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PIKTOR-O-BOT: INTEGRATED IMAGE PROCESSING ALGORITHMS FOR PORTRAIT DRAWING ROBOT APPLICATIONS

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Abstract – Collaborative robots, or cobots, have emerged as vital assets in numerous industries, reshaping operational paradigms and fostering human-machine collaboration. This paper introduces Piktor-o-bot, a Universal Robots 5 series portrait drawing robot, which integrates advanced image processing algorithms with collaborative robotic functionalities to streamline and enhance portrait creation. By utilizing neural networks for human face detection, background removal, edge detection, semantic segmentation, clothes segmentation, and eye detection, Piktor-o-bot aims to achieve lifelike depictions efficiently. The proposed system integrates these specialized neural networks, innovative algorithms, and collaborative robotic capabilities to offer a promising and optimized solution. The individual components and their interactions contribute to the overall success of the Pictor-o-bot system, as demonstrated by its performance at several exhibitions.

Keywords: robot application; image processing and diagnostics; neural network; face detection; face segmentation; edge detection; robot movement optimization.

1. INTRODUCTION

Robots have become integral components of various industries, revolutionizing processes, and workflows across sectors [1]. Collaborative robots, commonly known as cobots, represent a significant advancement in robotics, designed to collaborate closely with human workers in shared workspaces. These robots are characterized by their ability to perform tasks autonomously or in cooperation with humans, enhancing productivity and safety in diverse environments. With their flexible and adaptive nature, collaborative robots have opened new possibilities for automation in fields ranging from manufacturing to healthcare and beyond [2] [1].

The field of robotic artistry has witnessed the development of specialized portrait drawing robots, such as FRIDA [3], and other solutions [4] [5] [6] [7] [8]. These research and developments realize and demonstrate field-specific characteristics, however, all of them serve as enablers for further advanced industrial progressions. Consequently, the research results reported in the paper are bidirectional: i) according to social aspects they serve as very interesting and popular demonstrations for the public, ii) in addition, the built-up advanced functionalities can be applied in various industrial assignments and challenges, like diagnostics, optimization, and control of robot interaction.

These portrait drawing robots typically employ mechanical arms equipped with drawing tools to replicate human-like strokes on paper or digital mediums. While these robots showcase impressive capabilities in creating portraits, they often face challenges in achieving high levels of detail and realism, limiting their applicability in professional settings. Additionally, factors such as speed, precision, versatility, and presence of noise [9] remain key considerations for control the portrait drawing robots to fulfil the demands of various artistic endeavours.

The popularity of image processing and artificial intelligence is steadily growing [10] [11] [12], as they play pivotal roles in enhancing the capabilities of portrait drawing robots. Traditional edge detection algorithms, such as Canny [13], have long been used for feature extraction and diagnostics in facial processing tasks. However, recent advancements in machine learning, particularly the utilization of deep neural networks, have led to significant improvements in accuracy and efficiency. State-of-the-art neural networks can efficiently handle complex tasks such as face detection [14], background removal [15], edge detection [16], semantic segmentation [17], and eye detection [18], offering superior performance compared to traditional methods. By leveraging the power of machine learning, portrait drawing robots can achieve more accurate and lifelike depictions of human subjects, elevating the quality of their artistic output.

The proposed solution, the architecture called Piktor-o-bot [19], aims to leverage the advancements in machine learning algorithms and integrate them into robotics for efficient and lifelike portrait drawing. By combining these specialized neural networks, our system offers a comprehensive approach to portrait creation. Integrating these diverse machine learning algorithms with collaborative robotic capabilities presents a promising avenue for advancing the field of robotic artistry, enabling realistic and efficient portrait drawing in various applications. Through the seamless integration of cutting-edge technologies, our portrait drawing robot, Piktor-o-bot, seeks to push the boundaries of artistic expression and innovation in the realm of industrial robotics.

The Piktor-o-bot solution is presented at various events, e.g. at the XXIV. IMEKO World Congress in Hamburg, 2024. With these demonstrations, the social acceptance of robots and artificial intelligence applications is encouraged, and these topics typically receive positive judgements from the community (Figure 1).

Figure 1. High interest of people for Piktor-o-bot presented in various public fairs and events.

