & \frac{-j}{4} & \frac{-1}{4} & \frac{-j}{4} & \frac{-1}{4} \\ \frac{1}{2} & \frac{j}{2} & \frac{-1}{2} & \frac{-j}{2} & \frac{1}{2} & \frac{j}{2} & \frac{-1}{2} & \frac{-j}{2} \\ \frac{-j}{2} & \frac{-1}{2} & \frac{j}{2} & \frac{1}{2} & \frac{-j}{2} & \frac{-1}{2} & \frac{j}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{j}{2} & \frac{1}{2} & \frac{j}{2} & \frac{-1}{2} & \frac{-j}{2} & \frac{-1}{2} & \frac{-j}{2} \\ \frac{-j}{2} & \frac{-1}{2} & \frac{-j}{2} & \frac{-1}{2} & \frac{j}{2} & \frac{1}{2} & \frac{j}{2} & \frac{1}{2} \\ 1 & j & -1 & -j & -1 & -j & 1 & j \\ -j & -1 & j & 1 & j & 1 & -j & - \end{bmatrix} \quad (7)$$

3.4 Sectorization

The complex Walsh transform consists of real and imaginary parts that are divided into sections with proportions of 4, 8, and 12. Initially, the Walsh transform is broken down into 4 regions. To further break down these regions into 8 and 12, the 4-section transform is treated as the foundation, and the decomposition continues. This process is illustrated in Table 1, [28]. A set of attributes is then created by averaging all Walsh coefficients for each region. This value is unique for each image since the distribution of sequences for every hand image is distinct in different regions.

3.5 Feature Extraction

A set of features is created for each quadrant, which includes values like average, median, standard deviation, skewness, and median. Since each arrangement of veins is unique, the sequence distribution patterns and feature vectors are also unique. The number of vectors related to features is minimal compared to the significant Walsh coefficients that carry the most signal energy. This greatly reduces complexity and execution time. The division of Walsh transform coefficients into various sectors follows a standard procedure, as indicated in Table 1.

Table 1. Sector's division

Sign of Sal	Sign of Cal	phase	Quadrant Assigned	Sector
positive	positive	0^0-90^0	1st	1
positive	negative	90^0-180^0	2nd	2
negative	negative	180^0-270^0	3rd	3
negative	positive	270^0-360^0	4th	4

3.6 Veins Tracking using a Kalman Filter

The Kalman filter is a commonly used tool for tracking the movement of various objects. It makes predictions about the object's state by considering results influenced by noise and measurements. If possible, it assesses the actual current state of the object. Kalman filters find application in different linear dynamic systems. In this context, a "state" refers to any assessable physical parameter, such as the object's location, temperature, velocity, voltage, and so on. The Kalman filter operates in two stages and is used in a recursive manner. After each iteration, it predicts and updates the status of the parameter.

The prediction is based on the current location of the moving object, using previous information. After measuring the object's latest position (denoted as Zt), it combines this with the guessed current location (Xt) to obtain a more accurate estimate of the object's current location, Xt. The equations governing the operation of the Kalman filter are presented in equations (8) to (14).

At the level of prediction: Predicted (a priori) state

$$X_k = F_k X_{k-1} + B_k u_k + w_k \quad (8)$$

Predicted (a priori) estimate covariance

$$P_{\frac{K}{K-1}} = F_K P_{(K-1)/(K-1)} F_K^T + Q_K \quad (9)$$

Level of updation: measurement residual:

$$Y_K = Z_K - H_K X_{K/(K-1)} \quad (10)$$

Residual covariance

$$S_K = H_K P_{K/(K-1)} H_K^T + R_K \quad (11)$$

Optimized gain:

$$K_K = P_{\frac{K}{K-1}} H_K^T + S_K^{-1} \quad (12)$$

Updated (a posteriori) state estimate

$$X_{K/K} = X_{\frac{K}{K-1}} + K_K Y_K \quad (13)$$

Updated (a posteriori) estimate covariance

$$P_{K/K} = (I - K_K H_K) P_{K/(K-1)} \quad (14)$$

X_K is ongoing state vector at time t from the estimation of Kalman filtering, Z_K is the assessment vector computed at time t, P_K calculates the assessed exactness of X_K at time t, F characterizes the movement of the from one state to the other, that is projection of earlier state vector is to the further, presuming that noise is absent. (e.g. no acceleration). H defines the mapping from the state vector X_K, to the measurement vector, Z_K. Gaussian process is defined as Q and assessment noise is defined as R. These 2 parameters describe the system's variance. The control-input variables are B, u.

