Prioritizing skill action recognition of basketball using decision support system

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Research Article

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Abstract

Human action understanding is vital in many computer vision applications, including sports narrative, virtual reality games, and human computer interaction (HCI) systems. To recognize human actions, a video stream or image sequence must contain many actions. For example, modern video surveillance systems need to recognize human action to improve financial institution security. Human action recognition can help with automatic sports narrative and video captioning. It's important for HCI, notably for virtual reality games, sports storytelling, and video captioning. However, complex backgrounds, action occlusion, and fluctuating lighting conditions make human action identification difficult nowadays. Basketball high-difficulty action recognition technology is used to identify and evaluate player movement. Video recognition is a vital tool for improving basketball instruction. Technology and injury limit traditional sports target recognition, preventing the desired effect. The current study has used decision support system for prioritizing the skill action recognition of basketball. The tool of super decision was used for the process of experimental work. Results of the experiments reveal that the proposed work is effective for prioritizing skill action recognition showed satisfactory results.

1. Introduction

Human action understanding is vital in many computer vision applications. Complex backgrounds, action occlusion and fluctuating lighting make human action identification difficult nowadays. Human action recognition can help with automatic sports narrative and video captioning. Video recognition is a vital tool for improving basketball instruction. Schmidt [1] has proposed a methodology for the analysis of the movement patterns of free-throw shooters at various skill levels in the sport of basketball. The method analyzed the information that can be concluded from the movement outline as well as the procedural potential of pattern examination. A complex feature was computed and shown by a trajectory combined with several neurons of the network. The classification of throwing patterns was performed very precisely along with the establishment of stability and variability of the realized pattern. The study was conducted for the detection of motion in sports which can cause serious injuries to the players. The developed architecture is based on the convolutional neural network and big data to diagnose difficult motion images. Images were extracted with the employment of the discriminative power of a convolutional neural network for performing computational preprocessing for the recognition of images in a video stream. The main parts of the human body were recognized by the utilization of the LSTM-based skeleton recognition technique. All the movements, which are detected, were recombined through the object detection architecture [2].

In the proposed study, Jabri et al. [3] have presented a system for observing a basketball match by analyzing the position of a player from different angles. To find out the location of a player, three video streams of the ground were obtained from different angles and examined. To ensure the visibility of the player from different views, all the streams from different cameras are synchronized. Various pieces of information extracted from the streams are used for the tracking of the current and updated positions of

the players. A database is used to process the location that was found as a result of the proposed system. A polygon-like structure is made from it.

Pan and Li [4] have developed an innovative paradigm for the recognition of the activities of players during a basketball match. A dataset selected for the proposed architecture was comprised of sports video clips related to basketball. Motion regions were identified through the building of an affinity graph, while the motion block was extracted by the computation of entropy of the selected motion regions. By using efficient and effective integration of motion and posture descriptors, the presented approach employed the KNN technique to identify action during basketball. An effort was made to effectively optimize the target tracking of basketball players to improve the traditional procedures. The main drawback of these traditional procedures is that an extremely thick chart has been arranged to catch the traits of the target. Assuming the framework is checked, it shows a video picture of an edge-recognizing framework that can identify an exceptionally precise edge. The recent developments in the target identification results have employed learning methodologies of in-depth and brief examination [5]. To study the recognition of basketball motions, the presented research [6] combines neural computing and neural network algorithms. Furthermore, the study discusses that in basketball preparation, the investigation of players can visually indicate the performance of players for trainers, set corresponding preparation plans, as well as enhance team presentation. Now with the help of video investigation technology, it is possible to examine the activities of basketball athletes in preparation, also present an approach for guessing body position, as well as provide athletes with correct action investigation outcomes. The study presented an intelligent visual image decomposition approach of basketball projection angle using odd-difference value decomposition. Furthermore, the basketball shooting angle is identified by examining the alteration of the basketball shooting angle in different situations. Experiments indicate that the intelligent vision image decomposition decision approach can enhance the image contrast of shooting stroke decomposition. An action recognition strategy with leveraging double-core extreme learning machine and deep learning technology was presented to enhance the correctness of human action recognition in videos. The practical outcomes indicate that the presented approach reveals an extraordinary recognition accuracy for both data sets. Furthermore, the investigation outcomes presented that the enhanced model has a greater recognition ratio as well as an optimistic motion recognition effect as compared to their competitors [7].

