Information technology for joint decision making in machine embroidery with means of augmented reality

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Abstract

The described information technology for joint decision-making in machine embroidery leverages augmented reality (AR) and artificial intelligence (AI) to significantly enhance the design and production process. AR enables real-time visualization of embroidery patterns projected onto garments, allowing designers and stakeholders to interactively see and adjust designs directly on the clothing. This immersive visualization helps in identifying design flaws and making immediate adjustments, ensuring the design aligns perfectly with the intended outcome.

The AI system processes a comprehensive set of input data, including the input video signal from cameras, initial embroidery images, the geometry of the human body and clothes, general design requirements, and expert recommendations. The AI system uses this data to iteratively refine the embroidery design, continuously improving the quality and precision of the embroidery through sophisticated neural network models. The AI-generated correction signal is fed back into the AR system, updating the virtual embroidery projection in real-time. This dynamic feedback loop ensures that the design is constantly optimized to meet both aesthetic and technical standards. The integration of AR and AI fosters seamless collaboration among designers, production teams, and clients, allowing efficient communication and consensus building. This results in higher quality, more precise, and personalized embroidery designs, ultimately leading to more efficient production processes and enhanced customer experience.

Keywords

cyber-physical system, information technology, digital embroidery, augmented reality, optimization

1. Introduction

The advent of Industry 4.0 has changed traditional manufacturing processes significantly, including machine embroidery. Cyber-physical systems (CPS) integrate computational and

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physical processes, enabling seamless interaction between humans, machines, and data. Information technologies play a crucial role in facilitating joint decision-making within these systems, enhancing efficiency, quality, and innovation in machine embroidery. The real-time data analytics [1] is pivotal in CPS for machine embroidery. Internet of Things (IoT) sensors embedded in embroidery machines collect data on machine performance, thread tension, stitch quality, and operational status. This data is transmitted to a central system where it is analyzed to provide actionable insights. Decision-makers can monitor production in real-time, identify issues, and make informed decisions to optimize operations.

The modern cloud computing technologies provide a robust platform for collaborative decision-making. By centralizing data storage and processing, cloud platforms enable multiple stakeholders, including designers, production managers, and quality control teams, to access and share information simultaneously. This fosters a collaborative environment where decisions can be made based on the latest data and insights, ensuring coherence and alignment across the production process.

AI and machine learning (ML) algorithms are useful to optimizing decision-making in CPS. Predictive maintenance algorithms analyze historical data to forecast machine failures, allowing for proactive maintenance scheduling. ML models can also optimize embroidery patterns by analyzing previous designs and production outcomes, suggesting improvements to enhance quality and efficiency.

AR systems enhance joint decision-making by providing a visual and interactive platform for design and production planning. Designers can use AR to visualize embroidery designs on garments in a 3D space, making real-time adjustments collaboratively with other stakeholders. AR tools enable virtual prototyping, reducing the need for physical samples and accelerating the design approval process.

It should be noted that collaborative platforms, such as cloud-based project management tools, facilitate communication and coordination among teams. These platforms enable stakeholders to share updates, provide feedback, and track project progress in real-time. Features like version control, task assignments, and milestone tracking ensure that everyone is aligned and informed, leading to more effective joint decision-making.

Thus, information technologies can improve machine embroidery by enabling more efficient and effective joint decision-making within cyber-physical systems. Real-time data analytics, cloud computing, AI, AR and collaborative platforms collectively enhance the ability of stakeholders to make informed decisions, optimize processes, and innovate continuously. As Industry 4.0 continues to evolve, these technologies will play an increasingly important role in driving the future of machine embroidery.

2. The known joint decision making technologies in machine embroidery

In the context of Industry 4.0, machine embroidery has been revolutionized through various information technologies that enhance joint decision-making. These technologies include real-time data analytics, cloud computing, AI, ML, AR, blockchain, and digital twins, each playing a critical role in the decision-making process.

2.1. Real-time data analytics

Real-time data analytics techniques play a crucial role in information technologies for joint decision-making in machine embroidery, leveraging various methodologies to optimize production processes, enhance design quality, and ensure efficient operation. These techniques utilize a range of data sources, including IoT sensors, ML algorithms, and advanced data processing tools, to provide actionable insights. One of the primary techniques used is sensor data collection and monitoring. IoT sensors embedded in embroidery machines collect real-time data on various parameters such as thread tension, stitch density, machine speed, and operational status. This data is transmitted to a central system where it is processed and analyzed. For instance, sensors can detect anomalies in thread tension or stitch patterns, prompting immediate adjustments to prevent defects and ensure consistent quality. Real-time monitoring allows for proactive maintenance, reducing downtime and extending machine lifespan. Studies have shown that integrating IoT sensors in manufacturing can significantly enhance process efficiency and product quality [1].

