

Research on Computer Vision-Assisted Quantitative Analysis and Knowledge Graph Construction of Intangible Cultural Heritage Inheritors' Skills

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ABSTRACT The tacit knowledge embedded in intangible cultural heritage skills is difficult to capture, quantify, and systematically preserve using conventional documentation approaches. To address this challenge, this study proposes a computer vision-assisted framework for quantitative analysis and knowledge graph construction of intangible cultural heritage inheritors' skills. Human skeletal key-point detection, motion trajectory extraction, and force-related feature analysis are employed to achieve digital representation of operational behaviors. Ontology modeling and semantic association techniques are further integrated to construct a multimodal knowledge graph describing relationships among operational skills, cultural semantics, and inheritance knowledge. The proposed framework enables quantitative characterization of skill features and supports intelligent organization and retrieval of heritage knowledge. The study provides an effective solution for digital preservation and offers methodological references for computer vision, multimodal sensing, knowledge representation, and intelligent cultural-information systems.

INDEX TERMS computer vision, knowledge graph, multimodal sensing, cultural heritage preservation, knowledge representation

I. INTRODUCTION

INTANGIBLE Cultural Heritage (ICH), particularly the intricate mechanical logic and rhythmic weaving patterns of traditional textile manufacturing, serves as a vital repository of national cultural identity and has gained significant academic and industrial attention for its preservation. The systematic protection of these fiber-based crafts ensures that the evolution of material culture and technical excellence remains a sustainable foundation for modern heritage transmission. Under the guidance of the UN cultural organization's (UNESCO) Convention for the Safeguarding of the Intangible Cultural Heritage, different countries have undertaken a huge number of exploration practices regarding the digital protection of ICH. However there is often a technical knowledge embedded in traditional handicrafts and performing arts ICH projects, even this technical knowledge is in the form of "tacit knowledge" in the body memory and the operating habits of the inheritors, which is difficult for them to express and also to record. How to overcome the limitations of the issue of "emphasizing material preservation and neglecting technical analysis" in the digital process, and achieve accurate capture and scientific analysis of the

details of human operation, has become a key issue that needs to be urgently solved in terms of the field of ICH protection.

In recent years the technical development of computer vision technology has opened up new possibilities for the technical analysis of human motion and behavior. By analyzing video data using deep learning algorithms, it is possible to automatically identify and quantify parameters such as skeletal key points, joint angles and movement trajectories during the performance of inheritors. This technological paradigm changes the traditional paradigm of "oral and physical instruction in favor of the model of data-driven scientific analysis of the information opening up new possibilities for the extraction and representation of skill characteristics". On the other hand, the advent of knowledge graph technology offers a semantic response to the problem of the organization and management of multi-source heterogeneous intangible cultural heritage knowledge. By building a network between "skill characteristics - cultural semantics" the interlink between tacit and explicit knowledge can be achieved, which can bring a paradigm change in the field of intangible cultural heritage protection from archival heritage

preservation to knowledge-based services.

Supported by computer vision technology, this research focuses on the quantitative analysis of textile manipulation skills, specifically capturing the intricate spatial distribution of yarns and the high-precision movements of loom operation. By integrating knowledge graph technology, the study constructs a multidimensional semantic network that bridges these technical fiber-processing characteristics with the profound cultural connotations of intangible heritage. In the aspect of the research content, the characteristics are: first, to find key skeletal points and inherit trajectories based on the framework of OpenPose; second, to build the knowledge graph of ICH skills knowledge and to extract the entity relationship based on multimodal data; and third, to store and query the knowledge graph of ICH skills knowledge and to verify the application. Through this research, it is intended to give more accurate technical path and knowledge organization paradigm for digital protection of ICH.

II. RELATED WORK

In the study of digital protection of intangible cultural heritage, a series of progress has been made on issues such as digital narrative and experience design, tourism integration effect, education and dissemination mechanism and cultural space reconstruction. The relevant results have expanded the revitalization path of ICH from different dimensions. With the growth of demand for digital protection of intangible cultural heritage (ICH), how to vividly tell and share ICH stories through technical means has become a research hotspot. Mathioudakis *et al.* [1] introduced and evaluated the development and application of the “InCulture” collaborative platform. Starčević *et al.* [2] quantified the impact of intangible cultural heritage on the financial results of rural tourism. Cerquetti *et al.* [3] designed and implemented a series of tourism experience activities, incorporating these ICH elements. Nikolakopoulou *et al.* [4] designed a multi-sensory exhibition space, using projection mapping technology to project dynamic visual content onto physical models and walls, restoring the typical scenes of mastic tree planting, harvesting and processing. Howard [5] Explore the complex relationship between musical instruments as TCH (physical entities) and as ICH carriers (music, skills, rituals). Rivero *et al.* [6] explored how museums can collaborate with schools to implement co-creative educational communication projects around ICH. Alahakoon and Udunuwara [7] used Sri Lanka as a case study to explore the role of intangible cultural heritage in creating peak tourist experiences. Demgenski [8] revealed the power relations, meaning reconstruction, and cultural politics in the process of stripping ICH from everyday life contexts and placing it on the stage. Deshpande and Gangopadhyay [9] used Nashik, a historical and cultural city in India, as a case study to explore methods for mapping ICH in urban contexts. Way and Wei [10] conducted an in-depth analysis of the history, characters, puppetry skills, and stage art of glove puppetry,

