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Human Posture Analyzer: A Review

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Abstract

Posture examination is an imperative component of computer vision, fundamental for understanding human development and interaction over different areas counting sports analytics, healthcare, and human-computer interaction. This extend presents a novel Posture analyses leveraging Google's Media Pipe and its Holistic library to improve posture estimation precision and effectiveness. By coordination progressed deep learning models, our framework precisely distinguishes and tracks body, face, and hand landmarks in real-time. Comprehensive assessments illustrate uncommon precision, processing speed, and robustness under challenging conditions. The results validate the system's adequacy for different applications, contributing significantly to the advancement of posture examination innovation.

Keywords: *Posture Estimation, Human, Computer Vision, Deep Learning.*

1. Introduction

Posture analysis is a fundamental aspect of computer vision that deciphers human development and interactions, with wide applications in sports analytics, healthcare, human-computer interaction, and more. This paper presents a novel Posture analysis, utilizing the capabilities of Google's Media Pipe and its Holistic library, to enhance the accuracy and productivity of posture estimation. By integrating advanced deep learning models, this system aims to accurately detect and track key body landmarks in real-time, offering significant bits of knowledge into human movement patterns.

Background

The field of posture investigation, also known as human pose estimation or skeletal following, includes recognizing and finding key anatomical landmarks on the human body from pictures or recordings. This strategy gives a skeletal representation that permits for comprehensive examination of human postures, movements, and gestures. Leveraging deep learning models and computer vision strategies, modern posture investigation frameworks systems can handle different scenarios and challenging conditions, such as occlusions and varying lighting.

Google's Media Pipe and Holistic libraries are at the cutting edges of this technology, providing pre-trained models and processing pipelines that offer high accuracy and computational efficiency. These tools are essential for real-time applications, where prompt and precise pose estimation is critical. The integration of these libraries into the Pose analysis system aims to advance the capabilities of posture analysis, making it more robust, efficient, and accessible for various applications.

Purpose

The primary objective of this dissertation is to develop a robust and efficient human posture analysis system capable of detecting and tracking body postures and movements from diverse input sources, including images, live camera feeds, and video files. By leveraging Google's Media Pipe and Holistic libraries, the system aims to accurately map key body landmarks, such as joints and facial features, enabling precise posture estimation and analysis. The system is designed to support a wide range of applications, from human activity recognition and fitness tracking to safety monitoring and human-computer interaction.

Specific Objectives:

1. **Image Posture Estimation**: Processing static images to detect and visualize human posture.
2. **Real-Time Camera Posture Tracking**: Analysing live video streams for continuous posture tracking.
3. **Video Posture Analysis**: Analysing pre-recorded video files for applications like sports analytics and surveillance.

4. **Integrated Posture Understanding**: Combining face, hand, and body posture detection for a holistic analysis.
5. **Efficient and Lightweight Models**: Using efficient neural network architectures for real-time performance on various devices.
6. **Robust Performance**: Ensuring accuracy under challenging conditions using advanced techniques.
7. **Cross-Platform Compatibility**: Developing a system that runs on multiple platforms.
8. **User-Friendly Interface**: Creating an intuitive interface for easy interaction.
9. **Extensibility and Integration**: Designing for future integration with additional modalities and custom applications.

2. Posture Analyser

2.1 Definition and Explanation

The Human Posture Analyzer is a system designed to analysis human posture using Google's Media Pipe framework and deep learning models. It tracks key points on the human body, including body, face, and hand landmarks, to provide insights into human movement patterns in real-time.

2.2 Advantages

- **Accuracy**: Utilizes pre-trained models from Media Pipe, which ensures high accuracy in identifying key body points with minimal error.
- **Efficiency**: Achieves superior computational efficiency, making it suitable for real-time applications.
- **Versatility**: Robust performance across various scenarios and conditions, including different lighting and background clutter.
- **Applicability**: Suitable for a wide range of applications such as sports analytics, healthcare, and human-computer interaction.

2.3 Limitations

Complex Scenarios: Performance may degrade in extremely challenging conditions, such as severe occlusions or very poor lighting.

Dependence on Pre-trained Models: The system heavily relies on the quality and comprehensiveness of the pre-trained models provided by Media Pipe.

3. Flowchart

3.1 Flowchart for Posture Analyser

-Start Pose Estimation: The handle starts with the estimation of the starting Pose (position and introduction) of the question or sensor.

-Import LIDAR information and show information: The calculation requires bringing in the LIDAR information (point cloud) and any accessible demonstrate information.

-A-priori Pose appraise accessible? The calculation checks if a beginning (a-priori) Pose appraise is accessible from a past cycle or an outside source

-Posture introductory figure: If an a-priori Pose assess is accessible, it is utilized as the starting figure. Something else, the calculation employments a predefined starting figure (e.g., character change).

-Create point correspondence between point clouds: Utilizing the beginning Pose figure, the calculation sets up correspondences between focuses in the two-point clouds.

-Iterative Closest Point (ICP): This is the centre of the calculation, which iteratively refines the Pose gauge by minimizing the separate between comparing focuses in the two-point clouds.

