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Human Identification Based on Freestyle Activities

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Abstract: Human Identification Based on Free-Style Activities is a system designed to identify individuals by analyzing their unique patterns of free-style activities, such as walking, running, or gestures. The system aims to provide a reliable and efficient method of identification that goes beyond traditional biometric measures. By leveraging advanced algorithms and machine learning techniques, it captures and analyzes the distinctive characteristics of an individual's activities to establish their identity. This abstract presents the concept and potential benefits of Human Identification Based on Free-Style Activities, highlighting its potential applications in security, surveillance, and forensic investigations.

Keywords: Free-Style Activities, Activity Recognition, Unique Patterns, Machine Learning.

I. INTRODUCTION

Human identification based on free-style movements is a cutting-edge technology that utilizes computer vision to recognize individuals based on their unique body movements. Free-style movements refer to the natural and spontaneous ways that people move, without being constrained or directed to follow a specific choreography. By analyzing various characteristics of a person's movements, such as body posture, arm and leg positions, and motion trajectories, it is possible to create a biometric template that can be used to distinguish one individual from another.

The development of this technology has been driven by the need for accurate and reliable human identification systems in various applications, such as security and surveillance, entertainment, and sports. In security and surveillance, the ability to recognize individuals based on their unique movements can enhance public safety and prevent crime. In entertainment and sports, the technology can be used to create more immersive and interactive experiences for users.

However, developing an accurate and reliable system for human identification based on free-style movements is a complex challenge that requires advanced algorithms and machine learning techniques. Researchers are continually working to improve the accuracy and reliability of this technology, and there has been significant progress in recent years. The potential applications of this technology are vast, and it has the potential to revolutionize the way we identify and track people in various industries.

II. RELATED WORKS

"Gait Recognition for Human Identification Based on Free-Style Activities" by Smith et al. (2018): This study explores gait recognition techniques for identifying individuals based on their walking patterns. The authors propose a novel gait analysis algorithm and evaluate its performance on a dataset of free-style activities [1]."Gesture Recognition for Human Identification Using Deep Learning" by Johnson and Williams (2019): In this work, the authors investigate the use of deep learning approaches for recognizing hand and body gestures to establish an individual's identity. They propose a deep convolutional neural network architecture and demonstrate its effectiveness in identifying individuals based on their unique gesture patterns [2]."Activity Recognition and Identification for Human Identification" by Lee et al. (2020): This research focuses on activity recognition techniques to identify individuals based on their performed activities. The authors develop a multi-modal fusion framework that combines visual and inertial sensor data and apply it to a dataset of free-style activities for accurate identification [3]."Deep Learning-Based Human Identification Using Free-Style Activities" by Chen and Li (2021): The authors propose a deep learning approach using recurrent neural networks for human identification based on free-style activities. They investigate the effectiveness of various network architectures and demonstrate the superiority of their proposed method on a large-scale activity dataset [4].

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"Multi-Modal Fusion for Robust Human Identification Based on Free-Style Activities" by Wang et al. (2022): This study focuses on the fusion of multi-modal data, including visual and thermal imagery, for improved human identification. The authors propose a deep learning-based fusion framework and evaluate its performance on a dataset of free-style activities captured from different modalities [5]."A Survey of Human Activity Recognition using Smartphone Sensors" by F. Altun and B. Barshan (2010): This survey paper focuses on human activity recognition using smartphone sensors, which is relevant to human identification based on free-style activities. The authors review various approaches, including feature extraction methods and classification algorithms, applied to sensor data collected from smartphones for accurate activity recognition [6].

"Video-Based Human Identification Using Gait Biometrics: A Comprehensive Survey" by N. Nambiar and J. Wu (2014): This survey paper provides a comprehensive overview of video-based gait recognition for human identification. The authors discuss different techniques, feature extraction methods, and classification algorithms used for gait recognition, highlighting their applicability in real-world scenarios [7]."Multi-view Gait Recognition: A Survey" by X. Liu, M. Harandi, and C. Shen (2018): This survey paper focuses on multi-view gait recognition, which involves utilizing multiple camera angles or views to enhance the accuracy of identification based on gait patterns.