The proposed study contributed in the following manner:

- To identify various criteria and use decision support system for prioritizing the skill action recognition of basketball.
- Various experimental work was done in order to show validity of the approach.
- To show effectiveness of the proposed work by performing experiments for prioritizing skill action recognition
- Available alternatives were ranked and the most prioritized one was selected

2. Related Work

The advancements in the area of the Internet of Things (IoT) have changed the way people interact with modern technologies. The study collected data from the basketball coaches, especially about identifying players with the help of micro sensors. An innovative device was presented for the shooting of individual actions of each player. The developed tools need to be close to the knee pads. After designing and developing the system, it was tested thoroughly. The results revealed that it precisely tracks the position and movement of the players [8]. Qi et al. [9] have performed a study on the identification of zero-shots with the help of temporal information and object relations. The proposed architecture jointly detects the object relations of one static frame and the temporal motion patterns of adjacent frames. A three-dimensional convolutional network was employed for the purpose of modelling temporal information. The visual characteristics were studied with the assistance of visual-to-semantic modules by providing the above two outputs separately into it. This approach was evaluated by conducting thorough experiments on three datasets named Olympic Sports, HMDB51, and UCF101. Su et al. [10] have developed a procedure for the efficient detection of the future location and gaze path of a player during a basketball match. Visual social semantics are obtained by the implementation of three-dimensional reconstruction of various first-person videos. Based on this learning, the system developed numerous trajectories per player. Effective group trajectories are selected from the developed ones by the implementation of Dijkstra’s algorithm. The experimental results show that the proposed architecture, which is based on first-person videos, is far better than the existing approaches based on third-person views.

Chen et al. [11] have performed a study on the development of a screen-strategy recognition architecture for efficiently diagnosing and classifying screen arrangements in a basketball video. It can automatically detect court lines, track players, and classify the team as defensive or offensive. Screen patterns are recognized through the calibration of player trajectories to the real-world court paradigm. This recognition of screen patterns and derived trajectories enables the coaches, fans, and players to understand the tactics performed during the basketball match. A system was proposed for basketball shooting gesture recognition through the employment of image feature extraction and machine learning. In the first step, an image feature extraction procedure was used for the collection of action posture data of a player. The time and frequency domains were used for the extraction of multi-dimensional motion posture features. Then, by the utilization of feature selection Gaussian hidden variables methods, the precise and accurate shooting gesture was identified. The proposed architecture can work as a base for the creation of modern basketball training [12].

Evans and Fitzgerald [13] have conducted a study to add to strategic conversations inside ethnomethodology and discussion examinations connected with the joining of successive and categorical orders of association within the examination. The developed approach employs video information to investigate social activity inside a complex, categorical, and consecutive stream in which various 'layers' of arrangement become applicable as facilitated activity unfurls consecutively. The investigation, given video information recorded during basketball instructional meetings, portrays the

reflexive, consecutive, and categorical association of exemplified exercises in basketball training meetings, zeroing in on the association of talk and behavior between the mentor and players during rectification exercises. In particular, we inspect exhaustively the mentor's utilization of 'embodied mapping' through spatial arrangement gadgets during the time spent correcting the behavior of a player. A study was conducted for the productive solution of issues like large positioning results and small accuracy. The study proposed an indoor positioning procedure of WKNN grounded on the special properties of the object. Due to effective WKNN methodology, the hurdles of large computational results span and incorrect positioning of traditional algorithms are resolved. These traditional procedures are restricted and hence large interval jumps are avoided, which in turn reduces the complexity of the proposed architecture. The experimental data proved that the research performed can enhance the positioning accuracy [14].

A deep neural network has been widely used in recent years due to its wide range of usage. The study [15] presents a lightweight fine-grained action recognition network for basketball foul detection. The presented network has an optimistic effect on subtle classification activity and is lighter in parameters. The visualized foul feature distribution is focused on a few frames that assist the preliminary suggestion of the study that fouls generally occur instantly. In addition, the study results can be utilized to support referees in coaching basketball. The experiences of disabled youth in entertaining sports venues were analyzed by the present study using a new case study of a youth wheelchair basketball team. The study chose those sports venues which can efficiently improve disabled youth’s wellbeing and societal attachment. Furthermore, the research participants experienced physical health and societal advantages through participation in wheelchair basketball. Finally, the analysis concludes that youth-related, comprehensive sports generate facilitating environments that improve youth’s societal attachment, health, and life satisfaction [16]. The implementation of different innovative technologies in sports coaching can significantly enhance coaching effectiveness. The study presents a method for analyzing behavior that is based on a deep learning algorithm. The study designed an approach to automatically mine the basketball court and mark stadium lines. The research develops a behavior recognition and prediction approach based on an encoder-decoder context. The investigation outcomes can be sent back to trainers and data analysts immediately, so they can examine the strategies and technical choices in real-time. Experimental outcomes of the presented approach indicate that this technique efficiently identifies the motion of video characters while attaining the highest behavior investigation accuracy [17].

