AI Fencing Recommender using Cloud Technology and IoT

By Nilansh Dey Ghosh, Oliver Zeng, and Tony Xiao

Author Bio

We are all high school students who have a common interest in computer science. Two of the three authors have past experience with fencing, which is another major theme of this paper/project. We are all located in North America, and we range from rising grade 11 to rising university students. We received guidance from Dr. Jean-Claude Franchitti from New York University.

Abstract

The purpose of our project is to use artificial intelligence to provide feedback to a fencer through a video upload. Our project will use an artificial intelligence program capable of analyzing fencers through deep learning. We will specifically be examining Sabre. The general skeleton of our system relies on using motion capture technology to input data into our AI and applying deep learning technology to analyze successful moves and those that are less successful. IoTs have already been developed that allows for whole-body motion capture, and we hope to use something similar to conduct our motion capturing. We also hope to incorporate data from a variety of sources such as youtube videos and fencing clips taken by fencers, so we will create fencer skeletons and extract motion data from such sources. We will categorize moves as strong or weak against certain people by examining the effectiveness over a certain amount of touches, and other factors such as how difficult the move itself is to do. Our theoretical program will be capable of suggesting to an athlete the most optimal moves that he/she should take to win against a certain opponent.

Keywords: Fencing, Artificial Intelligence, Sport, Cloud technology, Internet of Things, IoT, Sports Performace

Introduction

Inspiration

With artificial intelligence being incorporated into many industries, there is little surprise that the sports industry is getting involved in AI. Many popular sports have already gone through or are going through AI-influenced changes, but less popular sports such as fencing are still in the process of implementing such AIs. Our group wanted to develop such AIs because of our interest in fencing as well as AIs.

One of our sources of inspiration came from the story of how Austrian math Ph.D. and cyclist Anna Kiesenhofer achieved an Olympic gold medal. Keisenhofer was in many ways a novice at cycling compared to her competitors. However, she utilized her extensive math background to create mathematical models that helped her in training, nutrition, and game plan. She ended up having 75 second lead over the second-place cyclist, showing the world that math and science could be used to help athletes prevail.

Intrigued by her story, our group conducted further research on examples of athletes who were able to use their academic expertise to achieve athletic excellence. We found that Dick Fosbury, one of the most influential high jumpers in history, revolutionized the high jump technique back in 1968 when he was a 21-year-old novice to high jumping. Fosbury utilized his knowledge in physics to create a more optimal jumping position that manipulates his center of gravity. He would go on to achieve an Olympic gold medal and change the sport forever. His jumping technique has since become the norm for high jumpers.

From these examples, we also wanted to use our skills and background to attempt to change a sport as all our predecessors did. In the end, we have chosen fencing because many of our team members do fencing, and we will be attempting to utilize AI because we all have a programming and big data background.

Importance

Artificial intelligence with the capability to analyze other fencers could be extremely helpful in the sport of fencing. Using deep learning, we can potentially create a program that will output not only moves and strategies that fencers should choose, but also mistakes and areas of improvement that they can work on. What could be realized through years of tournaments and training can be summarized in minutes through a deep learning algorithm, and this is our ultimate goal.

There are more than 210,000 fencers in the US alone, and is a sport of growing interest. Fencing also have a very rich background and great importance, for example, fencing is one of only four sports to be debuted in every single modern Olympic. Fencing also requires a great deal of training which results in magnificent feats, such as being the second-fastest sport in the Olympic game, just behind the shooting. Fencing is also known as flexible, as its rules changed a great deal over the years to adapt better and to improve. This rich history, combined with modern technology and bonded by its flexibility will very likely result in the perfect combination.

Basic rules of Fencing:

Originally, fencing was a military practice, where two soldiers dueled each other, but during the late 14th century, fencing slowly transformed into a sport that has a huge impact on society. From the Pirates of the Caribbean to Star Trek, fencing is all there; from regional competitions to Olympic games, fencing is there; from young children to elders, fencing is played by. Despite having a huge player base, long history, and many world-class competitions, fencing is not a popular sport, but it has a very strict set of rules like all popular sports do.

There are three types of weapons in fencing, being Epee, Foil, and Saber. They are quite different from each other, but they all have some similarities. We will only discuss the very basics of fencing for if we go into too much detail, then this paper would be on the rules of fencing.

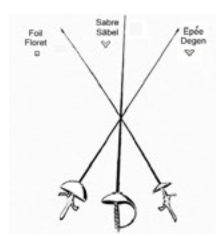


Figure 0.1 the shape of each blade

Epee is the heaviest and slowest one of the three. Historically, the epee is mainly used for dueling. Epee can hit anywhere on the body and it would count as a point. Whoever hits first will gain the point, but if both the fencers hit at the same time, then a point is awarded to both players. Epee can only register a point from compressing the tip, so the fencer must hit with the tip of the blade.