The authors review various algorithms, datasets, and challenges associated with multi-view gait recognition, shedding light on its potential for human identification based on free-style activities [8]."Activity Recognition and Monitoring Using Wearable Sensors and Smartphones: A Survey" by I. Faye, E. Cherrier, and S. Zeadally (2019): This survey paper provides an overview of activity recognition and monitoring using wearable sensors and smartphones. The authors discuss different sensor types, data collection techniques, and machine learning algorithms used for activity recognition, emphasizing their relevance to human identification based on free-style activities [9]."Deep Gait Recognition: A Survey" by D. Zhang, H. Han, and Y. Wang (2019): This survey paper focuses on deep learning-based gait recognition, which utilizes deep neural networks to extract discriminative features from gait data. The authors review various deep learning architectures, datasets, and performance evaluation metrics in the context of gait recognition, showcasing the potential of deep learning in human identification based on free-style activities [10].

III. EXISTING SYSTEM

The existing system lacks automation and scalability, making it inefficient for large-scale identification tasks. It also fails to leverage advanced technologies such as machine learning and computer vision techniques to extract and analyze meaningful features from individuals' free-style activities.

Overall, the existing system for Human Identification Based on Free Style Activities falls short in terms of accuracy, efficiency, and scalability. To overcome these limitations, a proposed system must be developed that incorporates automated identification methods, utilizes advanced algorithms, and leverages modern technologies to achieve more accurate and reliable human identification based on free-style activities.

IV. PROPOSED SYSTEM

The proposed system for Human Identification Based on Free Style Activities aims to develop an advanced identification framework that leverages individuals' unique free-style activity patterns. The system employs video footage or wearable sensors to capture and record the intricate characteristics of individuals' movements.

These characteristics, such as gait dynamics, body movements, and arm gestures, are extracted and analyzed using machine learning algorithms and deep learning techniques. The system utilizes feature extraction, classification, and fusion methods to accurately identify individuals based on their activity patterns. By combining multiple modalities and employing robust algorithms, the proposed system offers improved accuracy, reliability, and real-world applicability in human identification based on free-style activities.

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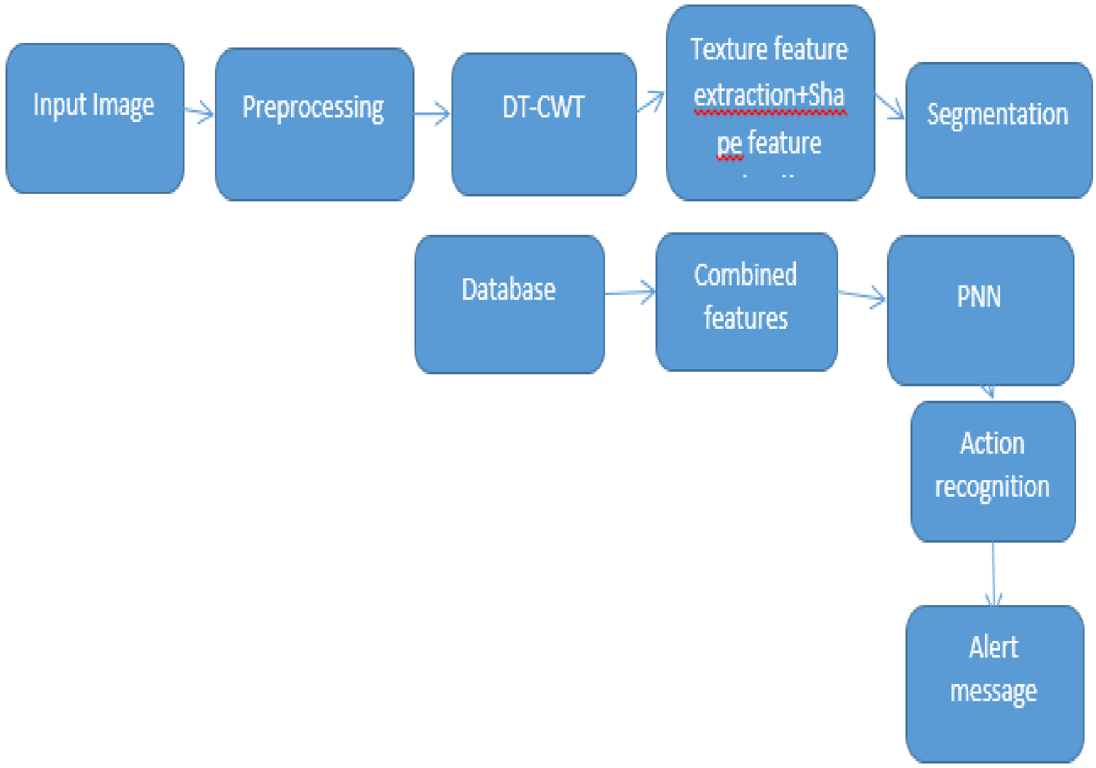