Data visualization tools are also useful in real-time data analytics. These tools transform complex data sets into easily interpretable visual formats such as graphs, charts, and dashboards. Real-time dashboards provide a comprehensive view of the production process, highlighting key performance indicators and alerting stakeholders to any deviations from the norm. This immediate visibility enables quick decision-making and fosters collaboration among team members. Visualization tools are particularly valuable in joint decision-making as they ensure that all stakeholders, regardless of technical expertise, can understand and act on the data [2]. Advanced statistical methods and algorithms are employed to analyze the data and derive insights. Techniques such as regression analysis, anomaly detection, and time-series analysis are used to understand trends and make predictions. For instance, regression analysis can identify the relationship between machine speed and stitch quality, enabling optimization of machine settings. Anomaly detection algorithms can identify outliers in the data that may indicate potential issues, allowing for quick intervention. Time-series analysis helps in understanding how production metrics evolve over time, providing insights into seasonal trends and helping in capacity planning [3].

In joint decision-making, these real-time data analytics techniques facilitate informed and timely decisions. By providing a continuous stream of actionable insights, stakeholders can collaborate effectively, address issues promptly, and optimize production processes. The integration of these techniques into machine embroidery systems represents a significant advancement, driving the industry towards greater efficiency, quality, and innovation.

2.2. Cloud computing

Cloud computing techniques impact significantly the joint decision-making in machine embroidery, leveraging advanced data storage, processing, and collaboration capabilities to enhance efficiency and innovation. One of the primary techniques is data centralization, where cloud platforms store vast amounts of data collected from embroidery machines and other sources. This centralization ensures that all stakeholders have access to the same data, facilitating real-time collaboration and decision-making. Cloud platforms such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud provide scalable storage solutions that can handle the large volumes of data generated in modern embroidery processes. This scalability is crucial for accommodating fluctuating workloads and ensuring that data is readily available when needed [4]. Another key cloud computing technique is the use of cloud-based analytics tools. These tools enable the processing and analysis of data in the cloud, eliminating the need for significant on-premises infrastructure. For example, cloud-based ML services can analyze historical and real-time data to identify patterns and predict future trends. These insights help in optimizing embroidery designs, improving machine performance, and reducing production costs. The ability to perform complex analytics in the cloud also allows for more sophisticated decision-making processes, as stakeholders can leverage advanced algorithms and models without needing specialized hardware or software on-site [5].

Cloud computing also supports the integration of IoT devices in machine embroidery. IoT sensors embedded in embroidery machines collect real-time data on various parameters, such as thread tension, stitch quality, and machine status. This data is transmitted to the cloud, where it can be processed and analyzed. The integration of IoT with cloud computing enables real-time monitoring and control of embroidery machines, allowing for immediate adjustments to improve quality and efficiency. Furthermore, cloud platforms can aggregate data from multiple machines and locations, providing a comprehensive view of the entire production process [6].

Collaboration and communication are further enhanced by cloud computing through the use of cloud-based project management and collaboration tools. These tools, such as Slack, Trello, and Asana, enable teams to share updates, provide feedback, and track project progress in real-time. This fosters a collaborative environment where all stakeholders can contribute to decision-making processes, regardless of their physical location. The use of these tools ensures that everyone is aligned and informed, leading to more effective and efficient decision-making [7]. Cloud computing also facilitates the deployment of digital twins in machine embroidery. Digital twins are virtual replicas of physical machines and processes, allowing stakeholders to simulate and optimize production scenarios without disrupting actual operations. By leveraging cloud computing, digital twins can be updated in real-time with data from IoT sensors, providing an accurate and up-to-date representation of the physical system. This enables stakeholders to experiment with different configurations and settings, identify potential issues, and implement improvements before making changes to the actual production environment [8].

2.3. Artificial intelligence and machine learning

AI and ML algorithms are pivotal in the modern information technologies for joint decision-making in machine embroidery, offering advanced methods to optimize design, production, and maintenance processes. These technologies use large datasets and sophisticated computational models to provide insights and predictions that enhance decision-making capabilities [9]. One key AI technique is predictive maintenance, which uses historical data and real-time monitoring to predict equipment failures before they occur. ML algorithms such as support vector machines, neural networks, and decision trees analyze data from IoT sensors embedded in embroidery machines to identify patterns indicative of potential issues. By predicting when a machine is likely to fail, maintenance can be scheduled proactively, thus preventing unexpected breakdowns and minimizing downtime [10]. This predictive capability is vital for maintaining continuous production and high-quality output. Another crucial application is design optimization. ML models can analyze vast amounts of historical design data to identify trends and preferences. Algorithms such as k-means clustering and principal component analysis can segment designs based on various features, helping designers understand which attributes are most popular or effective. This analysis can guide the creation of new designs that are more likely to succeed in the market. Additionally, generative adversarial networks are used to generate new embroidery patterns by learning from existing designs, fostering innovation and creativity [11].

Real-time quality control is also enhanced through AI and ML. Convolutional neural networks (CNNs), a type of deep learning model, are employed to inspect the quality of embroidery in real-time. These models can detect defects such as misaligned stitches, color inconsistencies, or thread breakages by analyzing images captured during the embroidery process. When a defect is detected, the system can automatically adjust machine settings to correct the issue or alert human operators for intervention [12]. This immediate feedback loop ensures high-quality production and reduces waste.