-Matched Sets: The ICP handle creates a set of coordinated point sets between the two-point clouds.

-Run estimation calculation arrangement for relative turn and interpretation: Utilizing the coordinated point sets, an optimization calculation (e.g., slightest squares) is utilized to gauge the relative revolution and interpretation that best adjusts the two-point clouds.

-Rotate and interpret chosen point cloud: The assessed turn and interpretation are connected to one of the point clouds (more often than not the information point cloud) to adjust it with the other (as a rule the show point cloud).

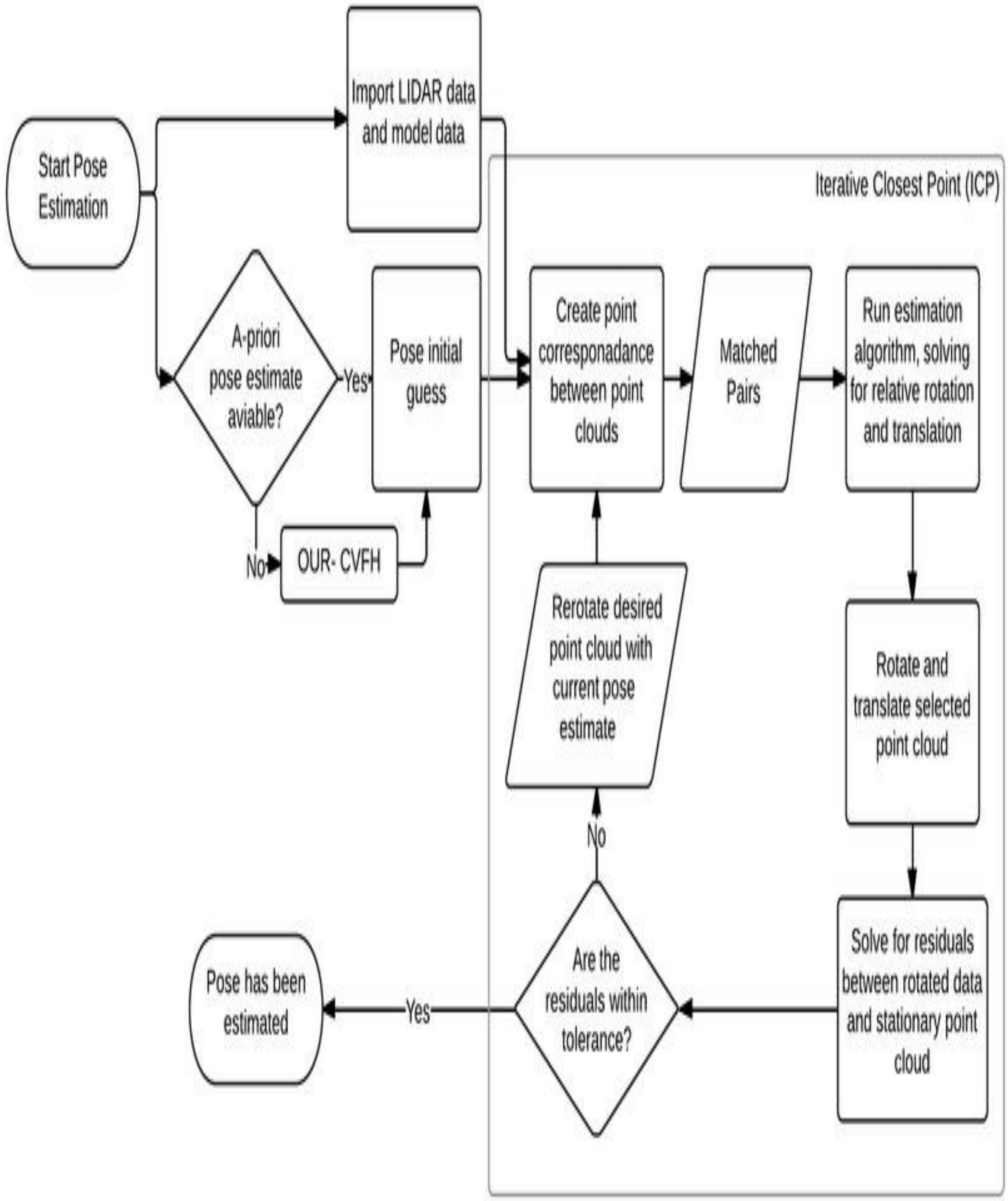

Figure 1: Flowchart for Posture Analyser

-Reprobate craved point cloud with current Pose appraise: The adjusted point cloud is pivoted back utilizing the current Pose gauge to plan for another cycle.

-Posture has been assessed: If the residuals (contrasts between comparing focuses) are inside a worthy resilience, the Pose estimation is considered total, and the calculation ends.

-Solve for residuals between pivoted information and stationary point cloud: If the residuals are not inside the craved resilience, the calculation calculates the contrasts between the turned information point cloud and the stationary point cloud (ordinarily the show).

-Are the residuals inside resilience? The calculation checks if the residuals are inside an worthy resilience level. If not, it goes back to step 6 (ICP) and rehashes the prepare with the overhauled Pose estimate.