Foil is the lightest weapon, and historically, it is the practice blade for epee so it is similar to the epee. The fencer can only score on the torso of the opponent, which means there will be no point awarded if the opponent hits the mask, hand, arm, leg, and foot of the opponent. Similar to epee, a foilist also needs to hit with the tip of the blade. In foil, whoever hits first is awarded a point, but if both fencers hit at the same time, then the system of the right of the blade is in play. A player can have the right of the blade if they are attacking or is the fencer who has the intention to attack. The point will be given if the player has the right of the blade, and if both players have the right of the blade, then both players are awarded a point.

Sabre is the fastest weapon of the three and historically, the sabre is derived from cavalry fighting. The fencer can only score on the waist up, which does not include leg and foot. Sabre does not need to register a hit with the tip of the blade, as long as the blade makes contact with the target, then it is a point. Whoever hits first will be awarded the point, and if they both hit, the system of the right of blade is in play. In the sabre, the right of the blade is the same as the foil.

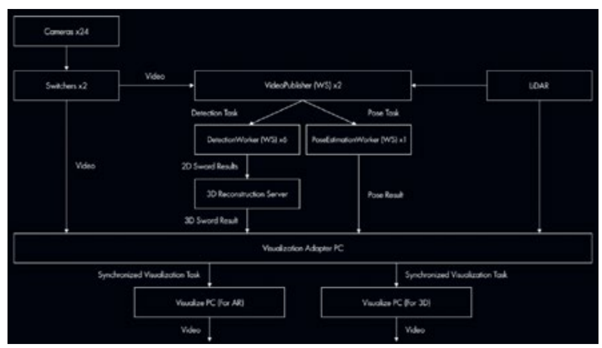
Figure 0.2 the red section are the target of the fencer in each sport

Related Work

Despite fencing being a less popular sport, surprisingly, it has a lot more related work than we have anticipated. There are many projects related to fencing which are ranging from extensive to just starting. We have grouped the related works into two categories, that of work related to motion capturing and the other category being the analysis of the fencing moves.

There are many projects which go into motion capturing and machine learning to assist referees. For example, Benkohn attempted to create a virtual sabre aid in which he used machine learning to break down the actions of performing sabre athletes. His project is however incomplete due to a lack of data, with only 250 available clips to use.

Another study was conducted by the Dentsu Lab of Tokyo, in which they applied motion capturing technology to highlight and track the blade movement of fencers. With more data, these results can easily be applied to a deep learning system and will make analyzing the video many times easier. The following is a summary of the route which they took.



Microsoft has also created a wearable suit that allows for full-body tracking. Features such as the degrees at which the legs of a fencer are bent as well as the position of all body parts are returned as data from the suit. This suit could be combined with motion capturing data to better gather data for a deep learning program.

Jason Mo also used OpenPose, a motion tracking program to attempt to create a program that would help referees in fencing. Using OpenPose, the background and extra visual data are removed from clips of fencing, leaving only the body motion of the fencers. This could also be extremely helpful in the data gathering for our theoretical AI.

Method

Expected challenges

We suspect that tracking the blade would be difficult because the blade would be just a few pixels, making it hard for the software to track.

We suspect that tracking the blade collision would be difficult because most videos are all in 2d, which makes it extremely hard to track the collision of two objects. There are some viable solutions such as tracking the sound, creating a 3d model or putting the fencers into a controlled environment such as a recording studio. Unfortunately, all these solutions are either time-consuming or cost extensive, which we could not complete, but we will attempt to give a hypothesized solution.

We have noticed that many of the videos are different angles and qualities, so it would be hard for the software to analyze the videos.

Gather Information and Data

If we gathered the information by ourselves, it would take an enormous amount of work and time to find the large quantities of video and input them, plus the work is very repetitive. So we wanted to create a simple AI for this task. It will take less time and less work to train an actual AI than to find all the videos by ourselves.

We will train a simple AI to gather fencing videos off Youtube, the AI will do a general search and attempt to identify the targeted videos. We will train the AI in two stages. In the first stage, we will provide random fencing videos to the AI, once the AI can find a basic pattern, we will then have the AI find videos, then we will determine if the video selected is correct. Once all videos selected from the AI are correct, then the AI will be put into an unsupervised mode where it will search for videos by itself.

In addition, using IoTs such as the wearable suit designed by Microsoft could also be a source of motion capturing data. However, that technology is still in development, so we won't be considering it in our current theoretical model.