AI and ML also improve supply chain management in machine embroidery. By analyzing data from various stages of the supply chain, algorithms can optimize inventory levels, forecast demand, and manage logistics more efficiently. Techniques such as linear regression, time-series forecasting, and reinforcement learning are used to predict demand trends and optimize stock levels, ensuring that materials are available when needed without overstocking [13]. This optimization leads to cost savings and improved operational efficiency. Moreover, collaborative AI platforms facilitate joint decision-making by integrating insights from various data sources and stakeholders. These platforms use natural language processing (NLP) to understand and process human language, enabling seamless communication between machines and human operators. NLP algorithms can analyze feedback from designers, operators, and customers to provide comprehensive insights that inform decision-making processes [14]. This integration ensures that decisions are based on a holistic view of the entire production ecosystem.

Thus, AI and ML algorithms significantly enhance joint decision-making in machine embroidery by providing predictive maintenance, design optimization, real-time quality control, supply chain management, and collaborative decision-making platforms. These technologies leverage sophisticated computational models and large datasets to offer insights and predictions that drive efficiency, quality, and innovation in the industry [15].

2.4. Augmented reality systems

AR systems improve joint decision-making in machine embroidery by providing immersive, interactive environments for design, visualization, and collaboration. These systems overlay digital information onto the physical world, enabling users to see and interact with embroidery designs in real-time. One of the primary applications of AR in this field is design visualization. Designers can use AR to project embroidery patterns onto fabrics, allowing them to see how the final product will look and make adjustments on the fly. This capability is particularly useful for customizing designs to meet specific customer requirements, as it provides a tangible preview before production begins [16]. AR also enhances collaborative decision-making by enabling multiple stakeholders to view and interact with the same design simultaneously, regardless of their location. Using AR headsets or mobile devices, team members can discuss and modify designs in real-time, ensuring that all feedback is incorporated before the final approval. This level of collaboration is facilitated by platforms like Microsoft HoloLens and Google Glass, which support AR applications tailored for industrial use [17].

Besides, AR systems provide interactive tutorials and simulations that help new designers and machine operators learn complex embroidery techniques more effectively. For instance, AR can guide users through the steps of setting up an embroidery machine or troubleshooting common issues, overlaying instructions directly onto the physical equipment. This hands-on approach to training accelerates learning and improves retention, ultimately enhancing overall productivity [18].

It should be noted that AR is also used for quality control in machine embroidery. By overlaying design templates onto finished products, AR systems can quickly identify deviations from the intended pattern, such as misaligned stitches or incorrect colors. This real-time inspection capability allows for immediate corrections, reducing waste and ensuring that the final products meet high-quality standards. Advanced AR systems can even integrate with machine vision technology to automate this inspection process, further enhancing efficiency [19].

In addition to these applications, AR supports marketing and customer engagement by providing interactive experiences. For example, customers can use AR applications on their smartphones to visualize custom embroidery designs on their clothing before purchasing. This personalized shopping experience enhances customer satisfaction and can drive sales by showcasing the potential of custom embroidery in a compelling way [20].

2.5. Collaborative platforms

Collaborative platforms are essential in the joint decision-making processes within machine embroidery, particularly through their ability to facilitate real-time communication, project management, and data sharing. These platforms integrate various functionalities that allow designers, production managers, and clients to collaborate seamlessly, ensuring that all parties are aligned and informed throughout the production cycle.

Slack is one of the most widely used collaborative platforms, offering real-time messaging, file sharing, and integration with other tools. Its channel-based communication system allows teams to organize discussions by projects or topics, ensuring that relevant information is easily accessible. Slack's integration capabilities enable users to connect with other software tools commonly used in machine embroidery, such as design software and project management applications, enhancing workflow efficiency [21]. Trello and Asana are popular project management tools that help teams track progress, assign tasks, and manage deadlines. Trello uses a card-based system to represent tasks, which can be moved across different stages of a project pipeline. This visual approach to task management helps teams understand the status of ongoing projects at a glance. Asana, on the other hand, offers more detailed task management features, including dependencies, milestones, and custom workflows. Both platforms facilitate collaboration by allowing team members to comment on tasks, upload files, and set reminders, ensuring that everyone stays on the same page [22]. Microsoft Teams combines the communication features of Slack with the project management capabilities of Trello and Asana. It offers chat, video conferencing, and integration with Microsoft Office applications, making it a comprehensive tool for collaboration. Teams' ability to host virtual meetings is particularly valuable for geographically dispersed teams, enabling real-time discussions and decision-making without the need for physical presence.

Additionally, Teams supports integration with various third-party apps, allowing users to customize their workspace to fit their specific needs [23]. Google Workspace, formerly known as G Suite, provides a suite of cloud-based productivity tools, including Google Docs, Sheets, and Drive. These tools allow multiple users to work on the same document simultaneously, making real-time collaboration straightforward. The commenting and suggestion features in Google Docs are particularly useful for reviewing and refining design documents, while Google Sheets can be used for project tracking and data analysis. Google Drive offers secure cloud storage, ensuring that all project files are accessible to authorized team members from any location [24].

Collaborative platforms also incorporate advanced data sharing and security features to protect sensitive information. Platforms like Slack and Microsoft Teams offer end-to-end encryption and compliance with industry standards such as GDPR and HIPAA, ensuring that data privacy is maintained.

