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Hand vein recognition with rotation feature matching based on fuzzy algorithm

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Abstract

The Bodily motion or emotion, which can be obtained for example from a hand or a face, originates gestures. Every individual has a unique pattern of dorsal hand veins. The vein pattern's orientation changes when one rotates their hand in a particular direction. This study focused on hand-gesture recognition using dorsal hand veins. The aim of this work is a novel technique to track and recognizing hand vein rotation using fuzzy neural network, and the change in orientation was considered as a gesture and measured. The algorithms were tested over various rotations ranging from $-45°$ to $+45°$. We successfully detected various rotations in both clockwise and anti-clockwise directions, achieving 93% accuracy and a reasonable time execution. This problem can be solved because a person can steer a car wheel merely by rotating his/her hand. An infrared camera captured the rotation of hand veins, so car wheel steering was unnecessary.

Keywords: Complex Walsh transform, Dorsal hand vein pattern, Feature extraction, Fuzzy neural network, Sectorization.
2010 MSC: Please write mathematics subject classification of your paper here.

1. Introduction

A symbol of emotional expression or physical behavior is called gesture, including hand and body gestures. It occurs in two types, namely, static and dynamic gestures. In static gesture, body posture or hand gesture denotes a sign. In dynamic gesture, hand or body movement expresses

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messages. Gestures can be utilized as a communication tool between human and computer compared with conventional hardware-based techniques. This tool accomplishes interaction between human and computer via gesture recognition. This approach involves determining the intent of a user via recognizing a body or a gesture or a body part movement. In the last decades, several researchers have enhanced hand gesture recognition [15, 19, 5]. This process is highly valuable in different applications, such as robot control, sign language interpretation for the disabled, augmented reality (virtual reality), and sign language recognition [20].

1.1. Injury of rotator cuff

The rotator cuff is the joint of the shoulder surrounded by a group of muscles and tendons, maintaining the upper arm-bone head tightly inside the shoulder shallow socket. The injury of rotator cuff can produce a dull ache in the shoulder that frequently worsens when sleeping on the shoulder with pain. Rotator cuff injuries usually occur in persons who are continuously doing overhead motions in their sports or jobs, such as tennis and baseball players, carpenters, and painters. The risk of rotator cuff injury increases with age. The severity of rotator cuff injuries can range from trouble-free inflammation to full tears. Rotator cuff tears can occur due to a single injury [3, 2]. A rotator cuff injury reduces the motion domain and is painful. Rotator cuff disease can cause a wear and tear of the tendon tissue, progressive degeneration, and a substantial injury to the shoulder. However, the tendon may be damaged or irritated with the development of bone spurs in the bones around the shoulder, heavy lifting over a prolonged period of time, and repetitive overhead activity. In these circumstances, the patient cannot put pressure on shoulders, such as when driving a car.

1.2. Dorsal hand veins

Biometrics is used to secure data and is extremely needed at present. The familiar and frequently used biometrics are fingerprint, retinal scan, voice recognition, and face recognition systems. The field of biometrics has been constantly developing because of a few drawbacks in every system. Dorsal hand vein biometrics is a secure and minimal fault biometric system. The vein pattern on the back of the palm is unique for each person [18, 1]. Statistics show that six in a million individuals have similar dorsal hand vein patterns, demonstrating the uniqueness of hand veins. Dorsal hand vein recognition provides the advantage of being invisible to the naked eye [12, 21]. It is also noncontact in nature, thereby providing a hygienic system. The characteristics essential for a good biometric system are those that do not change with time, easy to detect, difficult to spoof, accurate, and unique. These conditions are satisfied by dorsal hand vein biometrics.

1.3. Hand gesture detection and recognition

In this work, a new approach is developed to recognize hand gestures. A fully novel algorithm is proposed to solve a present challenge; this approach contributes to the development of practically recognized hand gesture applications for daily employment [13, 11]. The developed algorithm must fulfill the following conditions. Flexibility: the approach must be essentially accurate for use and properly recognize the identified gestures with 93% accuracy for effective and practical employment. Robustness: the system must have the ability to detect, track, and recognize various hand gestures effectively with a variety of cluttered backgrounds and lighting conditions. The system must be also robust in opposition to rotations and scale. Scalability: the approach should be user-independent, in which the system must have an ability for working with different persons rather than a specific person. The technique should recognize hand gestures with different persons rather than a specific person. The technique should recognize hand gestures for a variety of human hands with various colors and scales.