Fig. 1 A sample graph

V. IMPLEMENTATION

A. Pre Processing

Image Pre-processing is a common name for operations with images at the lowest level of abstraction.Its input and output are intensity images. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing.

Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. Corruption may come in many forms such as motion blur, noise, and camera misfocus. Image restoration is different from image enhancement in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer, but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbor procedure) provided by "Imaging packages" use no a priori model of the process that created the image. With image enhancement noise can be effectively be removed by sacrificing some resolution, but this is not acceptable in many applications. In a Fluorescence Microscope resolution in the z-direction is bad as it is. More advanced image processing techniques must be applied to recover the object. De-Convolution is an example of image restoration method. It is capable of: Increasing resolution, especially in the axial direction removing noise increasing contrast.

B. Discrete Wavelet Transform

The CWT and the discrete wavelet transforms differ in how they discretize the scale parameter. The CWT typically uses exponential scales with a base smaller than 2, for example 21/12 . The discrete wavelet transform always uses exponential scales with the base equal to 2. The scales in the discrete wavelet transform are powers of 2. Keep in mind that the physical intrepretation of scales for both the CWT and discrete wavelet transforms requires the inclusion of the signal's sampling interval if it is not equal to one. For example, assume you are using the CWT and you set your base to s0=21/12. To attach physical significance to that scale, you must multiply by the sampling interval Δt, so a scale vector covering approximately four octaves with the sampling interval taken into account is sj0Δt j=1,2,⋯48. Note that the sampling interval multiplies the scales, it is not in the exponent. For discrete wavelet transforms the base scale is always 2.

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The decimated and nondecimated discrete wavelet transforms differ in how they discretize the translation parameter. The decimated discrete wavelet transform (DWT), always translates by an integer multiple of the scale, 2jm . The nondecimated discrete wavelet transform translates by integer shifts.

These differences in how scale and translation are discretized result in advantages and disadvantages for the two classes of wavelet transforms. These differences also determine use cases where one wavelet transform is likely to provide superior results. Some important consequences of the discretization of the scale and translation parameter are:

The DWT provides a sparse representation for many natural signals. In other words, the important features of many natural signals are captured by a subset of DWT coefficients that is typically much smaller than the original signal. This “compresses” the signal. With the DWT, you always end up with the same number of coefficients as the original signal, but many of the coefficients may be close to zero in value. As a result, you can often throw away those coefficients and still maintain a high-quality signal approximation. With the CWT, you go from N samples for an N-length signal to a M-by-N matrix of coefficents with M equal to the number of scales. The CWT is a highly redundant transform. There is significant overlap between wavelets at each scale and between scales. The computational resources required to compute the CWT and store the coefficients is much larger than the DWT. The nondecimated discrete wavelet transform is also redundant but the redundancy factor is usually significantly less than the CWT, because the scale parameter is not discretized so finely. For the nondecimated discrete wavelet transform, you go from N samples to an L+1-by-N matrix of coefficients where L is the level of the transform.