Furthermore, these platforms provide detailed access controls, allowing administrators to define who can view, edit, or share specific information [25].

Comparing the described information technologies in terms of overall effectiveness and practical application, real-time data analytics and cloud computing stand out for their broad applicability and immediate impact on decision-making processes. AI and ML offer substantial long-term benefits through continuous learning and optimization. AR provide powerful visualization and simulation capabilities, crucial for design and planning stages. Each technology has its unique properties, and their combined use can significantly enhance the joint decision-making process in machine embroidery, driving the industry towards greater efficiency and innovation.

3. The information technology for joint decision making in machine embroidery with augmented reality

The use of AR systems in machine embroidery technologies offers several significant advantages. Firstly, AR enhances design visualization by overlaying digital embroidery patterns onto physical garments in real-time. This allows designers and stakeholders to see how the final product will look and make immediate adjustments, ensuring the design meets aesthetic expectations. AR also facilitates collaborative decision-making by enabling multiple users to view and interact with the same virtual design simultaneously, regardless of their physical location. This fosters better communication and quicker consensus, reducing the time needed for approvals.

Moreover, AR improves training and education for new designers and machine operators. Interactive AR tutorials can guide users through complex tasks, such as setting up embroidery machines or troubleshooting common issues, providing hands-on learning experiences that are more effective than traditional methods. In quality control, AR systems can overlay design templates onto finished products to quickly identify and correct deviations, ensuring high-quality output. This real-time inspection capability reduces waste and enhances production efficiency.

3.1. The joint decision-making information technology for machine embroidery

The information technology for joint decision-making in machine embroidery, integrating AR and AI systems, involves a complex, interactive process designed to optimize embroidery design and production. The system starts with the collection of multiple input data streams: video data from a camera, initial embroidery data, geometry of the human body, geometry of the clothes, general design requirements, and expert recommendations. These inputs are important for creating a personalized and precise embroidery design.
The diagram of the proposed information technology for digital embroidery with means of AR is presented in Fig. 1.

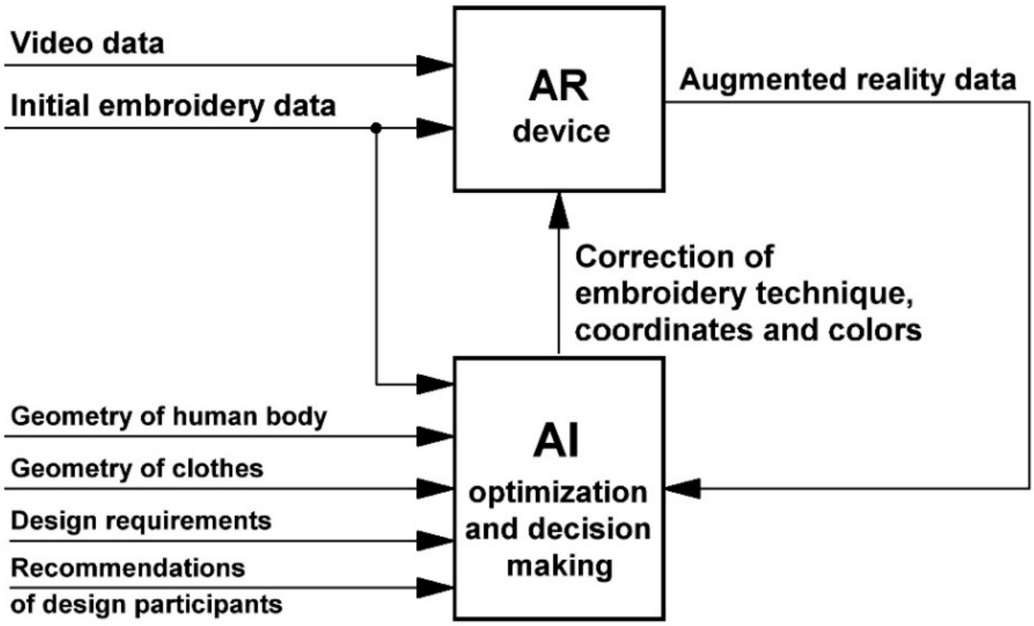

Figure 1: The diagram of proposed information technology for digital embroidery with AR.

The AR device receives video data and initial embroidery data to generate AR visuals. This allows designers, experts and other participants to see how the embroidery will appear on the garment in real time, facilitating immediate feedback and adjustments. The AI system simultaneously processes additional inputs such as the body and clothes geometries, design requirements, and expert recommendations to optimize the embroidery parameters. Using advanced algorithms, the AI system analyzes these data to refine the embroidery technique, coordinates, and colors, ensuring that the design meets both aesthetic and technical criteria.

After optimization, the AI system sends a correction signal back to the AR device, updating the embroidery technique, coordinates, and colors. This ensures that the AR representation remains accurate and synchronous with the real time. The output is a dynamic, real-time visualization of the optimized embroidery on the clothes, enabling effective collaboration among designers, production teams, and clients [26].