Data analytics aids basketball teams to make strategies. Manually data gathering is costly and not efficient. Therefore, Zhao et al. [18] have presented research that implemented a deep bidirectional long short-term memory (BLSTM) along with a mixture density network (MDN) method. The proposed model can produce novel trajectory samples and is capable of forecasting a basketball path based on real data. Its architecture is specifically appropriate for dealing with time series issues. BLSTM gets both forward and backward information in real-time, while assembling numerous BLSTMs additionally rises the learning capability of the model. The proposed model was tested through two experiments. Experimental outcomes of the presented model indicate that this model performs outclass in terms of precision and convergence speed. Nowadays most research concentrates on coarse-grained and fine-grained actions in

motion recognition, without being participation in numerous applications. Junjun [19] has presented a study that proposed an adaptive multi-label classification approach to incorporating the FPGA into a network of two data streams to identify the premium zones of basketball stroke recognition and mine the structures of the recognition system. The presented approach generated effective and efficient outcomes as compared to existing approaches. Generally, nonfictional videos can track normal well-being and can be connected to the group of individuals in the presented system.

3. Methodology

A popular research topic in computer vision and multimedia analysis is human activity recognition [20]. High-difficulty action recognition technology in basketball is mainly to identify and analyze the physical behavior of basketball players. Video recognition is an important guarantee for improving the level of basketball training. Traditional sports target recognition is limited by technology and injury, and cannot achieve the desired effect. Basketball offence is a crucial part of the game that involves cutting, dribbling, passing, screening, and shooting. Athletes and coaches alike benefit greatly from collecting and evaluating posture data. The current basketball action detection system is inefficient and has a high error rate. A typical human action recognition pipeline has three steps: action object detection, feature extraction, and recognition. Single-feature recognition is often incapable of delivering stable and precise performance. Multi-model feature fusion improves recognition accuracy [21, 22].

Traditional basketball education techniques can be reiterated, affecting severe basketball teaching effectiveness along with the gaining of technical requirements. Grounded on this issue, the basketball coaching reproduction structure is constructed using augmented reality invention. The proposed study [23] utilizes fundamental concepts, features, virtual reality strategies, literature and information approaches to describe the varieties of role play in basketball training. In addition, the study examines the application programs of basketball theory teaching, technical learning, strategic education, and institutional competitions that offer scientific principles for upcoming basketball teaching modification. Decision-making has an important role in basketball offenses. Tsai et al. [24] have presented an article that proposes a motion-aware offensive decision-making coaching system for basketball using virtual reality (VR) and artificial intelligence technologies. Novices wearing a head-mounted display (HMD) as well as an action capture outfit are prepared by instinctively cooperating with the VR system and obtaining judgment recommendations when a negative one is made. Furthermore, the research diverse the coaching mediums and approaches to make an immersive coaching atmosphere during the coaching phase and assessed the coaching efficiency. Experimental outcomes show that the coaching situation affects the preparation in terms of judgment time. Nowadays most researches concentrate on coarsely-grained motions, whereas fine-grained motion recognition is rarely focused which is of key significance in numerous uses like video retrieval. The article [25] issue a challenging dataset by interpreting the fine-grained motions in basketball game videos. A benchmark assessment of the state-of-the-art methods for motion recognition is also offered in the presented dataset. To locate the most instructive areas and mine more discriminative features for fine-grained motion recognition, the study presented a method by

incorporating the NTS-Net into two-stream network. Experimental outcomes indicate that the presented method performs very well as compared to the existing method.