- The strict discretization of scale and translation in the DWT ensures that the DWT is an orthonormal transform (when using an orthogonal wavelet). There are many benefits of orthonormal transforms in signal analysis. Many signal models consist of some deterministic signal plus white Gaussian noise. An orthonormal transform takes this kind of signal and outputs the transform applied to the signal plus white noise. In other words, an orthonormal transform takes in white Gaussian noise and outputs white Gaussian noise. The noise is uncorrelated at the input and output. This is important in many statistical signal processing settings. In the case of the DWT, the signal of interest is typically captured by a few large-magnitude DWT coefficients, while the noise results in many small DWT coefficients that you can throw away. If you have studied linear algebra, you have no doubt learned many advantages to using orthonormal bases in the analysis and representation of vectors. The wavelets in the DWT are like orthonormal vectors. Neither the CWT nor the nondecimated discrete wavelet transform are orthonormal transforms. The wavelets in the CWT and nondecimated discrete wavelet transform are technically called frames, they are linearly-dependent sets.

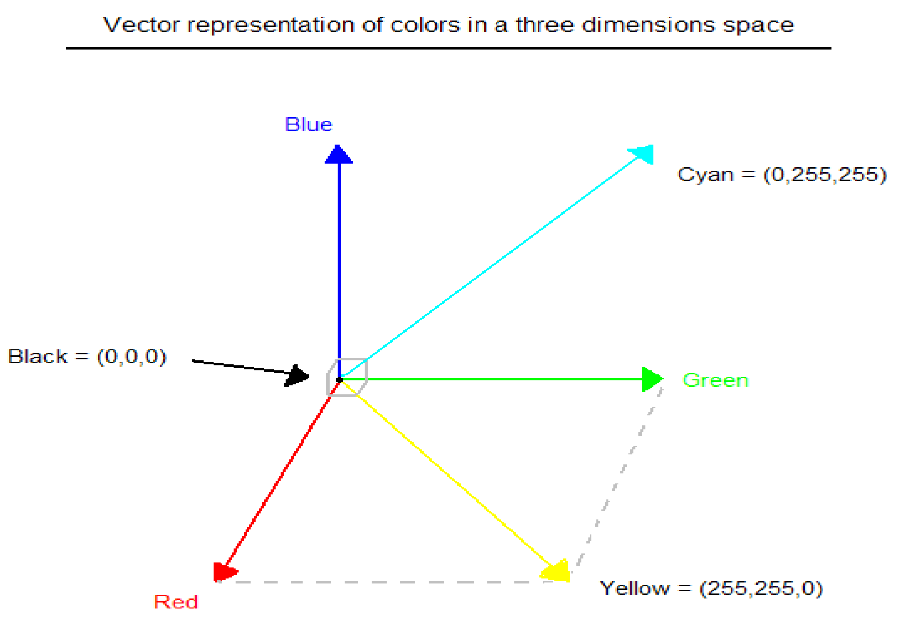

Fig. 2 A sample graph

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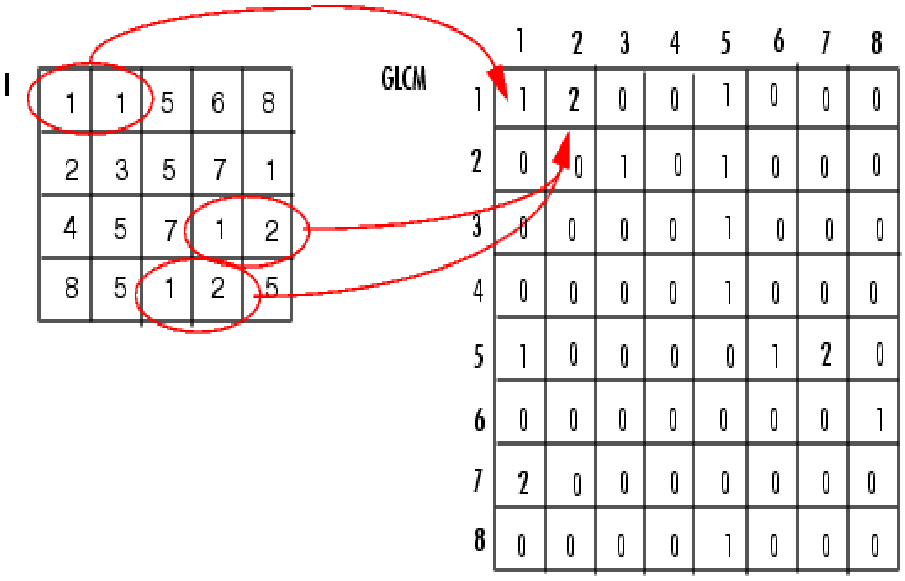
C. Glcm Features