and based on this, they conducted digital character and scene modeling. This paper uses computer vision technology as support, introduces a quantitative analysis method of the characteristics of intangible cultural heritage inheritors’ skills, and combines knowledge graph technology to construct a network of association between skill characteristics and intangible cultural heritage semantics, aiming to provide a more accurate technical path and knowledge organization paradigm for the digital protection of intangible cultural heritage.

III. METHODS

A. FEATURE EXTRACTION OF INHERITORS’ SKILLS BASED ON COMPUTER VISION

The quantitative analysis of the characteristics of skills is based on the high-precision acquisition and analysis of human motion data. In view of the movement patterns of various parts of the body during the operation of intangible cultural heritage inheritors, this study uses the OpenPose open-source framework to identify and track skeletal key points. As a human pose estimation system based on convolutional neural networks, OpenPose can detect a total of 130 key points of the body, hands and face at the same time, and has real-time processing capability and high analysis accuracy. In the process of technology selection, the study compared alternative solutions such as Dense Pose and RADICAL Motion AI, and the evaluation indicators included algorithm maturity, analysis speed, key point detection accuracy and code debuggability. The experiment showed that OpenPose is better than the comparison scheme in terms of the recognition accuracy of skeletal key points and multi-threaded processing capability, and can meet the technical requirements of refined analysis of intangible cultural heritage skills [11].

The data acquisition process included simultaneous data collection with two high-definition cameras (Nikon D3100 and D5500). The video resolution was 1920X1080 pixels and a frame rate of 60fps (interpolated via optical flow for high-frequency jerk analysis to minimize aliasing in acceleration change calculations). Two shooting angles were selected; 45 degrees side view and 90 degrees in front view, to make sure that important points were thoroughly recorded without much obstruction. The subjects were companies inheritors of traditional weaving techniques, paying attention to the trajectories of the motion of key body parts during the process, such as the wrists, elbows and shoulders. About OpenPose parameter setting, the detection sensitivity threshold was set to 0.015, which is lower than the default value of 0.02. This is a threshold to ensure a better comprehensiveness of detection with a key point confidence score of above 75, which prevents missed detections of subtle movements. Each frame was processed by a convolutional neural network to produce a JSON file with the coordinates of the skeletal key points and confidence score with a data foundation for the subsequent trajectory extraction and the calculation of movement features.

The movement trajectory of the wrist was determined to be the important object for extracting skill features. Field research found the flexible wrist usage to be an important factor determining the quality in traditional weaving techniques and the most difficult one for beginners to learn. This research took the two-dimensional coordinate sequence of key points on the wrist from the parsed out data of the JSON file and used the After Effects software to visualize and overlay the trajectory to create a motion path diagram. In order to quantify the characteristics of motion, the following three indicators were introduced to calculate: one is movement speed, i.e., the displacement distance of the position of the key wrist points per unit time, which reflects the smoothness of the operation; the other is movement amplitude, i.e., the difference between the extreme values of the operating wrist in the horizontal and vertical directions, and the amplitude of the operation in space; the third is the rate of change of acceleration, which reflects the rhythm characteristics in the process of pressing the force. The calculation results of these indicators will be used as skill feature vectors as the input for the next knowledge graph construction stage.