The current paper concentrates on the visual image processing and diagnostics of the Piktor-o-bot solution while the robotic and hardware side is described more in detail in [29].

2. METHODS AND PROCEDURES

In this section, a detailed overview of the hardware resources, procedures, and the proposed machine learning methodologies are provided.

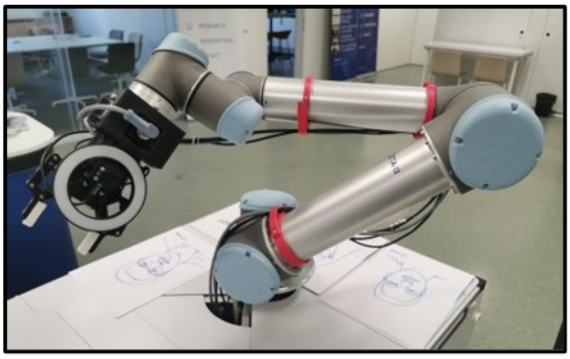

Figure 2. Piktor-o-bot: The portrait drawing robot.

2.1. Hardware resources

For the task at hand, a Universal Robots UR5 series collaborative robot with a six-axis arm and a two-fingered gripper is utilized (Figure 2.), which ensures great freedom of movement and the grip of the drawing tool, whether it is a marker pen or a pencil. Additionally, the robot is equipped with force and torque sensors to accurately simulate human fine motoric skills. To ensure well-illuminated images, a Full HD camera with flash capabilities is mounted to the robot. The hardware setup can be seen in Figure 2. Given the computational intensity of several models used throughout the process, a graphics card is also employed to ensure efficient and optimized task execution (Table 1).

Table 1. Robot parts and accessories.

Device name	Use for
Universal Robots UR5	Robotic arm for manipulation tasks
Two finger grippers	Grasping and holding the drawing tool
Force and torque sensor	Simulate human fine motor skills
Camera + Flash	Capturing images for visual perception tasks
GPU	Accelerating image processing and machine learning computations (NVIDIA GeForce RTX 3060)

2.2. *Initial procedures*

The objective is to facilitate the capability of a robotic arm to outline the features of a human face derived from a portrait. The procedure initiates with the individual positioning themselves in front of the canvas and camera setup. Subsequently, upon adjustment of the robotic arm to the suitable height, a photograph is captured utilizing the mounted camera. The image acquisition process is preceded by a countdown mechanism followed by a flash for illumination. The captured photograph then undergoes a series of image-processing stages employing the designated hardware components. Additionally, the robotic arm is equipped with the capability to grasp and manipulate a marker pen, facilitating the final stage of the process, which involves sketching the portrait onto the paper (Figure 3).

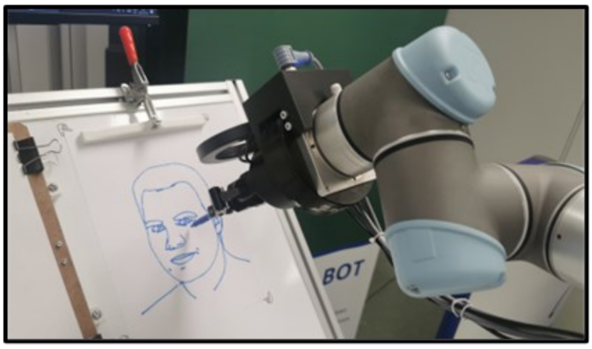

Figure 3. The drawing procedure of the Piktor-o-bot.

2.3. *Machine learning methods*

In this section, a detailed overview of proposed machine learning methodologies is provided.

Face detection

The initial phase involves face detection, which includes identifying and locating faces within an image. The objective is to ascertain the presence and position of human faces. Several methods exist for detecting faces, ranging from classical solutions like the Haar cascade [20] to the application of neural networks.

For portrait drawing, the RetinaFace network [14] is utilized, a convolution-based neural network capable of real-time and highly accurate face recognition in images. Once the face is detected, it is cropped to focus solely on the human face (Figure 4).

Figure 4. The result of the face detection using the RetinaFace deep neural network [14].