2. Materials

Veins are concealed beneath the skin and are commonly imperceptible to the open eye and other visual inspection systems. A monochrome near-infrared (NIR) charge-coupled device (CCD) camera supplied with an IR lens is used with NIR imaging for picking up the hand vein data. The vein system appears as a dark pattern of lines because hemoglobin in the blood absorbs NIR light-emitting diode light [17]. First, the CCD camera records the image. The raw data are then digitized and certified. The raw data are sent to a database of registered images. A hand vein dorsal image is illustrated in Figs. 1 and 2.

3. Proposed method

The steps involved in hand vein gesture recognition include the use of discrete wavelet transform (DWT), histogram of oriented gradients, and reversible complex Hadamard transforms [4]. An input image is converted into a gray image, and a region of interest is extracted. After preprocessing, a database is created by rotating hand vein images in clockwise and anticlockwise directions. Three different techniques, namely, DWT, histogram of oriented gradients, and four-phase reversible Hadamard transforms, are applied in this database.

1. Features are extracted from the decomposed planes of DWT and stored in the database for matching to identify the angle of rotation.
2. The histograms of oriented gradients are extracted from the database of images and stored as a feature database for finding the rotation angle.
3. Features are extracted from sectors of reverse Hadamard transform coefficients and stored as a database for feature matching and finding rotation angles.
4. For Kalman filtering-based tracking, edge detection is computed using Sobel and canny operators. A reference centroid is calculated, and a Kalman filter is applied to track the coordinates.

3.1. Preprocessing

In the preprocessing of hand vein patterns, images are cropped to the needed area of interest because veins appear protuberant. The fractions of fingers are eliminated, and adaptive histogram equalization is conducted to adjust the intensities uniformly [14, 10, 16]. The collected database is converted into a training set.

3.2. DWT

A pyramid structure composes the DWT architecture. Initially, the original image passes via a low-pass and high-pass decay filters for generating four low-resolution components [9]. The first component is called smooth image. It is the approximation of the original image, which is a low-low (LL) subimage. The three remaining components are the comprehensive subimages. They denote the direction of the original image, which are the diagonal direction (HH), vertical direction (HL), and horizontal direction (LH). The test input image is classified into the class of training image set. Compared with the test input image, the feature vector distance is minimal around the whole existing distances of the train image set. Many types of wave filter can be applied in DWT. Some of the wavelet families are Daubechies, Coiets, Symlets, and Fejer-Korovkin filters. We use Haar, which is under the Daubechies family [8]. Haar wavelet is a sequence of rescaled square-shaped functions that together form a wavelet family or basis. After applying Haar transform, we obtain four coefficients of DWT, namely, approximation, horizontal, vertical, and diagonal coefficients. These coefficients are used when performing feature vector extraction.