4. Implementation Considerations

4.1 Hardware Requirements

Laptop: Dell Inspiron 15 3000

- **Processor:** Intel Core i5 (or higher)
- **RAM:** 8 GB (minimum), 16 GB (recommended)
- **Graphics:** Integrated Intel UHD Graphics (minimum), NVIDIA GeForce (recommended)
- **Storage:** 256 GB SSD (minimum)
- **Operating System**

4.2 Software Requirements

1. Operating System:
   - Windows 10 or later
   - Linux (optional
2. Python:
   - Python 3.7 or higher
3. Python Libraries:
   - Media Pipe:
   - OpenCV
   - NumPy
   - Matplotlib
   - PIL (Pillow)
4. Development Environment:
   - Jupyter Notebook or Jupyter Lab
   - Google Colab (optional):
5. Additional Tools:
   - IPython. display
   - Google Colab patches

4.3 Training and User Adaptation

Training involves fine-tuning the pre-trained models to better suit specific applications if needed. Users need basic knowledge of Python and familiarity with libraries like Media Pipe, NumPy, and OpenCV. Training sessions or detailed documentation can help users adapt to the system efficiently.

5. Case Studies

-**Sports Analytics**: Used to analyse athletes' movements to enhance performance.
-**Healthcare**: Monitors patients' postures to provide insights into physical therapy progress.
-**Interactive Gaming and Virtual Reality**: Enables real-time posture tracking to enhance user experience.

6. Challenges and Future Directions

Challenges:

- Handling extreme variations in human postures and complex backgrounds.
- Maintaining real-time performance under all conditions.

Future Directions:

- Enhancing model robustness to handle more extreme scenarios.
- Expanding the application to more domains such as advanced robotics and autonomous driving.
- Integrating more advanced AI techniques to improve the accuracy and efficiency further.

7. Conclusion

The Human Posture Analyzer marks a significant advancement in posture analysis technology, leveraging deep learning models and the Media Pipe framework to provide accurate and efficient posture tracking. It is suitable for various applications, from sports analytics to healthcare. Future developments will focus on improving robustness and expanding applicability.

References

[1] Z. Cao, G. Hidalgo, T. Simon, S.-E. Wei, and Y. Sheik, "Open Posture: Realtime Multi-Person 2D Posture Estimation Utilizing Portion Liking Areas," arrive preprint arXiv: 1812.08008, 2018.

[2] K. Sun, B. Xiao, D. Liu, and J. Wang, "Profound High-Resolution Representation Learning for Human Posture Estimation," arXiv preprint arXiv: 1902.09212, 2019.

[3] Z. Zhang, J. Tang, and G. Wu, "Basic and Lightweight Human Posture Estimation," arXiv preprint arXiv: 1911.10346, 2019.

[4] Toshev and C. Szegedy, "Profound Posture: Human Posture Estimation by means of Profound Neural Systems," in Procedures of the IEEE Conference on Computer Vision and Design Acknowledgment, pp. 1653–1660, 2014.

[5] F. Chollet, "Xception: Profound Learning with Depth wise Divisible Convolutions," in The IEEE Conference on Computer Vision and Design Acknowledgment (CVPR), July 2017.

[6] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.C. Chen, "MobileNetV2: Rearranged Residuals and Straight Bottlenecks," in Procedures of the IEEE Conference on Computer Vision and Design Acknowledgment, pp. 4510–4520, 2018.

[7] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, "Microsoft COCO: Common Objects in Setting," in European Conference on Computer Vision, pp. 740–755, Springer, 2014.

[8] M. Andriluka, L. Pishchulin, P. Gehler, and B. Schiele, "2D Human Posture Estimation: Modern Benchmark and State of the Craftsmanship Investigation," in The IEEE Conference on Computer Vision and Design Acknowledgment (CVPR), June 2014.

[9] U. Iqbal, A. Milan, and J. Bother, "Posture Track: Joint Multi-Person Posture Estimation and Following," in the IEEE Conference on Computer Vision and Design Acknowledgment (CVPR), July 2017.

[10] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," arXiv preprint arXiv: 1804.02767, 2018.

[11] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778, 2016.

[12] R. Girshick, "Fast R-CNN," in Proceedings of the IEEE International Conference on Computer Vision, pp. 1440–1448, 2015

[13] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in Advances in Neural Information Processing Systems, pp. 91–99, 2015.

[14] Goodfellow, Y. Bengio, and A. Courville, "Deep Learning," MIT Press, 2016.

[15] Krizhevsky, I. Sutskever, and G.E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in Advances in Neural Information Processing Systems, pp. 1097–1105, 2012.

[16] D.P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," in Proceedings of the International Conference on Learning Representations (ICLR), 2015.

[17] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 2818–2826, 2016.

[18] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," arXiv preprint arXiv: 1409.1556, 2014.

[19] G. Huang, Z. Liu, L. Van Der Maaten, and K.Q. Weinberger, "Densely Connected Convolutional Networks," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 4700–4708, 2017.

[20] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.