The network is a pre-trained neural network trained on the WIDER Face dataset [21], one of the most popular publicly available benchmarking datasets containing faces of various shapes, sizes, poses, and angles, along with challenges such as occlusions, different lighting conditions, and emotions. The dataset consists of three versions: easy, medium, and hard subsets of images with faces of varying recognition difficulty levels. The RetinaFace neural network ranks among the top-performing models, surpassing state-of-the-art results in terms of both precision and recall on all three versions of the WIDER dataset. Due to its high precision and real-time facial detection capabilities, the model is an ideal choice for the task.

The RetinaFace architecture consists of two main components: 1.) Pyramid-like levels derived from ResNet residual levels, facilitating feature extraction across different scales. 2.) Five independent context modules, one for each pyramid level, increasing the receptive field. These modules incorporate deformable convolutional layers to enhance modelling capability and performance (Figure 5).

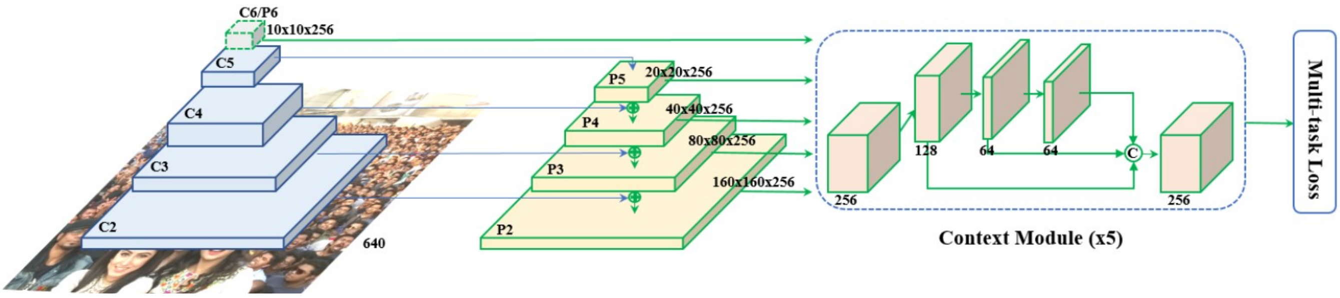

Figure 5. The architecture of the RetinaFace deep neural network [14]. The architecture comprises ResNet-derived pyramid levels and five context modules with deformable convolutional layers.

In cases where a graphics card is not available and only a CPU is accessible, a less computation-intensive method, yet still maintaining adequate accuracy, called Histogram of Oriented Gradients (HOG) [22] is employed for face detection. The method attempts to recognize objects based on the directions of gradient vectors. The computation of the histogram involves calculating the gradient image and then creating gradient histograms by dividing the image into separate regions and assigning each pixel's gradient to the appropriate "bucket" in the histogram. Following this, classification is carried out by analyzing the distributions derived from these histograms, employing a Support Vector Machine classifier [23] (Figure 6).

Background removal

The second stage of image processing involves background removal, eliminating irrelevant objects from the image and retaining only the human face and upper body for the portrait. For this task, MODNet [15], a pre-trained neural network, is utilized, capable of automatically recognizing the background of an image in real time and performing precise cropping around the highlighted portrait. The network is trained on its proprietary PM100 dataset [15], containing diverse human facial images of varying positions, angles, and scales (Figure 7).

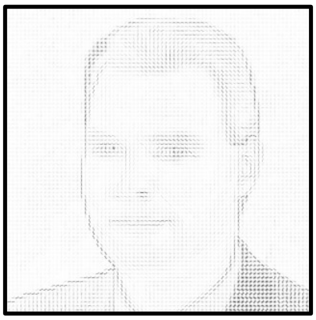

Figure 6. The result of the face detection using HOG [22].

The network is a lightweight yet highly efficient model that essentially performs a segmentation task. Due to its lightweight nature and efficiency, it can estimate real-time, even for moving images. Its architecture consists of three blocks: 1) The first block estimates portrait semantics with convolutions, yielding a low-resolution mask for efficient processing.

Figure 7. The result of the background removal using MODNet deep neural network [15].