The study presents an innovative method to fuse the global and local gesture pattern separation as well as vital visual information for semantic recognition in basketball videos. For group activity recognition and for success or failure estimation, these both KVI and MPs charters were mined. At first, the study presented an algorithm to predict the global actions from mixed actions grounded on the intrinsic property of camera adjustments. While the local actions can be achieved from the mixed and global actions. Secondly, a two-stream 3D CNN outline is used for group task recognition and thirdly, the basket is identified as well as its exterior features were mined via a CNN framework. The features are used to forecast success or failure. Experimental outcomes indicate that the presented approach achieves superior performance [26]. By using triple Kinect sensors, Yao et al. [27] have presented a novel human motion recognition system. A weighted incorporation approach is utilized to incorporate the multi-view skeleton data. The study utilizes joint velocities, angles, as well as angular velocities as features to identify human motion. For capturing the temporal characteristic of human motion, the study utilizes the average of joint velocities, average angles, along with angular velocities as temporal features. In addition, the proposed study constructed the classifier grounded on part-aware lengthy short-term memory (PLSTM) to determine human action. The feasibility of the presented system has been proved by the experimental outcomes.

This study used a decision support system to prioritize basketball skill action recognition. The super decision tool was employed in the trial process. The process was initially divided into three parts, the goal which is the skill action recognition, the criteria which are cutting, dribbling, passing, screening, and shooting, and the available six alternatives (A1, A2,…A6). Figure 1 depicts basketball court and the process of plotting the super decision tool is shown in Fig. 2. Those are the five primary offensive skills. Each player must build a good basis for each skill set, even if some players excel in certain skills. The following criteria have been followed.

- **Cutting**

The defense cannot stop two activities at the same moment in basketball. The defense will focus on on-ball actions like dribble penetration, allowing the offence to cut off-ball.

- **Dribbling**

Dribbling is another key technique when a player with the ball bounces it up and down on the floor with one hand. For example, during a live turnover fast break opportunity with just one player to beat, dribbling allows players to advance the ball towards the hoop.

- **Passing**

The passing game is very vital in basketball offence. The offence will likely stagnate if players cannot make precise and/or timely passes. The offensive team's ability to generate high percentage shots will be

severely hampered.

- **Screening**

Basketball players should master and use the fundamental technique of screening. Basketball screens can be on-ball screens used in pick and roll action or off-ball screens like the down screen or cross screen.

- **Shooting**

Shooting is undoubtedly the most vital skill in any basketball offence since without it, a team cannot score points.

After the process of plotting, the process of pair wise comparisons were done in the software and Fig. 3 shows the process of comparison of criteria.

The same process was done for rest of the available criteria. Figure 4 describe the process of comparison for available alternative 1. The rest of the process of pair wise comparison of alternatives was done in the same manner.

Once the process of comparisons of all the criteria alternatives were done then the results were summarized into unweighted matrix which is shown in Table 1.

Table 1. Unweighted matrix

	A1	A2	A3	A4	A5	A6	Cutting	Dribbli~	Passing	Screeni~	Shooting	skill a~
A1	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.05635	0.07269	0.30023	0.34159	0.34869	0.16667
A2	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.10819	0.09794	0.25245	0.23012	0.21603	0.16667
A3	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.11930	0.11810	0.15383	0.14604	0.15455	0.16667
A4	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.18626	0.14366	0.12341	0.11725	0.14267	0.16667
A5	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.24130	0.28769	0.08792	0.09248	0.07828	0.16667
A6	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.28861	0.27992	0.08217	0.07253	0.05978	0.16667
Cutting	0.08215	0.41475	0.07384	0.37356	0.37432	0.41228	0.00000	0.00000	0.00000	0.00000	0.00000	0.20000
Dribbli~	0.11056	0.19857	0.12733	0.26589	0.25107	0.22088	0.00000	0.00000	0.00000	0.00000	0.00000	0.20000
Passing	0.20397	0.17662	0.16399	0.15799	0.16508	0.16203	0.00000	0.00000	0.00000	0.00000	0.00000	0.20000
Screeni~	0.26088	0.12244	0.28005	0.11390	0.11284	0.10901	0.00000	0.00000	0.00000	0.00000	0.00000	0.20000
Shooting	0.34243	0.08763	0.35479	0.08866	0.09668	0.09580	0.00000	0.00000	0.00000	0.00000	0.00000	0.20000
skill a~	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

The unweighted matrix was normalized further to obtain the weighted matrix which is shown in table 2.

