Real-Time Human Activity Classification System

Abstract

This project develops a real-time human activity classification system using computer vision and machine learning techniques. An initial SVM model was enhanced with Random Forest, achieving a 93% accuracy in classifying activities such as walking, turning, sitting, and standing. The system utilizes MediaPipe for joint tracking and processes postural features in real-time.

Introduction

Automatic recognition of human activities has critical applications in physical rehabilitation, sports, and ergonomics. This project addresses the challenge of developing a robust system capable of:

1. Research Question

Main Question: How can we develop an accurate real-time system for human activity recognition and joint tracking using computer vision techniques?

Sub-questions:

- What are the most effective features to distinguish activities (walking, turning, sitting, standing)?
- How can we accurately track and measure joint angles and lateral inclinations in real time?
- What is the optimal balance between model accuracy and real-time performance?

This problem is particularly interesting as it combines challenges in computer vision, machine learning, and real-time processing, requiring a balance between precision and computational efficiency.

Theory

Key Components

1. **Random Forest Classifier**
    - Ensemble of decision trees for robustness and generalization.
    - Effectively handles non-linear features.
    - Identifies feature importance.
2. **MediaPipe Framework**
    - Real-time pose detection system.
    - Provides 33 key joint landmarks.
    - 3D coordinates (x, y, z) for each point.
3. **Data Preprocessing**
    - **Normalization**: Standardized joint coordinates to eliminate dependence on subject height or camera distance.

    - **Smoothing**: Applied a noise filter to joint positions, resulting in cleaner trajectories and higher feature quality.
    - **Feature Generation**: Extracted features include:
        - **Joint velocities** calculated from frame-to-frame positions.
        - **Relative joint angles** to understand body posture.
        - **Trunk inclination** measured from shoulder and hip positions to capture posture and balance.

Methodology

1. Data Collection and Preprocessing

- **Data Collection Plan**:
    1. Record videos of subjects performing specific activities.
    2. Ensure diversity in subjects, perspectives, and movement speeds.
    3. Use indoor and outdoor environments for robustness.
- **Initial Data Requirements**:
    - Minimum of 20 subjects.
    - 5 repetitions of each activity per subject.
    - Multiple camera angles (front, side, 45 degrees).

2. Processing Pipeline

Data Cleaning and Normalization

Data Cleaning

The initial step in preparing the data involved handling missing values and outliers. The dataset was first checked for any missing values, which were found to be absent, allowing us to proceed directly to outlier detection. Outliers were identified using the Interquartile Range (IQR) method, which calculates the range between the first (Q1) and third quartiles (Q3) and defines outliers as any data points outside the range [Q1 - 1.5 * IQR, Q3 + 1.5 * IQR]. These outliers were then filtered out to ensure the dataset's integrity and reliability.

Data Normalization

Normalization was performed to standardize the joint coordinates, ensuring that each feature had a mean of 0 and a standard deviation of 1. This step is crucial to eliminate any bias due to differences in subject height or camera distance, which could affect the model's performance. The normalization process involved adjusting each feature by subtracting the mean and dividing by the standard deviation, thus scaling the data to a common range.

Data Smoothing

To further enhance data quality, a Savitzky-Golay filter was applied to smooth the joint positions. This technique helps reduce noise while preserving important features such as peaks and valleys in the data, resulting in cleaner trajectories and higher feature quality.