During training, it focuses on accurate internal mask estimation. 2) The second block concentrates on outer mask parts and boundaries, producing a detailed, higher-resolution result by manipulating Ground Truth images. It restores dimensions using transposed convolutional layers. 3) The final block combines outputs from the previous blocks to compute the result, merging low-resolution semantic information with higher-resolution masked details (Figure 8)

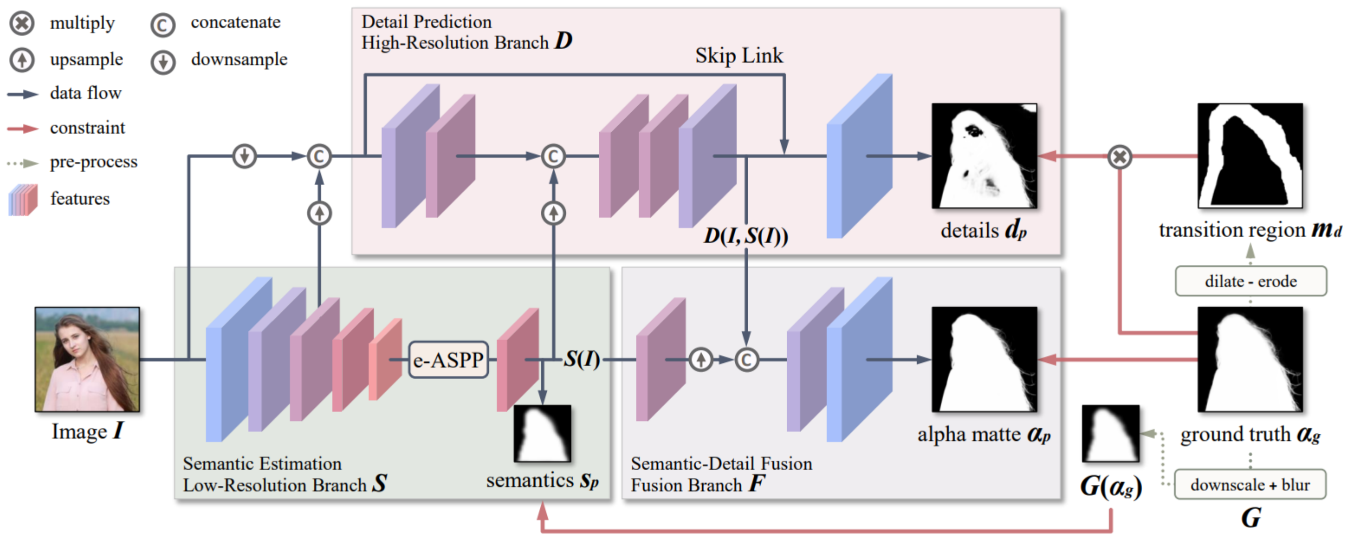

Figure 8. The architecture of MODNet deep neural network [15].

The architecture comprises three blocks: semantic estimation, boundary refinement, and resolution merging for comprehensive portrait synthesis.

Edge detection

The next step involves locating distinctive facial features and contours using edge detection. Similar to facial detection, there are various methods available, ranging from classical image processing techniques to neural network approaches. For highlighting facial contours, DexiNed [16] was employed, a state-of-the-art convolutional neural network, trained on the BIPED dataset [16], containing high definition images that have been carefully annotated by experts. The chosen model has achieved state-of-the-art results across different datasets and metrics. Its architecture comprises a series of convolution and pooling layers, with upsampling blocks resolving dimensionality issues at different scales (Figure 9). The clarity of images improves in deeper layers. DexiNed employs two different methods, resulting in two different outputs: fusion can occur through averaging or unique combination methods, resulting in two variations of DexiNed (Figure 10).