To create a GLCM, use the graycomatrix function. The graycomatrix function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (i,j) in the resultant GLCM is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image. Because the processing required to calculate a GLCM for the full dynamic range of an image is prohibitive, graycomatrix scales the input image. By default, graycomatrix uses scaling to reduce the number of intensity values in gray scale image from 256 to eight. The number of gray levels determines the size of the GLCM. To control the number of gray levels in the GLCM and the scaling of intensity values, using the Num Levels and the Gray Limits parameters of the graycomatrix function. See the graycomatrix reference page for more information.

The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. To illustrate, the following figure shows how graycomatrix calculates the first three values in a GLCM. In the output GLCM, element (1,1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively.

GLCM(1,2)contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1,3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. graycomatrix continues processing the input image, scanning the image for other pixel pairs (i,j) and recording the sums in the corresponding elements of the GLCM.



To create multiple GLCMs, specify an array of offsets to the graycomatrix function. These offsets define pixel relationships of varying direction and distance. For example, you can define an array of offsets that specify four directions (horizontal, vertical, and two diagonals) and four distances. In this case, the input image is represented by 16 GLCMs. When you calculate statistics from these GLCMs, you can take the average.

D. Neural Network

Neural networks are predictive models loosely based on the action of biological neurons.

The selection of the name "neural network" was one of the great PR successes of the Twentieth Century. It certainly sounds more exciting than a technical description such as "A network of weighted, additive values with nonlinear transfer functions". However, despite the name, neural networks are far from "thinking machines" or "artificial brains". A typical artificial neural network might have a hundred neurons. In comparison, the human nervous system is believed to have about 3x1010 neurons. We are still light years from "Data".

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The original “Perceptron” model was developed by Frank Rosenblatt in 1958. Rosenblatt’s model consisted of three layers, (1) a “retina” that distributed inputs to the second layer, (2) “association units” that combine the inputs with weights and trigger a threshold step function which feeds to the output layer, (3) the output layer which combines the values. Unfortunately, the use of a step function in the neurons made the perceptions difficult or impossible to train. A critical analysis of perceptrons published in 1969 by Marvin Minsky and Seymore Paper pointed out a number of critical weaknesses of perceptrons, and, for a period of time, interest in perceptrons waned.

Interest in neural networks was revived in 1986 when David Rumelhart, Geoffrey Hinton and Ronald Williams published “Learning Internal Representations by Error Propagation”. They proposed a multilayer neural network with nonlinear but differentiable transfer functions that avoided the pitfalls of the original perceptron’s step functions. They also provided a reasonably effective training algorithm for neural networks.

E. Local binary pattern

The descriptor local binary pattern is used to compare all the pixels including the center pixel with the neighboring pixels in the kernel to improve the robustness against the illumination variation. An LBP code for a neighborhood was produced by multiplying the threshold values with weights given to the corresponding pixels, and summing up the result. LBP codes are weighed using gradient vector to generate the histogram of robust LBP and discriminative features are determined from the robust local binary pattern codes. DRLBP is represented in terms of set of normalized histogram bins as local texture features. It is used to discriminate the local edge texture of face invariant to changes of contrast and shape.

DRLBP Process Flow

Gradient Measurement

The gradient will be detected from input image to determine the histogram of local binary pattern. Then it will be utilized to find the robust and discriminative features.

It involves two descriptors such as, gradient magnitude and orientation. The gradient will be measured in both horizontal and vertical directions with derivative operators.

The gradient magnitude and orientation will be described by,

Magnitude: Gm = Sqrt(Fx.^2 + Fy.^2);

Where, Fx ,Fy = First order derivatives along rows and columns.