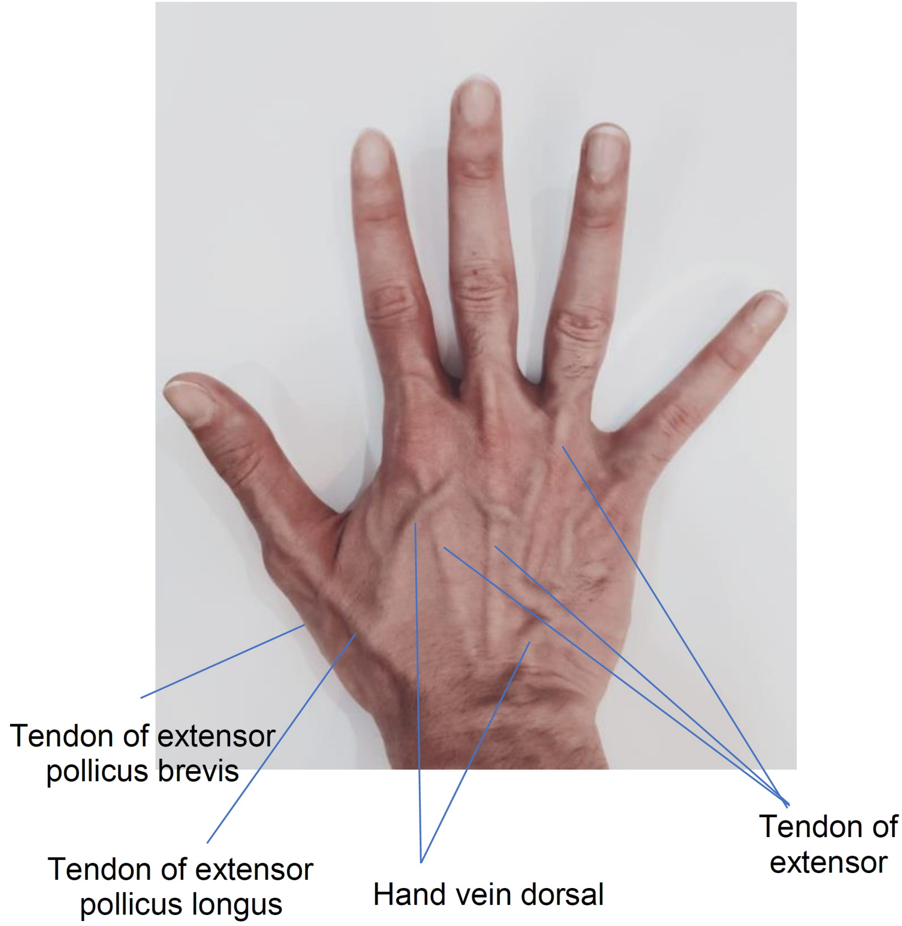

Figure 1: Hand vein dorsal

Figure 2: Hand vein using a monochrome NIR CCD camera

Table 1: Sector information

Sign of Sal+	Sign of Cal+	Phase $0° - 90°$	Quadrant Assign I	Sector I
+	-	$70° - 155°$	III	II
-	-	$170° - 260°$	I	III

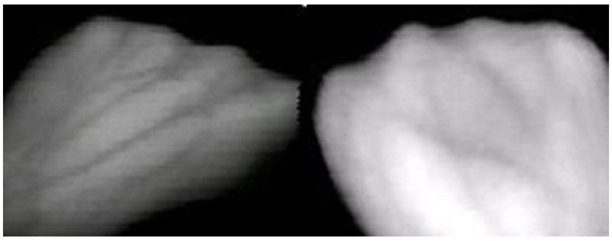

Figure 3: Samples of test Image in different rotations

3.3. Reversible coplex Hadamard Transform

The complex Hadamard matrix K of order A is a unitary matrix with elements ± 1; $\pm I$; where $I = \sqrt{1}$, is given in Equation (3.1)

$$KK^* = K^4 * A = A^2 I_K \tag{3.1}$$

where K^* represents the complex conjugate transpose of matrix k. Matrix $[CK]_{2A} = (1^I)$ is an example of a complex Hadamard matrix of order four. Complex Hadamard matrices [10, 7] of orders higher than four can be generated recursively by using Kronecker product

$$[CK]_{2A} = k_4[CK^4]_{2A+K} \tag{3.2}$$

3.4. Fuzzy feature extraction

Every single sector generates a feature vector. Each sector extracts various features, such as median, skewness, standard deviation, and mean [6]. These values are distinctive for every single vein pattern because the sequence distribution of every single vein is distinctive in various sectors (4). Compared with the whole or with those transform coefficients that contain a main portion of the signal, energy feature vectors created by sectorization are considerably smaller numbers. Thus, the complexity and processing time are reduced, as illustrated in Table 1.

4. Results and discussion

The total images of the database contain 192 hand vein images rotated in anticlockwise and clockwise directions, as shown in Fig. 3. The cropped image is shown in Fig. 4. Fig. 5 shows the discrete wavelet-based hand vein tracking. Fig. 6 displays the angle rotated using extracted veins with fuzzy algorithm and canny edge detection. The results show a good response for detecting hand angle rotation, with an accuracy of 93%, as presented in Table 2.

5. Practical comparisons

This work compares the proposed method with three algorithms, namely, histogram of oriented gradients, reversible complex Hadamard transform, and DWT. Various feature extraction techniques are applied with the same classification strategy. The recognition accuracy shows well-behaved performance compared with different techniques under the same benchmark.

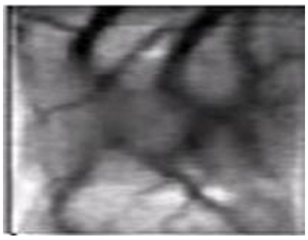

Figure 4: Cropped image

Figure 5: Discrete wavelet-based hand vein tracking

Figure 6: Fuzzy features of extracted veins using canny edge detection

Table 2: Results of fuzzy neural network in comparison with other algorithms

Algorithm	Accuracy	Execution time
Histogram of oriented gradients	79%	1.611 ms
Reversible complex Hadamard transform	83%	1.091 ms
DWT	89%	0.982 ms
Fuzzy neural network	93%	0.413 ms

6. Conclusions

The algorithms are tested over various rotations ranging from $-45°$ to $+45°$. The database contains 96 hand images rotated in anticlockwise direction and 96 hand images in clockwise direction. Various rotations in clockwise and anticlockwise directions are successfully detected. Five different methods are implemented to track hand vein rotation. These methods include DWT, reverse Hadamard transform, histogram of oriented gradients, Kalman filter, and fuzzy neural network. Various results are obtained in each of these methods, and these methods vary in terms of accuracy and time execution. The tracking of coordinates of the reference point with a Kalman filter has a precision of $2.6°$. The proposed fuzzy algorithm is better in terms of accuracy and execution time.

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