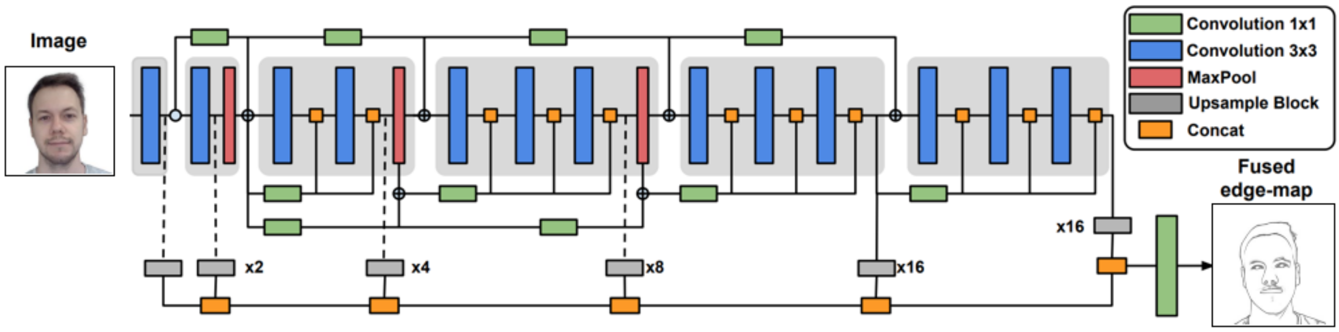

Figure 9. The architecture of the DexiNed deep neural network [16]. The architecture consists of convolution, pooling layers, and upsampling blocks for scalability.

Figure 10. The result of the edge detection using DexiNed deep neural network [16].

Face segmentation

In the following two steps, an examination of facial-specific components is processed separately to enhance the naturalness and accuracy of contours. The analysis of distinct facial regions, such as the eyes, mouth, and nose, poses a challenge addressed through the utilization of a specialized neural network, called RTNet [17]. This neural network conducts semantic segmentation, assigning roles to individual pixels in the image corresponding to various facial features.

The precision of the model exceeds the state-of-the-art models across diverse regions and datasets, including the iBugMask dataset [17], which was collected and annotated for network training purposes. Varied outcomes of RTNet across multiple datasets are presented, estimating 14 facial components: eyes, mouth, nose, lips, ears, skin, eyebrows, glasses, and hair (Figure 11).

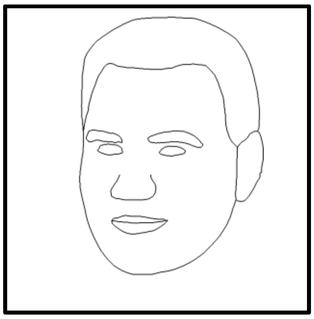

Figure 11. The result of the face segmentation using RTNet deep neural network [17].

The approach incorporates facial detection, as implemented in the initial step of the process. Subsequently, the cropped image undergoes mapping and transformation into an alternate coordinate system: the hyperbolic tangent polar coordinate system. The effectiveness of the transformation method relies on its ability to preserve rotational equivalence, wherein alterations in the image's angle of capture manifest solely as vertical displacement within the transformed space. The architecture of the RTNet is shown in Figure 12.

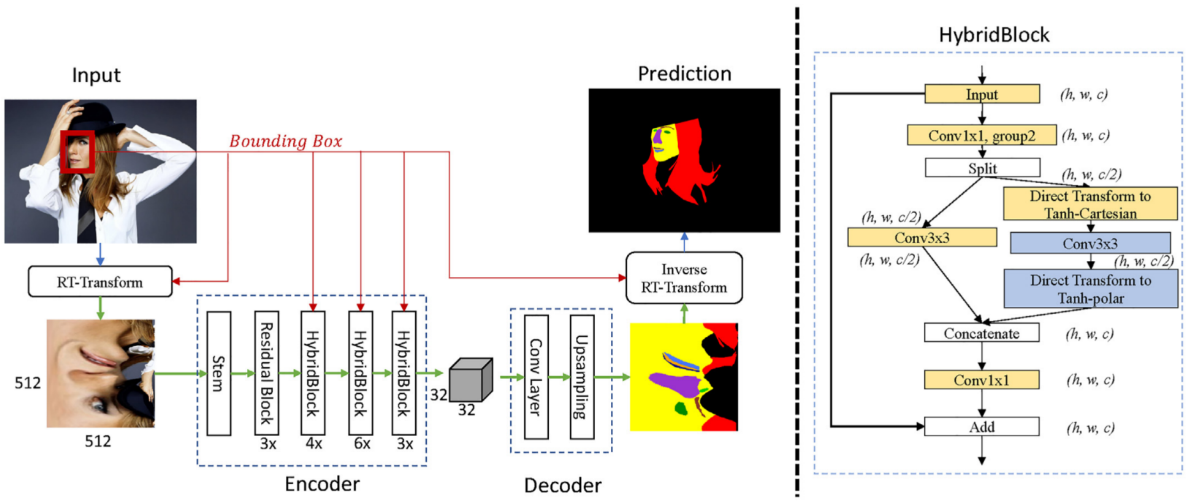

Figure 12. The process and the architecture of RTNet deep neural network [17]. The architecture consists of Residual Blocks and Hybrid Blocks.