B. CONSTRUCTION OF THE KNOWLEDGE ONTOLOGY OF INTANGIBLE CULTURAL HERITAGE SKILLS

To achieve an effective association between the characteristics of skills and the semantics of intangible cultural heritage, it is necessary to construct a standardized knowledge representation framework. This study uses ontology modeling to formally describe the core concepts, attributes and their interrelationships in the field of intangible cultural heritage. Based on a thorough survey of existing cultural heritage metadata standards, and referring to mature thesauri such as CIDOC CRM and Schema.org, and combined with the characteristics of intangible cultural heritage resources, a knowledge ontology model for intangible cultural heritage skills was constructed. This model organizes intangible cultural heritage knowledge from three dimensions: the object layer corresponds to the tools, materials and finished product forms involved in the skill operation, including subcategories such as tool type, material attributes, and pattern features; the behavior layer corresponds to the process characteristics of the skill operation, including subcategories such as process flow, technique movements, and timing of force application; and the spiritual layer corresponds to the cultural semantics carried by the skill, including subcategories such as lineage of inheritance, cultural connotation, and ritual function. This three-layer classification system maintains compatibility with existing metadata standards and highlights the dynamic and physical characteristics of skill transmission [12,13].

In designing conceptual attributes, the research emphasizes strengthening the mapping relationship between technical characteristics and semantic concepts. For example, regarding the concept of "pattern" in weaving techniques, it not only records its geometric shape and color matching, but

also associates it with the corresponding weaving techniques (such as picking one over one, picking two over two) and cultural connotations (such as praying for blessings and warding off evil). Regarding the concept of "exertion," it not only labels its biomechanical parameters, but also associates it with the personal style of the inheritor and the lineage of teachers and students. Through this multi-dimensional attribute labeling, technical characteristics are transformed from simple physical quantities into knowledge units with cultural semantics.

C. CONSTRUCTION OF THE ASSOCIATION NETWORK BETWEEN CRAFT CHARACTERISTICS AND INTANGIBLE CULTURAL HERITAGE SEMANTICS

Building on the already completed work on ontology modeling, in this work, knowledge graph technology is additionally used to implement semantically based organization and relational queries on craft features. The technical route of "entity extraction-makers-relations-storage knowledge graphs" applies to the construction process of knowledge graphs. In the entity extraction stage the source of data is in the form of textual records, interview recordings, and video material gathered in the field surveys. Named entity recognition technology is implemented to automatically extract the entity information such as inheritors, craft names, tool names, pattern types, and process flows. Addressing problems like ambiguous entity boundaries and non-standard terminology of intangible cultural heritage corpora data, this study proposes an entity recognition model that combines features of boundaries. An attention mechanism is increasing the ability to extract associated information from entity tags to improve recognition accuracy.

The relation extraction stage is aimed at the establishment of semantic relations between entities. This study identifies the following key types of relations: inheritance relations (e.g., apprenticeship, family tradition), operational relations (e.g., tool use, technique adherence), representational relations (e.g., pattern symbolism, technique characteristics) and spatiotemporal relations (e.g., geographical distribution, historical period). Relation extraction uses remote supervision technique with an existing knowledge as seeds to automatically annotate training data and learns a relation classification model using bidirectional LSTM network. Experimental results indicate that an F1 score over 85% and a relation extraction method for intangible cultural heritage data.

The knowledge storage part uses the graph database Neo4j as the storage engine (the B2P node and edge are stored as nodes and edges). To promote association capabilities between domains cross-linked knowledge, the research is also related to open-link data sources such as DBpedia and GeoNames, to inter-link intangible cultural heritage knowledge with general knowledge bases. The resulting intangible cultural heritage skills knowledge graph with 187 inheritor nodes, 56 skills nodes, 124 tools nodes and 89 patterns nodes adds up to 3245 relationships. Beyond

the 240 minutes of primary video data, these edges were populated by performing entity and relation extraction on a secondary corpus of 2,000 digitized historical documents, apprenticeship contracts, and interview transcripts gathered during the field research phase. The knowledge graph has a complex semantic-based query supporting capability. For example, searching for "the weaving techniques mastered by a certain inheritor and their corresponding movement characteristics," the system can return relevant data along the track of "inheritor- mastered- technique- possessing- movement characteristics", achieve deep association between the characteristics of skills and intangible culture semantics.

IV. RESULTS AND DISCUSSION

A. QUANTITATIVE ANALYSIS RESULTS OF TECHNOLOGICAL CHARACTERISTICS

This study selected weaving-related intangible cultural heritage projects as experimental subjects, collecting operation video data from three inheritors, totaling 240 minutes of effective time. Approximately 430,000 frames of skeletal keypoint coordinate data were obtained through OpenPose parsing, with a mean confidence score of 82.3 for wrist keypoints, meeting the accuracy requirements for subsequent analysis. Based on the above data, three motion characteristic indicators were calculated, and the results are shown in Table 1. The data in the table show significant differences in the average wrist speed among the three inheritors. Inheritor A had the fastest weaving speed, reaching 12.7 cm/s, while Inheritor C had the slowest, at only 8.2 cm/s. The amplitude of motion indicator reflects the spatial range of operation; Inheritor B had the largest horizontal amplitude, while Inheritor C had the smallest. The rate of change of acceleration indicator reflects the smoothness of the force application rhythm; Inheritor A had the highest rate of change of acceleration, indicating a strong sense of rhythm in their force application, while Inheritor C had the lowest rate of change of acceleration, indicating a smoother operating style. The above data demonstrate that the same skill exhibits individualized operational characteristics among different inheritors. These differences are difficult to clearly convey through verbal descriptions but can be quantitatively represented using computer vision methods.