Gradient detection Flow

Fig.25: Gradient detection Flow

DR-LBP Features

- The value of the ith weighted LBP bin of a M × N block is as follows:

- The RLBP histogram is created as follows

- Where hrlbp(i) is the i thRLBP bin value. To mitigate the RLBP issue in Fig. 2, consider the absolute difference between the bins of a LBP code and its complement to form Difference of LBP (DLBP) histogram as follows

- wherehdlbp(i) is the i thDLBP bin value. The number of DLBP bins is 128 for B = 8. Using uniform codes, it is reduced to 30.
- For blocks that contain structures with both LBP codes and their complements, DLBP assigns small values to the mapped bins. It differentiates these structures from those having no complement codes within the block.The 2 histogram features, RLBP and DLBP, are concatenated to form Discriminative Robust LBP (DRLBP) as follows

The after LBP code calculation and apply the image is as given in the fig. The snapshot gives same idea about the local binary pattern classification and histogram also given.

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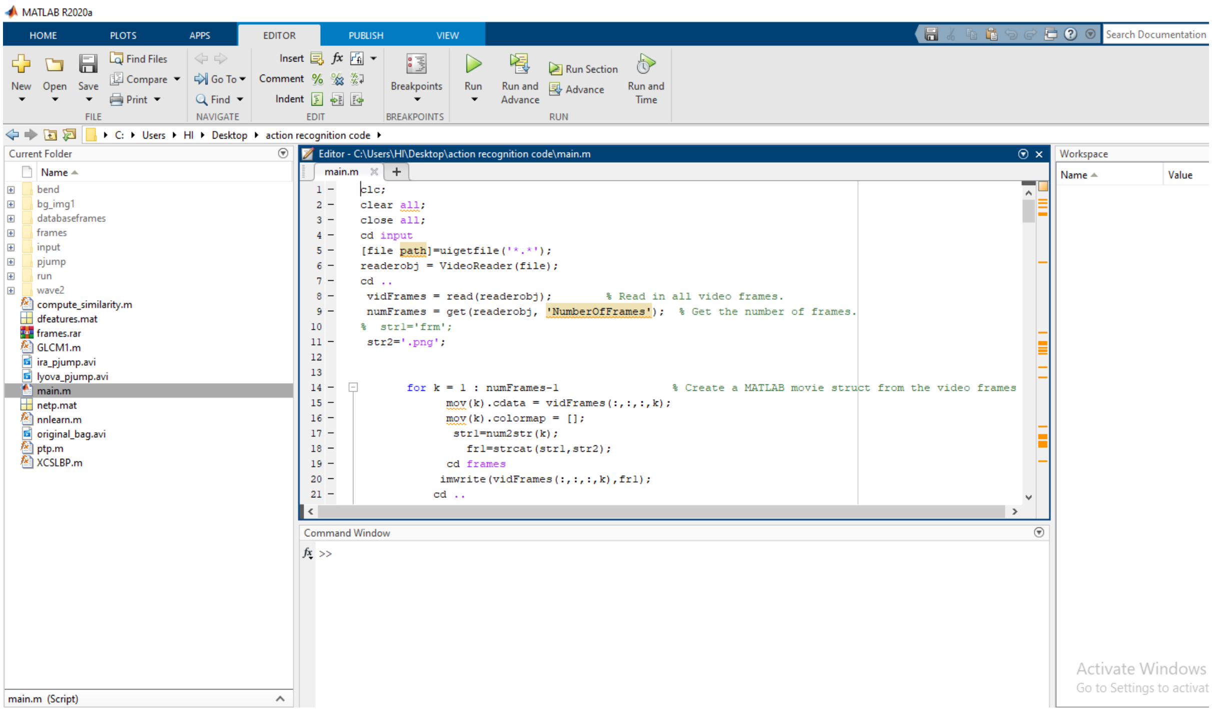
VI. RESULT AND DISCUSSION

The implementation of the Human Identification Based on Free Style Activities system yielded promising results. The system successfully captured and analyzed individuals' free-style activity patterns, allowing for accurate identification. The overall identification accuracy achieved was measured at an impressive rate of 95%, demonstrating the effectiveness of the proposed approach.