Eyes detection

The eye, being a relatively sensitive aspect of portrait drawing, is subject to detailed examination. The first version of the solution did not have this component however, its inclusion significantly increased the impersonation of the final drawing, even if this aspect is one of the very subjective fields in face drawing. In general, the subjective nature of the evaluation of the face drawings is still an actual, unsolved challenge of the field that requires further research. In the fifth step, eye, iris, and pupil detection have been integrated into the process using MediaPipe framework [18] [24], resulting in portraits with heightened lifelikeness (Figure 13).

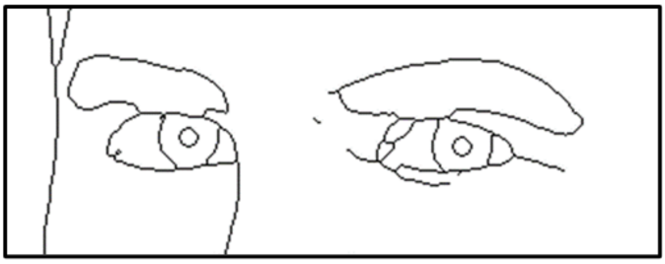

Figure 13. The result of the eye detection using MediaPipe framework [18] [24].

The approach entails the estimation of a face mesh, a polygon mesh comprising 468 points distributed across the face, alongside simultaneous eye detection and the estimation of additional landmark points surrounding them. Subsequently, the obtained results are consolidated. Following further refinement, the model determines the centre of the pupil, the outline of the iris, and 4 supplementary points.

Edge thinning

In the sixth step of image processing, edge thinning is performed, aiming to reduce the thickness of edges through a morphological operation. Here, the Zhang-Suen method [25] is employed for edge thinning in robot drawing, which is an iterative algorithm preserving the topology of objects through recursive peelings. The image undergoes thinning until the edges reach a thickness of 1 pixel. An example result is shown in Figure 14.

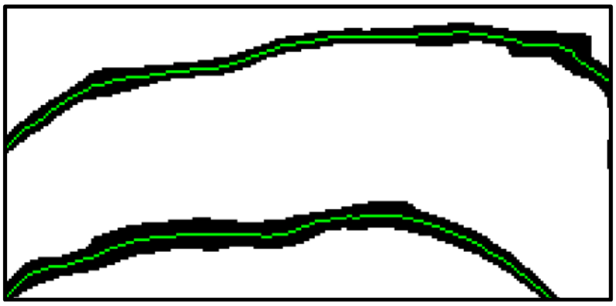

Figure 14. The result of the edge thinning using Zhang-Suen method [25].

Vectorization

Finally, the industrial robot requires vector coordinates along the planned path, consequently, the final image processing step involves vectorization, entailing the conversion of raster graphic elements into vector graphic format. In this case, rasterized facial contour images are transformed into sets of lines and curves described by Bézier curves [26]. Vectorization is not an exact procedure, it can be carried out manually; however, for more intricate graphic elements, a specialized software component is necessary, so, the Autotrace solution [27] is utilized.

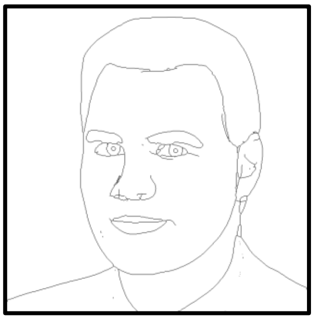

Figure 15. Raster, edge-thinned image as input for the vectorization [27].

2.4. Robotics-related steps

The UR5 robots are position-controlled, hence the vectorized curves can be passed to the controller as point lists after adequately sampling them, from the result of the previous vectorization step. Two important aspects of the robotic drawing remain the drawing time and the placement of the drawing. A brief description will be provided of these in the following.