3.7 Orientation of Histogram

The histogram of oriented gradients is a way to describe an image by looking at the appearance and shape of small neighborhoods within it. It focuses on the spread of intensity gradients or the directions of edges in the image. Initially designed to detect human faces, we are suggesting its use in our work to identify the orientation of veins on the back of the hand, [29].

4 Results and Discussions

In Figure 8 and Figure 9, we can see images from the database featuring hands rotated both clockwise and anti-clockwise. Figure 10 shows the image of the hand pattern, while Figure 11 displays the cropped image and Figure 12 presents the thresholded image. Results from Discrete Wavelet-based hand vein tracking are demonstrated in Figure 13 and Figure 14. For reverse Hadamard transform-based hand vein tracking, you can refer to Figure 15 and Figure 16. The input hand image for Histogram of Oriented Gradients is illustrated in Figure 17, and Figure 18 displays the angle rotated using Histogram of Oriented Gradients. Results from the Kalman filter using Sobel and Canny Edge detection can be found in Figure 19, Figure 20, Figure 21, Figure 22, Figure 23 and Figure 24.

Fig. 8: Database of the hand rotated clockwise

Fig. 9: Database of the hand rotated anti-clockwise

Fig. 10: Input image

Fig. 11: Cropped Image

4.1 Results of Discrete Wavelet Transform

Fig. 12: Thresholded image

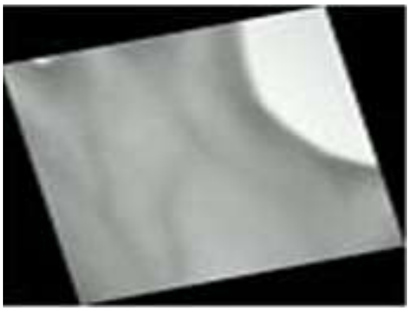

Fig. 13: Test Image for DWT

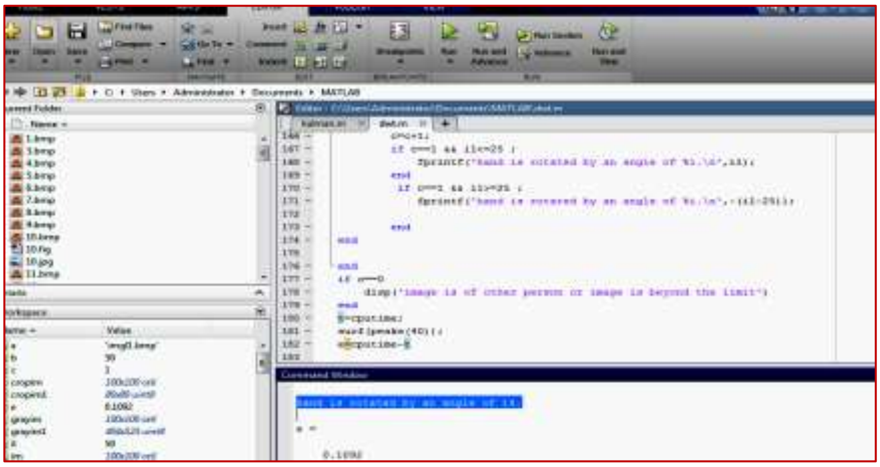

Fig. 14: Displaying angle rotated using DWT

4.2 Results of Reverse Hadamard Transform

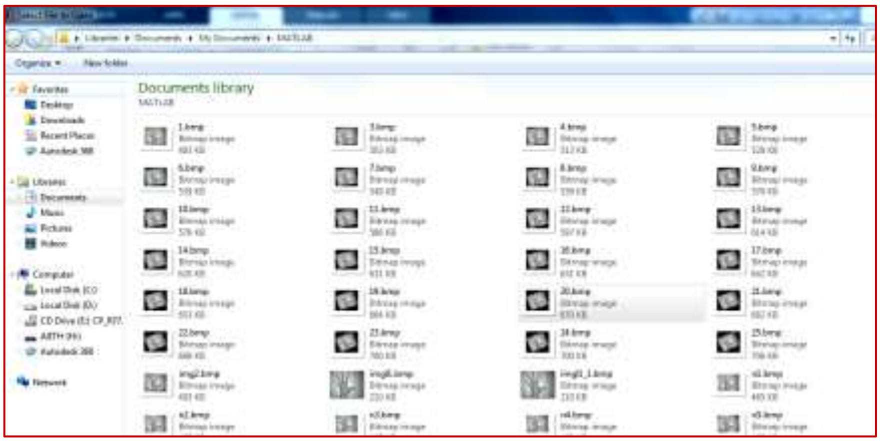

Fig. 15: Input image with 20^0 rotation of hand for the reverse Hadamard transform

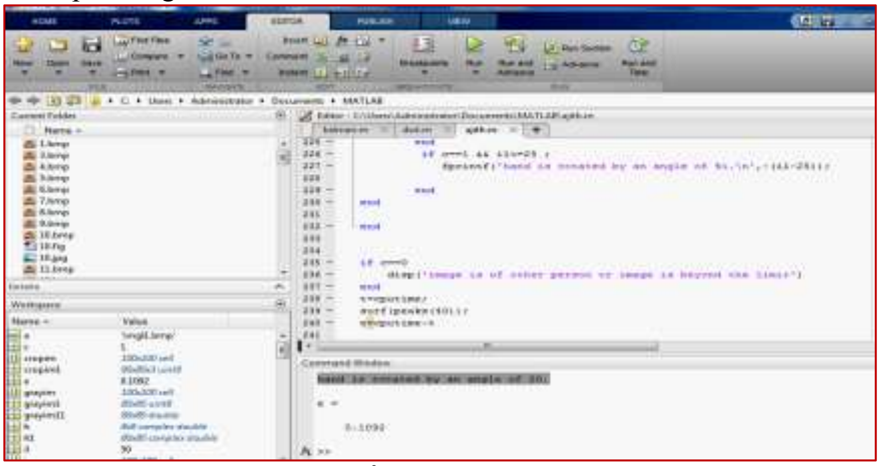

Fig. 16: Displaying the angle 20^0 rotated using Reverse Hadamard transform

4.3 Results of Histogram of Oriented Gradients

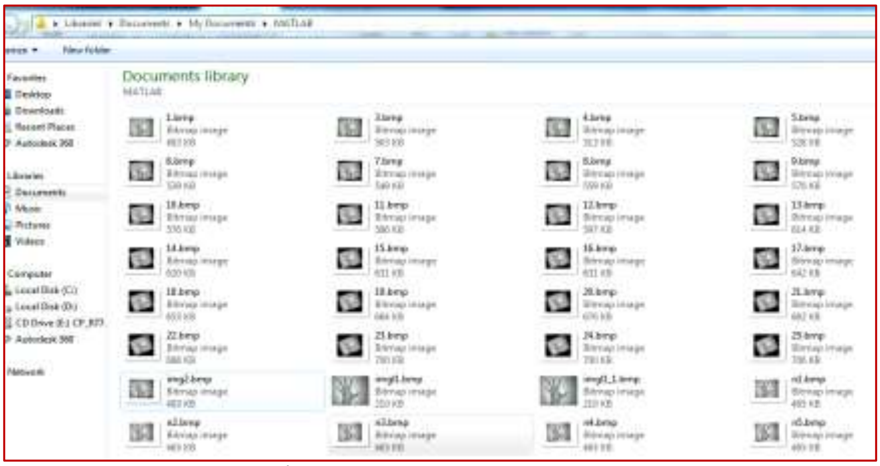

Fig. 17: Input hand for with 3^0 rotation of hand Histogram of Oriented Gradients