This integration of AR and AI facilitates a seamless and iterative design process, where continuous feedback loops between the AI and AR systems allow for constant refinement of the designs. The technology enhances joint decision-making by providing a visual, interactive platform for evaluating and optimizing embroidery designs, leading to higher quality outcomes and more efficient production processes.

3.2. The design requirements and conditions

For the efficient realization of the information technology for joint decision making in machine embroidery with AR, the AR device and AI system must meet specific technical requirements. The AR device requires high-performance graphics processing units (GPUs) to handle the rendering of complex embroidery designs in real-time. These GPUs must support advanced shading techniques and high frame rates to ensure smooth and realistic visualizations. Additionally, the device should incorporate precise tracking systems, such as optical trackers or inertial measurement units (IMUs), to maintain accurate alignment of virtual elements with the physical garment, even during rapid movements. The AR device must also include high-fidelity audio components to provide auditory feedback and enhance the immersive experience. This involves integrating spatial audio technology, which allows sounds to be placed and moved in 3D space, aligning with the visual elements. The device should support multiple input modalities, including voice commands, hand gestures, and touch interfaces, to facilitate intuitive interaction with the virtual environment and design elements. Connectivity is a critical aspect, requiring the AR device to support low-latency wireless communication standards like Wi-Fi 6 or 5G. This ensures seamless data transfer between the device and cloud-based AI systems, enabling real-time processing and feedback. The device must also feature robust security protocols to protect sensitive design data and user information, employing encryption standards and secure authentication methods.

For the AI system, the requirements include powerful computational resources capable of handling large-scale data processing and ML tasks. This necessitates the use of multi-core processors and high-memory bandwidth to support deep learning frameworks. The AI system should be equipped with extensive storage capacity to manage vast datasets, including historical design data, user preferences, and sensor readings. The AI system must incorporate advanced neural network architectures tailored for image recognition, pattern detection, and optimization tasks. These models should be trained on diverse datasets to ensure high accuracy and generalization across different embroidery designs and fabric types. Additionally, the system should employ real-time inference engines to deliver instantaneous feedback and adjustments to the AR device. Integration with cloud services is essential for the AI system to leverage distributed computing resources and facilitate collaborative design processes. The system should support scalable cloud infrastructure, allowing for dynamic allocation of resources based on computational demands. It should also include robust APIs and software development kits to enable seamless integration with various AR devices and third-party applications. The AI system must feature comprehensive data analytics capabilities, utilizing ML algorithms to derive insights from user interactions and design outcomes. This involves implementing predictive analytics to anticipate design trends and recommend optimizations. Furthermore, the system should support continuous learning, updating its models based on new data and user feedback to improve performance over time.

User interface design is another critical component, requiring the AI system to present data and recommendations in a clear, actionable format. This involves developing intuitive dashboards and visualization tools that allow users to monitor design progress, review suggestions, and make informed decisions. The system should also provide collaborative features, enabling multiple users to contribute to the design process simultaneously, regardless of their physical location (Table 1).

3.3. The proposed mathematical model

The information technology for joint decision-making in machine embroidery, as shown in the structure diagram (Fig. 1), integrates AR and AI systems to optimize embroidery designs and processes. The input data includes the video signal $V=\{v_R,v_G,v_B\}$ from the camera, initial embroidery image $X=\{x_R,x_G,\ldots,x_B\}$, geometry of the human body $H=\{h_1,h_2,\ldots,h_M\}$, geometry of the clothes $G=\{g_1,g_2,\ldots,g_L\}$, general embroidery design requirements $R=\{r_1,r_2,\ldots,r_N\}$, and expert recommendations $D=\{d_1,d_2,\ldots,d_K\}$. The output data is the AR video image $Y=\{y_R,y_G,y_B\}$, which displays the virtual embroidery projected onto the real clothes.

The AR system functions by projecting the embroidery image X onto the cloth surface depicted in the video signal V. This process is described by the model $Y=F(X,V)$, where Y represents the AR output. The AR system ensures that the embroidery design is correctly aligned and proportioned on the garment as seen in the video feed.

The AI system plays a critical role by analyzing both the input data (including X, H, G, R, D,) and the AR output Y. Using a neural network model $C=W(X,Y,H,G,R,D)$, the AI system optimizes the embroidery technique, coordinates, and colors. The correction signal $C=\{c_R,c_G,c_B\}$ generated by the AI system is then transmitted back to the AR system. This signal adjusts the embroidery parameters, ensuring that the virtual projection is refined and improved continuously. The neural network model within the AI system processes the multi-dimensional input data to identify optimal settings for the embroidery process. It uses learning algorithms to evaluate various configurations and predict the best outcomes based on historical data and expert inputs. This iterative optimization ensures that the final embroidery design not only meets aesthetic requirements but also adheres to technical constraints, such as thread tension and stitch density.