Table 2. Weighted matrix

	A1	A2	A3	A4	A5	A6	Cutting	Dribbli~	Passing	Screeni~	Shooting	skill a~
A1	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.05635	0.07269	0.30023	0.34159	0.34869	0.08333
A2	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.10819	0.09794	0.25245	0.23012	0.21603	0.08333
A3	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.11930	0.11810	0.15383	0.14604	0.15455	0.08333
A4	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.18626	0.14366	0.12341	0.11725	0.14267	0.08333
A5	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.24130	0.28769	0.08792	0.09248	0.07828	0.08333
A6	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.28861	0.27992	0.08217	0.07253	0.05978	0.08333
Cutting	0.08215	0.41475	0.07384	0.37356	0.37432	0.41228	0.00000	0.00000	0.00000	0.00000	0.00000	0.10000
Dribbli~	0.11056	0.19857	0.12733	0.26589	0.25107	0.22088	0.00000	0.00000	0.00000	0.00000	0.00000	0.10000
Passing	0.20397	0.17662	0.16399	0.15799	0.16508	0.16203	0.00000	0.00000	0.00000	0.00000	0.00000	0.10000
Screeni~	0.26088	0.12244	0.28005	0.11390	0.11284	0.10901	0.00000	0.00000	0.00000	0.00000	0.00000	0.10000
Shooting	0.34243	0.08763	0.35479	0.08866	0.09668	0.09580	0.00000	0.00000	0.00000	0.00000	0.00000	0.10000
skill a~	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

4. Results And Discussions

In order to develop athletes' basketball skills, coaches must create customized training routines for each athlete. Training plans are traditionally developed using the coach's own training philosophy and experience, together with the player's ability level. Because it is impossible to objectively evaluate the athlete's training effect, the coach must spend a lot of time analyzing the athlete's posture. Modern sports training is all about precision and efficiency. The proposed research has considered the decision support system to evaluate the skill action recognition of basketball. Various computational experiments were performed and the results were shown in different charts and tables. Table 3 show the limit matrix obtained from the calculation performed.

	A1	A2	A3	A4	A5	A6	Cutting	Dribbli~	Passing	Screeni~	Shooting	skill a~
A1	0.10068	0.10068	0.10068	0.10068	0.10068	0.10068	0.10068	0.10068	0.10068	0.10068	0.10068	0.10068
A2	0.08536	0.08536	0.08536	0.08536	0.08536	0.08536	0.08536	0.08536	0.08536	0.08536	0.08536	0.08536
A3	0.06789	0.06789	0.06789	0.06789	0.06789	0.06789	0.06789	0.06789	0.06789	0.06789	0.06789	0.06789
A4	0.07393	0.07393	0.07393	0.07393	0.07393	0.07393	0.07393	0.07393	0.07393	0.07393	0.07393	0.07393
A5	0.08495	0.08495	0.08495	0.08495	0.08495	0.08495	0.08495	0.08495	0.08495	0.08495	0.08495	0.08495
A6	0.08720	0.08720	0.08720	0.08720	0.08720	0.08720	0.08720	0.08720	0.08720	0.08720	0.08720	0.08720
Cutting	0.14405	0.14405	0.14405	0.14405	0.14405	0.14405	0.14405	0.14405	0.14405	0.14405	0.14405	0.14405
Dribbli~	0.09697	0.09697	0.09697	0.09697	0.09697	0.09697	0.09697	0.09697	0.09697	0.09697	0.09697	0.09697
Passing	0.08658	0.08658	0.08658	0.08658	0.08658	0.08658	0.08658	0.08658	0.08658	0.08658	0.08658	0.08658
Screeni~	0.08324	0.08324	0.08324	0.08324	0.08324	0.08324	0.08324	0.08324	0.08324	0.08324	0.08324	0.08324
Shooting	0.08916	0.08916	0.08916	0.08916	0.08916	0.08916	0.08916	0.08916	0.08916	0.08916	0.08916	0.08916
skill a~	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

The normal ranking of alternatives is shown in Fig. 7.

The alternatives ranking based on ideal is depicted in Fig. 8.

The total ranking of alternatives is shown in Fig. 9.

From the calculation process, the figure shows that A1 is considered as the most prioritized alternative, followed by A6, and so on.

5. Conclusion

Many computer vision applications require human action understanding, such as sports storytelling, virtual reality games, and HCI systems. A video or image series must have many human actions to be recognized. Modern video surveillance systems, for example, must recognize human action to increase bank security. The use of human action recognition in sports narrative and video captioning It's vital for HCI, especially VR gaming, sports storytelling, and video captioning. Changing lighting and background complexity make it difficult to identify human action anymore. Identify and assess player movement with high-difficulty action recognition. Basketball instruction can benefit from video recognition. Traditional sports target recognition is hampered by technology and injuries. This study used a decision support system to prioritize basketball skill action recognition. The super decision tool was employed in the process of experiments. The process of pair wise comparisons were done for the criteria and alternatives and various representations were shown in the form of tables and charts. The results suggest that the proposed work is successful for prioritizing skill action recognition.