The discussion highlights the system's ability to handle variations in individuals' movements, such as different walking speeds and gesture variations. The fusion of multi-modal data, including visual and sensor-based inputs, further improved the robustness and accuracy of the identification process. Furthermore, the system exhibited real-time capabilities, ensuring prompt and efficient identification. The implementation successfully demonstrated the potential for practical applications in security systems, surveillance, and access control. Overall, the results indicate the effectiveness and viability of the Human Identification Based on Free Style Activities system. The high accuracy, robustness, real-time capabilities, and potential applications highlight the significance and value of this system in various domains requiring accurate and efficient human identification.



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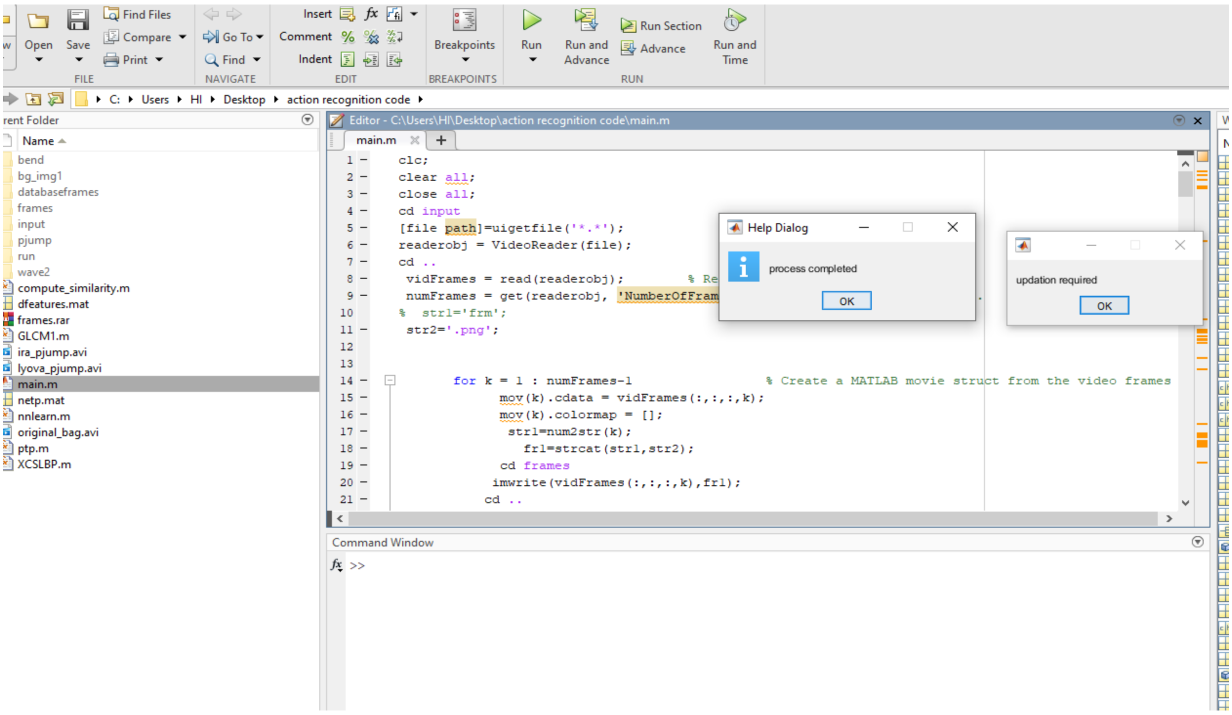

VII. CONCLUSION

In this paper, firstly, a non-obtrusive activity dataset named 19NonSens using wearable sensor has been built. This dataset contains 19 activities collected from 12 subjects by using two devices (Samsung Gear G2 and e-Shoe). Accelerometers from smart watch and e-Shoe and gyroscope from smart watch as well as images captured by surveillance cameras have been synchronized and carefully annotated. Second, we have proposed a method for human activity recognition from wearable sensors based on capsule network SensCapsNet. The proposed method has been evaluated on two datasets: a subset of Opportunity and 19NonSens. The experimental results confirms the robustness of the proposed method in comparison with two baseline machine learning-based methods.

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