TABLE 1. Comparison of Quantitative Data on Wrist Movement Characteristics of Successors

Inheritor Number	Average wrist speed (cm/s)	Horizontal movement amplitude (cm)	Vertical motion amplitude (cm)	Rate of change of acceleration (cm/s ²)
Successor A	12.7	28.4	15.2	3.86
Successor B	10.3	32.1	18.7	2.94
Successor C	8.2	24.5	12.3	2.31

Further analysis of the timing characteristics of force application during the operation process revealed that the time window for weaving a complete pattern unit was selected, and the curves of wrist displacement in the X

and Y axes as a function of time were calculated. The results showed that Inheritor A's movement curve exhibited obvious periodic fluctuations, with alternating peaks and troughs at even intervals, reflecting a stable rhythmic pattern in their operation. Inheritor B's movement curve had a larger amplitude but irregular period, reflecting the greater influence of material properties on their operation. Inheritor C's movement curve showed gentle changes and a longer period, reflecting a more cautious and meticulous operating style. These timing characteristics provide a preliminary quantitative baseline for individualized styles; however, while the current sample of three primary inheritors offers high-depth case study data, the study acknowledges that broader statistical generalizations require a larger cohort to establish formal significance across different weaving lineages.

B. EVALUATION OF ENTITY RECOGNITION AND RELATION EXTRACTION PERFORMANCE

To verify the effectiveness of key technical modules in the knowledge graph construction process, this study quantitatively evaluated the entity recognition and relation extraction stages. The entity recognition task used 2000 manually annotated intangible cultural heritage (ICH) corpora as the test set, comparing the recognition performance of three models. The results are shown in Table 2. The baseline model, employing a bidirectional LSTM+CRF structure, achieved a precision of 78.4% and a recall of 76.2%. After introducing pre-trained word vectors on top of the baseline, the precision improved to 82.6% and the recall to 80.1%. The ER-BFAS model, further incorporating entity boundary features and an attention mechanism, achieved a precision of 85.3%, a recall of 84.7%, and an F1 score of 85.0%. In terms of entity type, the recognition accuracy for inheritor names and craft names was relatively high, both exceeding 90%; the recognition of process flow-related entities was more difficult, with an accuracy of approximately 82%. This result indicates that the method of fusing boundary features can effectively address the problem of ambiguous entity boundaries in ICH corpora, significantly improving the overall performance of entity recognition.

TABLE 2. Comparison of Entity Recognition Model Performance in the Intangible Cultural Heritage Field

Model	Accuracy (%)	Recall rate (%)	F1 score (%)
BiLSTM+CRF	78.4	76.2	77.3
BiLSTM+CRF+pre-trained word vectors	82.6	80.1	81.3
ER-BFAS (used in this paper)	85.3	84.7	85.0

The relation extraction task was evaluated using a 10-fold cross-validation method, and the results are shown in Table 3. Six core relation types were defined. The "Using Tools" relation performed best, achieving an F1 score of 88.2%, likely due to the high discriminative power of tool-related entities in the corpus. The "Mastering Techniques"

relation performed well with an F1 score of 86.3%. The "Implication" relation was the most difficult to identify, with an F1 score of only 79.5%, primarily because the expression of meaning often relies on contextual understanding, and the same pattern may correspond to multiple meanings, increasing the ambiguity of classification. To mitigate this, the system incorporates a probabilistic weight to relationships, allowing a single movement pattern to map to multiple semantic connotations based on cultural context weights, thereby addressing inherent semiotic ambiguity. To ensure scientific verifiability, the 'ground truth' for these subjective cultural meanings was established through a Delphi-method consensus involving five senior inheritors and three cultural anthropologists, who cross-validated the annotated corpora against authoritative local gazetteers and lineage records. The F1 scores for the "Master-Apprentice Relationship" and "Distribution Region" relations were 84.1% and 85.7%, respectively, while the "Process Flow" relation achieved 82.4%. Overall, relation extraction can meet the practical application needs of knowledge graph construction.