Declarations

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The authors have not disclosed any funding.

Data availability

No data is available.

Conflict of interest

The authors have no conflict of interest.

Ethical approval

The paper does not deal with any ethical problems.

Informed consent

We declare that all the authors have informed consent.

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Figures

Figure 1

Basketball court

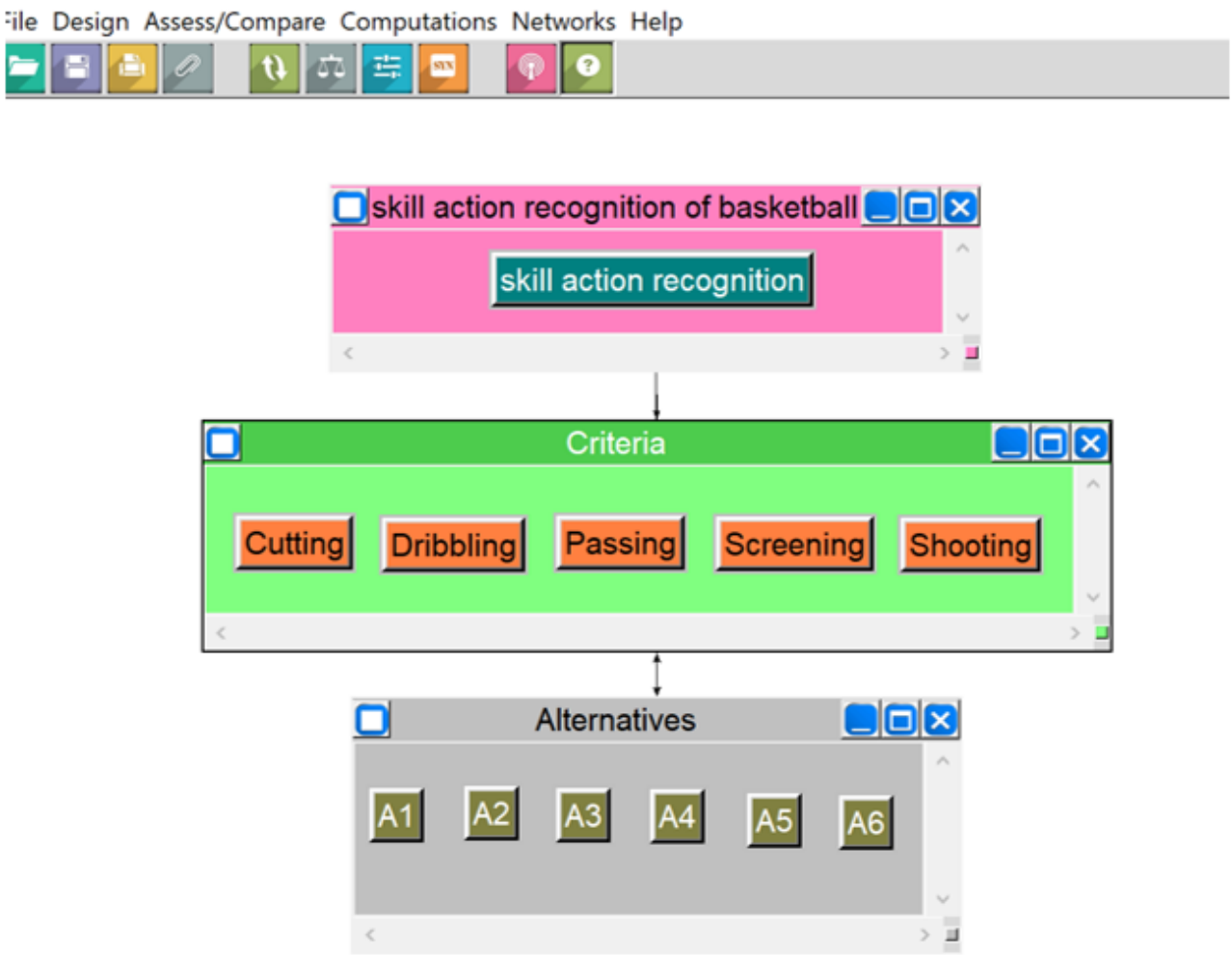

Figure 2

Process of the proposed research

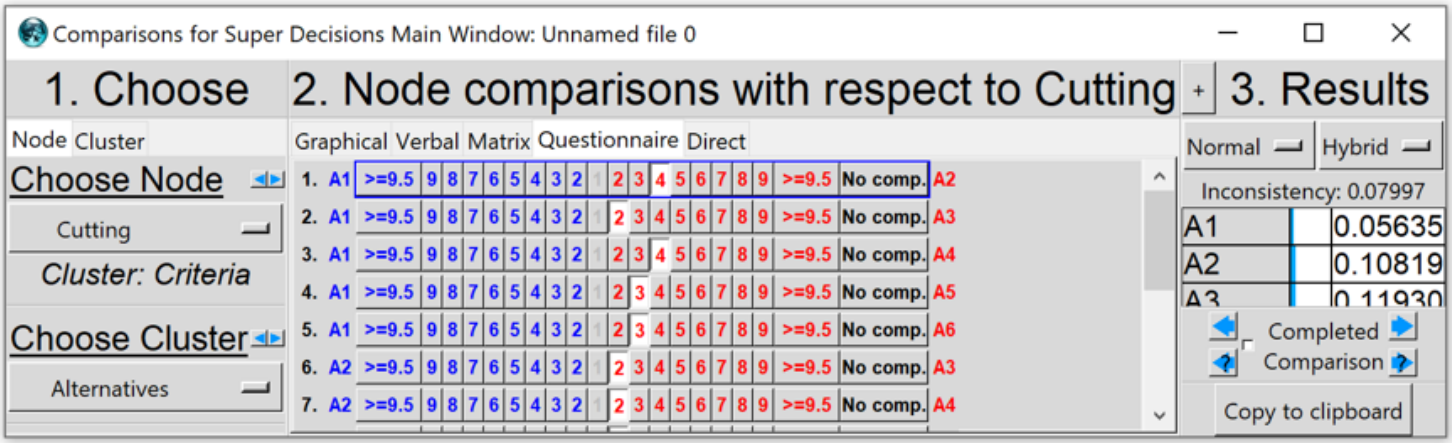

Figure 3

Process of comparison of criteria