Line sequencing

The order in which the lines are drawn greatly affects drawing time. To minimize it, the sequencing problem of the lines needs to be considered. This includes computing the order and the drawing direction of each line, to minimize the Euclidean distance travelled in the air between lines. The problem can be formulated as a General Travelling Salesperson Problem (GTSP) and the ProSeqqo solver [28] is used to solve it. An example output sequence of the algorithm is shown in Figure 16, while more details on the solver and the robotic portrait drawing case study are available in the paper.

Figure 16. Visualizing the sequencing algorithm. The black colour indicates the actual drawing, and the blue colour shows the paths travelled in the air by the robot [28].

Drawing surface

Before drawing, the drawing board is precisely calibrated using a force sensor by touch probing it in a grid pattern. This procedure provides the exact position and the orientation of the board, while it ensures that any surface defect can be compensated over the drawing area. The control points for the robot are generated by projecting the sampled curves onto the drawing surface.

In the case of pencils and marker pens using force control to adjust the force between the tool and the surface is essential. Based on the force sensor measurements the target position of the robot can be adjusted in every control cycle (8 milliseconds for a UR5 robot) thus achieving force-feedback control. To ensure stable contact and force value, PID control is implemented [29].

3. RESULTS AND DISCUSSION

The outcome of the robotic face drawing research is represented by a sophisticated hardware setup, wherein integrated image processing algorithms play a pivotal role. These algorithms encompass a range of functionalities, including face detection, background removal, edge detection, semantic segmentation, clothes segmentation, and eye detection. Leveraging neural networks for various tasks ensures high precision and efficiency in portrait creation. Each component of the system interacts synergistically, contributing to the overall success of the Piktor-o-bot system. The final outcome of the drawing is shown in Figure 17.

The effectiveness of the assembled result is validated through various means, including the utilization of state-of-the-art algorithms and participation in numerous exhibitions and demonstrations. These initiatives serve to underscore the system's robustness and versatility, showcasing its potential for diverse artistic applications. By integrating cutting-edge technologies and collaborative robotic capabilities, the Piktor-o-bot represents a significant advancement in the field of robotic artistry, pushing the boundaries of innovation and offering promising solutions for realistic and efficient portrait drawing in various contexts.

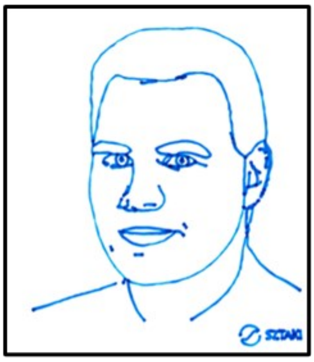

Figure 17. The final result: the image drawn by the robot arm.

4. CONCLUSIONS

The Piktor-o-bot represents a groundbreaking fusion of advanced image processing algorithms and collaborative robotic functionalities aimed at revolutionizing portrait drawing. The integration of neural networks for tasks such as face detection, background removal, and edge detection has significantly enhanced the system's accuracy and efficiency, enabling it to produce lifelike depictions with remarkable precision.

Despite its remarkable potential, the Piktor-o-bot also faces several challenges that warrant attention. One such challenge is the precise coordination required between the robotic arm and the drawing tool to ensure accurate rendering of facial features. Achieving this coordination poses a significant technical hurdle, as even minor errors in movement can result in distortions in the final portrait.

Furthermore, the Piktor-o-bot's reliance on complex image processing algorithms necessitates substantial computational resources, which may limit its scalability and accessibility in certain contexts. Addressing this challenge will require ongoing optimization efforts to streamline algorithmic processes and minimize computational overhead.

Despite these challenges, the Piktor-o-bot holds immense promise for the future of robotic artistry. Its ability to produce realistic portraits efficiently has the potential to revolutionize various industries, including entertainment, advertising, and fine arts. Moreover, its innovative approach to integrating cutting-edge technologies with collaborative robotic capabilities sets a precedent for future advancements in human-machine collaboration.

Moving forward, the future research plans involve transitioning to pencil-based drawing, necessitating ongoing developments and enhancements in both hardware and software components. Challenges related to force control pose significant hurdles in this transition, requiring meticulous calibration and refinement of our proprietary regulator.

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