TABLE 3. Results of Relationship Extraction in the Intangible Cultural Heritage Field

Relationship type	Accuracy (%)	Recall rate (%)	F1 score (%)
Master-disciple relationship	85.6	82.7	84.1
Mastering techniques	87.2	85.4	86.3
Use tools	89.3	87.1	88.2
Process Flow	83.7	81.2	82.4
Implied meaning	81.4	77.8	79.5
Distribution area	86.9	84.5	85.7

C. CASE STUDY OF KNOWLEDGE GRAPH QUERY APPLICATION

Based on the constructed knowledge graph of intangible cultural heritage skills, three typical query scenarios were set to check the application effect. The first is the level of query in the inheritors. Inputting "the skills mastered by some inheritor and their movement characteristics", the system replies a list of the skill names corresponding to that inheritor, and fetches the quantitative data of movement characteristics. For example, querying inheritor A gives results including "weaving skills-average speed 12.7 cm/s Horizon amplitude 28.4 cm acceleration rate of change 3.86 cm/s³". This query function offers support for data to help with the horizontal comparison of styles of skills.

The second category one is the skill based queries. By doing input "the core techniques of a certain skill and its lineage", the system returns the name of the techniques involved, the description of operational essentials and information on a many people in whose hands those have been achieved from the time as for the successor. For instance, a search for 'the 'pick-and-press technique'', one will obtain results including the chronological characteristics of the operation of the technique, as well as a display of its line from the late Qing Dynasty until the present, and the active periods and the representative works of each

generation of its inheritors. This query function aims at the research and development of intangible cultural heritage preservation plans. The third type is cross-domain related queries. For example inputting "the cultural meaning of a certain pattern and its corresponding weaving technique" returns the meaning of the pattern, its appearance with regard to different contexts, and the name and inheritor information of the weaving technique. For example, a query of 'human-shaped pattern' will return results including the connotations of the pattern such as 'blessing' or 'ancestor worship,' which are stored as context-dependent nodes tied to specific geographical regions and lineages rather than static attributes. This allows the system to reflect the dynamic and varied interpretations of the same motif across different inheritance environments, in association with the 'embroidery technique' and the corresponding inheritors. It also presents the motion trajectory information from the weaving segments of the videos of inheritors. This query function ensures whole retrieval from cultural semantics to technical characteristics results in a knowledge infrastructure for in-depth research and innovative design for intangible cultural heritage.

V. CONCLUSION

This study mainly focuses on the quantitative analysis and knowledge organization of the intricate fiber manipulation and loom tensioning skills characteristic of textile heritage inheritors. It proposes a computer vision-assisted technical framework and an implementation path to bridge the semantic gap between the high-precision geometric data of weaving movements and the profound cultural connotations of intangible craftsmanship. The main achievements include: First, constructing a method of extracting the motion features of inheritors based on OpenPose, which can quantify the major features of the skills such as the wrist speed, screen amplitude and the rate of change of acceleration, providing the data foundation for representing skills in a more refined manner; Second, constructing the knowledge ontology model of intangible cultural heritage skills, which organizes the intangible cultural heritage knowledge from three dimensions, the object layer, the behavior layer and the spiritual layer, providing the formal structure for describing the semantic information in multi-source heterogeneous data; Third, completing the construction and validation of intangible.

This study also has some limitations. First, the scope of experimental data collection is limited, focusing only on weaving-related intangible cultural heritage projects, and the conclusions need more verification in order to be extended to other types of intangible cultural heritage. Second, the choice of motion feature indicators is concentrated on the wrist, and the study of finger small movement and whole body combined movement is not enough. Third, the quality of the corpus has the implication on the extraction of entity relationships in the knowledge graph, and the ability to handle semantic ambiguity and implicit relationships needs

to be improved. Future research can be further improved in the following aspects: First, introduce multi-view 3D reconstruction technology to achieve quality capture of fine hand movements; second, combine multimodal data cities (images, text, audio, etc.) to facilitate high semantic richness of the knowledge graph, and third, investigate the deep mapping mechanism between skill characteristics and cultural semantics, reveal the inner connection between "skill" and "Tao" and provide a more solid theoretical support for the living inheritance and innovative transformation of intangible cultural heritage.

AUTHOR CONTRIBUTIONS

Conceptualization – Junbo Wang and Linxin Wang; methodology – Junbo Wang and Linxin Wang; investigation – Junbo Wang and Linxin Wang; writing-original draft preparation – Junbo Wang and Linxin Wang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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