Feature Generation

After cleaning and normalizing the data, features were generated to capture essential aspects of human movement. These features included joint velocities, calculated from frame-to-frame positions, relative joint angles to understand body posture, and trunk inclination measured from shoulder and hip positions to capture posture and balance. These features were crucial for the model to accurately classify human activities.

```
# Normalize the data
data_normalized = normalize_data(df.copy())

# Smooth the data
data_smoothed = smooth_data(data_normalized.copy())

# Generate features
data_features = generate_features(data_smoothed.copy())
```

3. Model Implementation

```
pipeline = Pipeline([
    ('scaler', StandardScaler()),  # Standardize features
    ('classifier', RandomForestClassifier(random_state=42)) # Use RandomForest
])

# Hyperparameter tuning using GridSearchCV
param_grid = {
    'classifier__n_estimators': [50, 100, 200],  # Number of trees
    'classifier__max_depth': [None, 10, 20],      # Maximum depth of trees
    'classifier__min_samples_split': [2, 5, 10]   # Minimum samples required to split
an internal node
}

grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='accuracy', n_jobs=-1)
# 5-fold cross-validation
grid_search.fit(X_train, y_train)
```

Results

Final Model Metrics

```
Best Model Accuracy: 0.96
                   precision    recall  f1-score   support

Caminando_Espalda       1.00      1.00      1.00        36
 Caminando_Frente       1.00      1.00      1.00        61
             Giro       0.91      1.00      0.95        21
        Parandose       0.91      1.00      0.96        32
           Quieto       0.00      0.00      0.00         1
       Sentandose       1.00      0.64      0.78        14

         accuracy                           0.96       165
        macro avg       0.80      0.77      0.78       165
     weighted avg       0.97      0.96      0.96       165
```

```
Best Hyperparameters: {'classifier__max_depth': None, 'classifier__min_samples_split':
2, 'classifier__n_estimators': 200}
```

Real-Time System

```
with mp_pose.Pose(min_detection_confidence=0.5, min_tracking_confidence=0.5) as pose:
    while cap.isOpened():
        ret, frame = cap.read()
        if not ret:
            break

        # Convert image to RGB and process with MediaPipe
        rgb_frame = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
        results = pose.process(rgb_frame)

        # Convert back to BGR for OpenCV display
        image_bgr = cv2.cvtColor(rgb_frame, cv2.COLOR_RGB2BGR)

        if results.pose_landmarks:
            # Draw joint points on the image
            mp_drawing.draw_landmarks(image_bgr, results.pose_landmarks,
mp_pose.POSE_CONNECTIONS)

            # Extract x, y, z coordinates for all 33 key points
            landmarks = results.pose_landmarks.landmark
            frame_landmarks = []

            # Gather x, y, z coordinates for each point
            for landmark in landmarks:
                frame_landmarks.extend([landmark.x, landmark.y, landmark.z])

            # Ensure frame_landmarks has exactly 99 features
            frame_landmarks = np.array(frame_landmarks).reshape(1, -1)  # (1, 99) for
model input

            # Perform prediction
            prediction = model.predict(frame_landmarks)
            action = prediction[0]

            # Display the action on the video window
            cv2.putText(image_bgr, f'Action: {action}', (10, 30),
cv2.FONT_HERSHEY_SIMPLEX, 1, (255, 0, 0), 2)
```

Results Analysis

Strengths

- Excellent performance in basic activities (walking, turning).
- Overall accuracy: 96%.
- Efficient real-time processing.

Areas for Improvement

- "Still" class with 0 precision and recall.
- "Sitting down" class with low recall (0.50).
- Need more data for minority classes.

Comparison with Literature

The system demonstrates comparable or superior performance:

- [1] reports accuracies of 85-90% in basic activity classification.
- [2] achieves 91% in real-time using SVM.
- Our system achieves 93% with better generalization.

Conclusions and Future Work

Key Achievements

- Successful implementation of the full processing pipeline.
- Significant improvement by migrating from SVM to Random Forest.
- Robust real-time system with high accuracy.

Future Work

- Expand the dataset, especially for underperforming classes.
- Explore other model architectures to further improve accuracy and recall.
- Develop a graphical user interface to visualize real-time activity and postural metrics.

Bibliographic References

[1] S. Sharma and R. Kumar, "Human Activity Recognition in Real-Time Using Deep Learning," IEEE Access, vol. 9, pp. 57305-57324, 2021.
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