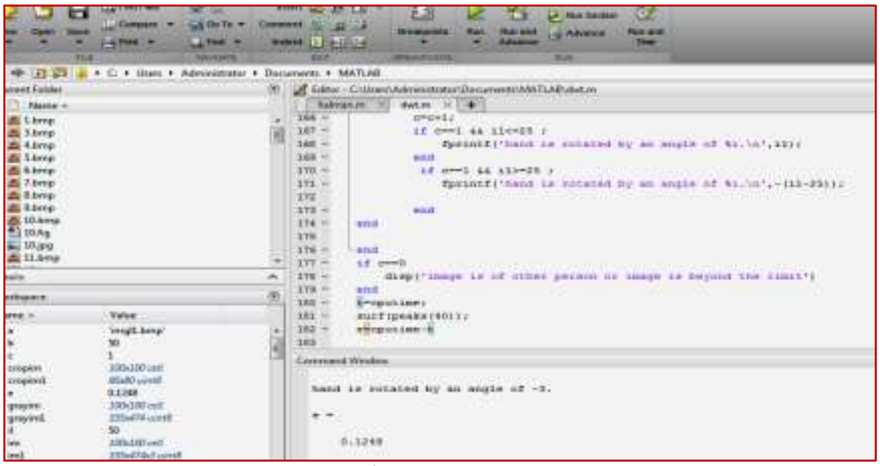

Fig. 18: Displaying the angle with 3^0 rotated using Histogram of Oriented Gradients

4.4 Results of Kalman filter (using Sobel and Canny edge detection)

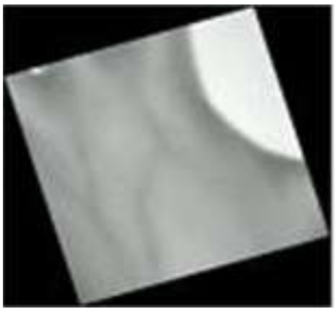

Fig. 19: Input image for Edge detection

Fig. 20: Extracted veins using Sobel Edge detection

Fig. 21: Extracted Veins using Canny edge detection

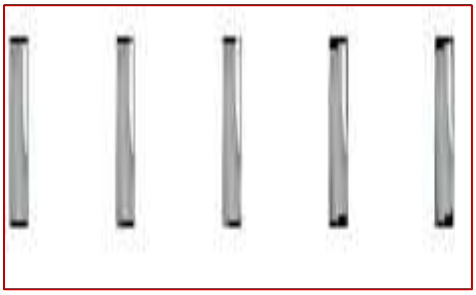

Fig. 22: Input sequences of images for Kalman Filter

Fig. 23: Output of the coordinates of image sequence using Kalman Filter (Sobel)

Fig. 24: Output of the coordinates of image sequence using Kalman Filter (canny)

5 Conclusions

We tested the algorithms with rotations from -60 degrees to +60 degrees and achieved successful detection of rotations in both clockwise and anti-clockwise directions. There are four methods we used for tracking hand rotation: DWT, reverse Hadamard, orientation histogram, and Kalman filter. Each method produced different results, and their accuracy varied. The details of the time it took for each method are given in Table 2 for a comparison of execution times.

Table 2. Comparison of execution times

Algorithm	DWT	Reversible complex Hadamard transform	Orientation of Histogram
Time taken for execution	0.1126 msec	0.1043msec	1.1254 msec

We discovered that when tracking the coordinates of the reference point with the Kalman filter, the precision is 2 degrees. In terms of execution time, we found that the Reversible four-phase complex Hadamard transform is a better method, taking less time to complete.

6 Future Scope

This technique will serve as a good initiation for hand gesture based car driving. It will be very much useful for driving wheelchair for the patients who are suffering from paralysis. It can be used for gaming incorporated with augmented reality using hand gestures. It will serve as better biometric technique with low cost and greater accuracy for industrial and real time usage for authentication. It can be used to develop remote control applications.

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