Table 1
Technical requirements for the information technology realization

Component	Technical Requirement	AR Device	AI System
Processing Power	High-performance CPUs and GPUs	Advanced shading techniques, high frame rates	Multi-core processors, high-memory bandwidth
Tracking Systems	Precise tracking systems	Optical trackers, IMUs	N/A
Input Modalities	Multiple input methods	Voice commands, hand gestures, touch interfaces	N/A
Connectivity	Low-latency wireless	Wi-Fi, 5G recommended	N/A
Security Protocols	Robust security	Encryption standards, secure authentication	N/A
Neural Network Models	Advanced neural network architectures	N/A	Tailored for image recognition, pattern detection, optimization
Real-time Inference	Real-time processing and feedback	N/A	Real-time inference engines
Cloud Integration	Scalable cloud infrastructure	Low-latency wireless communication with AI	Distributed, scalable computing resources
Data Analytics	Comprehensive data analytics	N/A	Predictive analytics, continuous learning, deriving insights from user interactions
User Interface Design	Intuitive and actionable data presentation	High-resolution display, intuitive interaction interfaces	Intuitive dashboards, visualization tools, collaborative features

The objective is to minimize the error E between the desired AR output Y_{opt} and the actual AR output Y. The error function E can be defined as the mean squared error (MSE) between the two outputs:

$$E(Y_{\text{opt}}, Y) = \frac{1}{N} \sum_{i=1}^{N} (Y_{\text{opt},i} - Y_i)^2 . \tag{1}$$

The neural network aims to minimize this error by finding the optimal correction signal C that adjusts the AR projection. Thus, the optimization problem can be expressed as:

$$\min_C E(Y_{\text{opt}}, F(X, V, C)). \tag{2}$$

Subject to the constraint that the correction signal C is generated by the neural network model:

$$C = W(X, Y, H, G, R, D). \tag{3}$$

The neural network model W processes the input data and current AR output through multiple layers, each with its own set of weights and activation functions. The goal is to iteratively adjust these weights to minimize the error function E.

The neural network (3) is a complex multilayer model designed to determine the vector of embroidery correction parameters C based on diverse input data: initial embroidery data X, AR data Y, human body geometry H, garment geometry G, design requirements R, and expert recommendations D. This network leverages a hierarchical structure where each layer is tailored to process different aspects of the input data, integrating them to produce optimized outputs. The primary learning method employed here is the minimization of an error function, augmented by attention mechanisms that direct the network's focus to the most critical parameters of the embroidery.

The first layer of the neural network consists of input units for each data type. These units are followed by specialized sub-networks that process the respective data types individually. For instance, CNNs handle the image data from X and Y, extracting features such as edges, textures, and patterns. These CNNs can be mathematically represented by a series of convolution operations:

$$f(X) = \sigma\left(\sum_{i=1}^{N} W_i * X_i + b_i\right), \tag{4}$$

where σ denotes the activation function, W_i are the convolution filters, * represents the convolution operation, X_i are the input image patches, and b_i are the biases.

Parallel to the image-processing sub-networks, recurrent neural networks (RNNs) or transformers process sequential data from R and D, capturing temporal dependencies and semantic context. The operations in an RNN layer can be represented as:

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b), \tag{5}$$

where h_t is the hidden state at time t, W_h and W_x are weight matrices, x_t is the input at time t, and b is the bias.

The geometric data H and G are processed through fully connected layers, transforming these spatial coordinates into a feature space. This transformation can be represented as:

$$g(H) = \sigma(W_h H + b_h)\,, \tag{6}$$

$$g(G) = \sigma(W_g G + b_g)\,, \tag{7}$$

where W_h and W_g are the weight matrices, and b_h and b_g are the biases.

The outputs from these specialized sub-networks are concatenated to form a comprehensive feature vector. This vector serves as the input to subsequent fully connected layers that integrate the information and perform higher-level feature extraction. The integrated feature vector F is then passed through attention mechanisms, which enhance the network's focus on the most relevant parts of the input data.

The attention mechanism can be mathematically described using the concept of attention weights. Let P be the query, K the key, and V the value, which are derived from the integrated feature vector F. The attention output A is given by:

$$A = \mathrm{softmax}\left(\frac{PK^T}{\sqrt{d_k}}\right)V\,, \tag{8}$$

where d_k is the dimensionality of the key vectors. The attention weights $\mathrm{softmax}\left(\frac{PK^T}{\sqrt{d_k}}\right)$ determine the importance of each value V based on the query P and the key K.

Finally, the output of the attention mechanism is fed into the final fully connected layers, which compute the embroidery correction parameters C. The overall transformation can be represented as:

$$C = \phi(A)\,, \tag{9}$$

where ϕ denotes the non-linear transformation applied by the fully connected layers.

The learning process involves minimizing an error function $E(C_{\mathrm{p}}, C_{\mathrm{tr}})$, where C_{p} is the predicted correction vector and C_{tr} is the true correction vector. The error function is typically the mean squared error (MSE):

$$E(C_{\mathrm{p}}, C_{\mathrm{tr}}) = \frac{1}{N}\sum_{i=1}^{N}(C_{\mathrm{p},i} - C_{\mathrm{tr},i})^2\,. \tag{10}$$

The network parameters are optimized using gradient descent techniques. The gradient of the error function with respect to the network parameters u is computed as:

$$\nabla_u E = \frac{1}{N}\sum_{i=1}^{N}(C_{\mathrm{p},i} - C_{\mathrm{tr},i})\frac{\partial C_{\mathrm{p},i}}{\partial u}\,. \tag{11}$$

It should be noted that the optimization (11) can be improved by using of fractional calculus methodologies with accounting of relaxation-like processes [27,28]. But, such calculations add a significant computational burden with the known algorithms which require the further development of fast discrete fractional transforms.