Figure 4

Process of comparison for alternatives

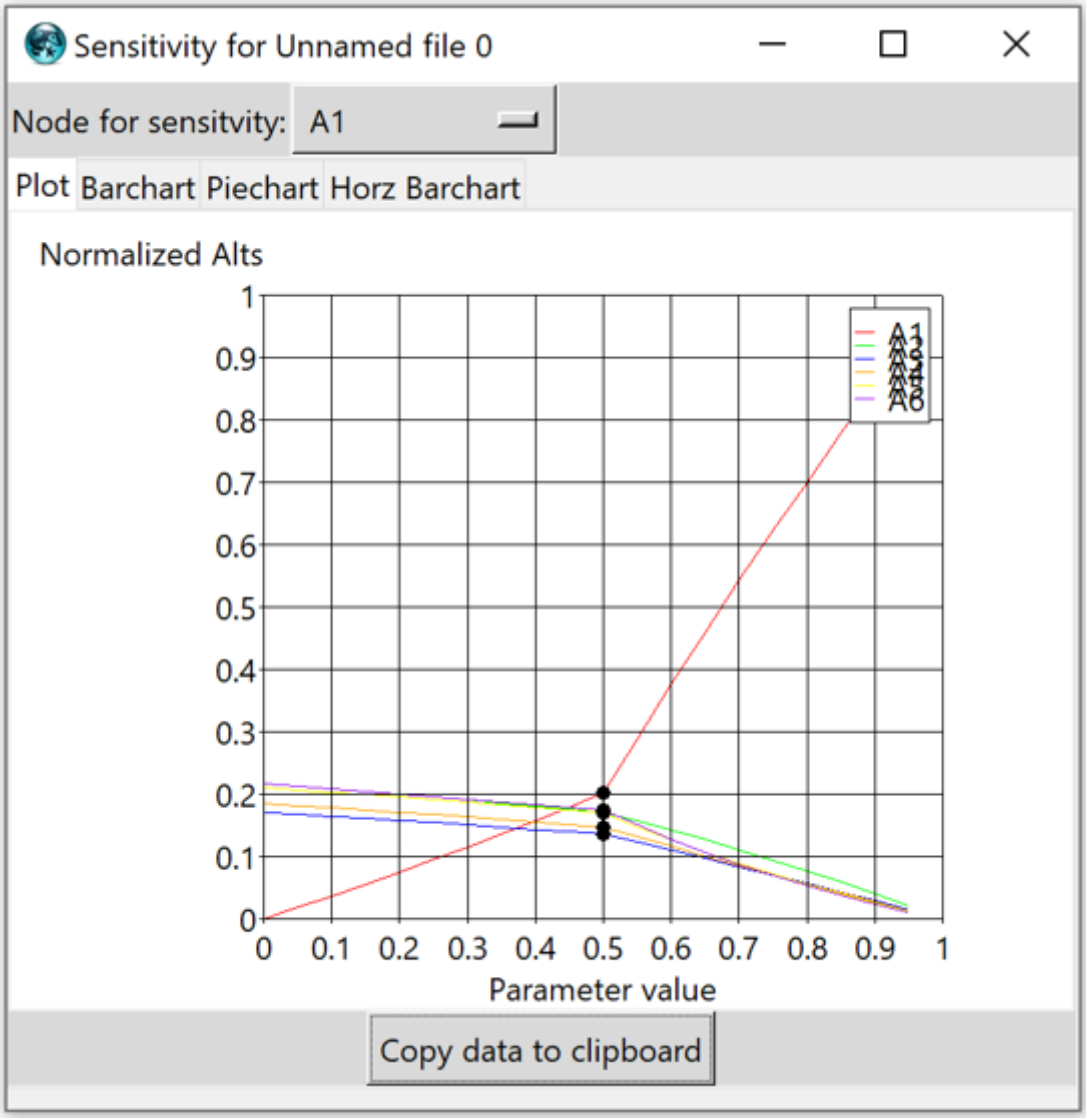

Figure 5

Node sensitivity

Figure 6

Sensitivity analysis

Figure 7

Normal ranking of alternative

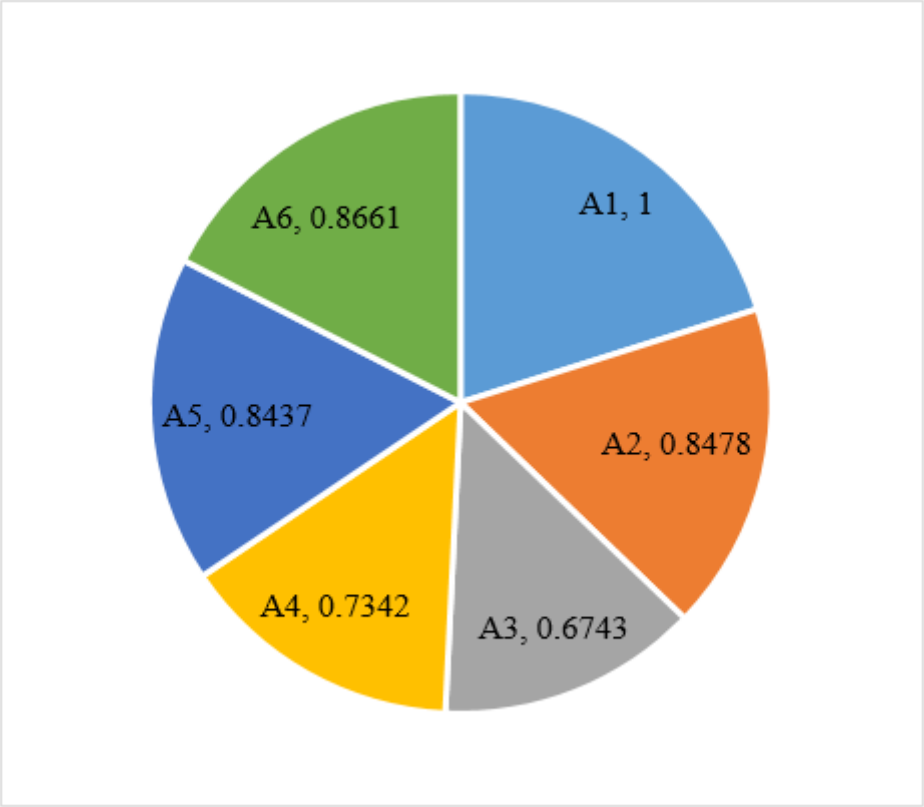

Figure 8

Ideal ranking of alternatives

Figure 9

Total ranking of alternatives