The parameters are then updated using the Adam optimization algorithm [12-14,16], which adjusts the learning rate adaptively:

$$u_{t+1} = u_t - \eta \frac{m_t}{\sqrt{v_t} + s}. \tag{12}$$

Here, u_t represents the parameters at iteration t, η is the learning rate, m_t is the first moment estimate (mean of the gradients), v_t is the second moment estimate (uncentered variance of the gradients), and s is a small constant to prevent division by zero.

The Adam algorithm initializes the first moment vector m_0 and the second moment vector v_0 as zeros. It also initializes a timestep $t = 0$. The hyperparameters β_1 and β_2 are set to control the exponential decay rates for the moment estimates, typically with values $\beta_1 = 0.9$ and $\beta_2 = 0.999$. At each iteration t, the gradient of the objective function $E(u)$ with respect to the parameters u_t is computed:

$$g_t = \nabla_u E(u_t). \tag{13}$$

Next, the first moment estimate m_t is updated as an exponential moving average of the gradients:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t. \tag{14}$$

The second moment estimate v_t is updated as an exponential moving average of the squared gradients:

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2. \tag{15}$$

Because m_t and v_t are biased towards zero initially, the algorithm computes bias-corrected first and second moment estimates:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \tag{16}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}. \tag{17}$$

The bias-corrected first moment estimate $\hat{m}_t$ is an estimate of the mean of the gradients, while the bias-corrected second moment estimate $\hat{v}_t$ is an estimate of the uncentered variance of the gradients. These bias corrections are crucial for maintaining accurate estimates during the initial stages of training.

The Adam optimization algorithm's strength lies in its ability to adapt the learning rates of each parameter individually based on the first and second moment estimates of the gradients. This adaptability makes Adam particularly effective for training deep neural networks with large and noisy datasets. The algorithm combines the benefits of AdaGrad's ability to handle sparse gradients and RMSProp's ability to handle non-stationary objectives, providing a robust and efficient optimization method.

Incorporating attention mechanisms ensures that the network focuses on the most significant parameters, dynamically weighting different parts of the input data based on their relevance. This allows the network to make more accurate predictions and optimizations, leading to improved performance in joint decision-making for machine embroidery with AR. The integration of advanced learning methods and attention mechanisms within this multilayer neural network facilitates the efficient and effective realization of the described information technology.

4. Results and Discussion

In this experiment setup, we aim to demonstrate the functionality and efficiency of the information technology for joint decision making in machine embroidery with AR. The setup involves a smartphone with an integrated high-resolution camera acting as the Virtual Reality (VR) device [29]. This smartphone captures real-time video data of the garment on which the embroidery is to be performed [30]. The AI system, deployed on a personal computer, processes this data to optimize the embroidery design. The smartphone and the personal computer are connected via WiFi, enabling seamless data transmission between the two devices.

The AI system uses an external GPT model to analyze the recommendations from experts, creating an array D that encapsulates the expert advice. This array, along with other input data such as the initial embroidery design X, the video data Y, the human body geometry H, the garment geometry G, and the design requirements R, is processed by the neural network to produce optimized embroidery data C.

The personal computer, equipped with sufficient computational power and storage, ensures that the AI system can handle these complex data inputs and perform real-time optimization. The optimized embroidery data C and the AR output Y are crucial outcomes of this process. The Y data allows for real-time visualization of the embroidery on the garment through the VR interface on the smartphone.

This visualization helps in making immediate adjustments and ensures that the final design aligns with the intended specifications.

The C data is used to generate the sequence of commands required by the digital embroidery machine to execute the design.

The Janome Memory Craft 350E digital embroidery machine was used to test the proposed information technology.

This machine is known for its precision and advanced features, making it ideal for complex embroidery tasks. The technical characteristics of the Janome Memory Craft 350E include a maximum embroidery speed of 650 stitches per minute, an embroidery area of 5.5 x 7.9 inches, and a variety of built-in embroidery designs and fonts. It supports USB connectivity, allowing it to receive embroidery designs directly from a computer.

The Janome Memory Craft 350E supports a variety of file formats, including JEF, which is specific to Janome machines. This compatibility allows users to import a wide range of designs from different sources. The machine's backlit LCD screen provides a clear and intuitive interface for selecting and customizing designs, adjusting settings, and monitoring the embroidery process.

The screen displays essential information such as stitch count, design size, and estimated time to completion, helping users manage their projects effectively. Furthermore, the machine includes features like an auto-declutch bobbin winder, which automatically stops winding when the bobbin is full, ensuring consistent thread tension and reducing waste.

The Janome Memory Craft 350E also offers multiple hoop sizes, allowing users to switch between different hoop configurations based on their project requirements. The machine's sturdy construction and durable components contribute to its reliability and longevity, making it a dependable choice for continuous use.

Once the optimized embroidery data C is ready, it is transformed into a sequence of commands compatible with the Janome Memory Craft 350E. This transformation involves converting the design data into a format that the machine can understand, such as JEF files, which are specific to Janome embroidery machines.

The personal computer sends these commands to the Janome Memory Craft 350E via USB or direct computer connectivity.

The embroidery machine then executes the design, stitching the optimized embroidery pattern onto the garment with high precision.

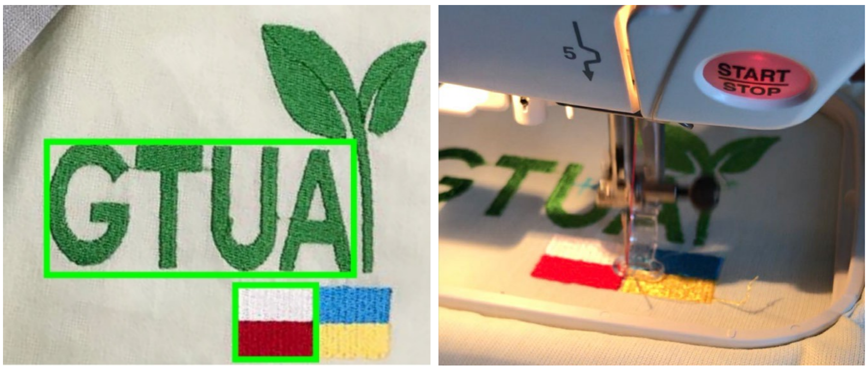

Figure 2: The machine embroidery process (Janome Memory Craft 350E embroidery machine).

Throughout the embroidery process, the smartphone VR device continues to provide real-time visual feedback, allowing for any necessary adjustments to be made promptly.

This integrated system ensures that the final embroidered garment meets the desired quality and design specifications. The combination of advanced AI optimization, AR visualization, and precise embroidery execution demonstrates the effectiveness of this information technology for joint decision making in machine embroidery.

The integration of AR and AI in machine embroidery for joint decision-making offers several advantages and disadvantages.

One of the main advantages is enhanced design visualization. AR enables designers to overlay digital embroidery patterns onto physical garments in real-time, allowing stakeholders to see how the final product will look and make immediate adjustments. This interactive visualization ensures that the design aligns with aesthetic expectations and reduces the likelihood of errors. Additionally, the use of AI for optimizing embroidery techniques, coordinates, and colors ensures that the final product meets high-quality standards. The AI system continuously analyzes input data, including the geometry of the human body and clothes, to refine the embroidery parameters, leading to a more precise and tailored outcome.

Another significant advantage is improved collaboration. By utilizing AR, multiple users can view and interact with the same virtual design simultaneously, regardless of their physical location. This facilitates better communication and faster consensus among designers, production teams, and clients. The iterative optimization process enabled by AI allows for continuous improvement of the design based on real-time feedback, ensuring that all stakeholders are satisfied with the final product before production begins.

Training and education also benefit from this technology. AR provides interactive tutorials that guide new designers and machine operators through complex tasks, enhancing their learning experience and improving retention. This hands-on approach to training can accelerate the onboarding process and increase overall productivity.

However, there are also disadvantages to consider. The implementation of AR and AI systems requires significant investment in advanced hardware and software. High-quality AR devices and powerful AI computational resources can be expensive, potentially limiting accessibility for smaller companies.

Additionally, the technology necessitates specialized skills for development and maintenance, which may require additional training for existing staff or hiring new personnel with the necessary expertise.

Data privacy and security are also concerns, especially when dealing with sensitive design information and customer data. Ensuring that the AI system complies with data protection regulations and implementing robust security measures can be challenging and costly. Furthermore, the reliance on continuous data input and feedback loops means that any disruption in data flow can impact the accuracy and effectiveness of the system.

Therefore, the described information technology for joint decision-making in machine embroidery with AR and AI offers significant advantages in terms of design visualization, collaboration, and training. However, it also presents challenges related to cost, technical complexity, and data security. Balancing these factors is crucial for successful implementation and maximizing the benefits of this advanced technology.

5. Conclusions

The integration of AR and AI in machine embroidery for joint decision-making presents significant advantages and promising prospects. The primary advantages include enhanced design visualization, where AR allows stakeholders to see and interact with embroidery designs in real-time, ensuring alignment with aesthetic and technical requirements. This technology also facilitates improved collaboration, enabling simultaneous input from geographically dispersed teams, and providing interactive training modules that accelerate skill acquisition and productivity. AI's role in optimizing embroidery techniques, coordinates, and colors ensures high-quality outputs tailored to individual garments.

The prospects of this technology are promising as it drives innovation, efficiency, and quality in the embroidery industry. It allows for continuous improvement through real-time data analysis and iterative optimization, leading to more precise and customized designs. As the technology matures and becomes more accessible, it can revolutionize the industry by reducing errors, speeding up the design-to-production cycle, and enhancing customer satisfaction through personalized, high-quality products. The future of machine embroidery with AR and AI looks bright, promising significant advancements and broader adoption across the industry.

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