Processing Data

As mentioned, processing our data will come down to a machine learning program. This program will use motion capturing data already in development to extract important information from the clips that are inputted into the program, such as the position of the hands, legs, torso, speed, acceleration, blade movement, and blade collision. As mentioned previously, motion data of the body can easily be extracted from videos. Blade tracking, although significantly more difficult, can also be made to happen. In this scenario, we will be using a combination of the OpenPose technology that allows for body motion capturing as well as the blade tracking developed by Dentsu lab to analyze both the body and the blade. In addition, the problem of finding blade contact, which was mentioned as a challenge above, can in fact be solved by conducting 3D analysis on the 2D videos. For this, technology that allows for the reconstruction from 2D to 3D will be implemented. Using a combination of a detection server, a 3D reconstruction server and a visualization adapter, we can make this happen. This processed data will then be sent through the neural net of our program, in which scoring vs. not scoring will be analyzed. The data inputs will be as such: we will have the motion information of both fencers, inputted together as one set of data into the neural net. After creating a list of moves available, the neural net will analyze this combination of moves from opposing fencers, and strengthen a network for a set of motion data that worked well against a different set of motion data. This will be added to the list so that we will have numerical indicators of how successful a set of moves is against opposing moves. For example, a row in our data may look as such:

	Double Disengage	**Step Forward Circle Six**	**Counterattack learning forward**
Preparation on lower right blade position	1.642	2.435	4.430
Straight lunge	5.052	0.392	4.218

With each number indicating how effective the move on the horizontal was against the vertical option. The higher the number, the better the success chance. Building upon this data with consistent data additions, the program will have an accurate data value for each move and counter move.

Furthermore, deep learning can also be used to analyze and categorize fencers. For example, for each time that a fencer uses a certain move set, the neural network will up the value for this move under the fencer's name. Whether or not the move succeeds will also be collected as information. Through deep learning, the program will be able to give data of the fencer, like their likely offense and defense tactics, as well as what moves may be successful against those moves. The program would be extremely helpful in pointing out moves that usually result in the opponent losing a point.

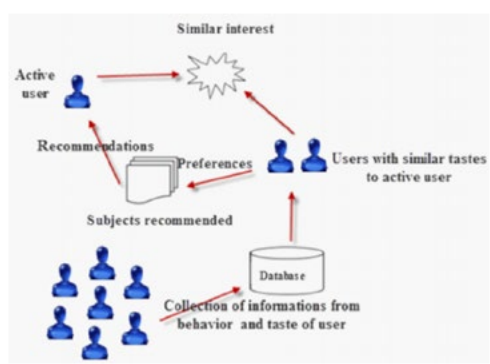
Motion capturing can also be combined with deep learning to determine the accuracy of moves compared to what they should be when successful. For example, the program may suggest bending the legs at approximately 80 degrees when lunging for optimal success, related to speed and ability to retreat to defense. The deep learning program will analyze both moves and fencers to provide encompassing data to its users.

Analysis and Results

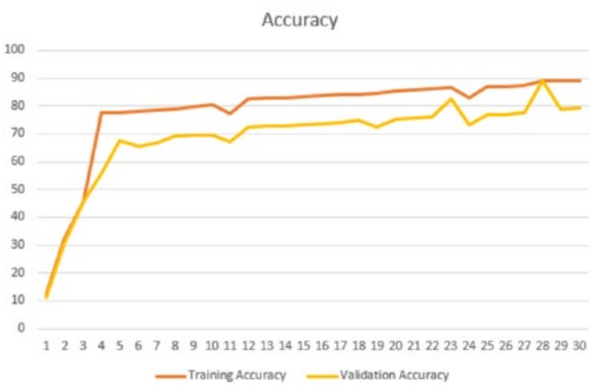
The goal of our model is to be able to recommend different moves and key improvements to help fencers and their coaches win matches. With video clips that can be visualized in 2D, creating an AI recommender system for fencing is challenging yet attainable. Using the work of other fencing object detectors on Github, we were able to produce an artificial intelligence model that can detect and recommend different fencing moves based on the opponent's actions. The first step in the process was to identify the fencing suit and the sabre. Creating our dataset proved to be a challenge. We converted many videos of fencing from different camera angles and lighting mechanics using OpenCV into smaller/shorter clips that were taken right before a point was scored. Having only a small video decreases the time for which the recommender will run and thus producing results more efficiently. In addition, due to sizing issues, we had to cut down on numerous clips which were either stretched or taken in portrait mode. In the end, we were able to come out with about 6,000 clips and about 12,000 after we horizontally flipped each clip to give more training to the model. Flipping the video also helps the model analyze more fencers with various playstyles. Next, we had to be able to process these video clips. Using the InceptionV3 net on each frame of a clip, we were able to take out the convolutional features (i.e converting each frame into a 1x2048 vector). That feature vector is then interpreted by one fully connected layer for the Imagenet database in the inception network, but the same feature vector should perform quite well as representations of what is going on in my frames.

Then, using the clips of these feature vectors, a multi-layer LSTM is trained. To train the model, we utilized an AWS p2 spot instance. As we don't have a lot of clips, it is more practical to utilize transfer learning to extract features rather than training my convolutional layers. Only the recurrent net on top must then learn from the ground up. I tried a few other topologies and found that 4 layers with a dropout of 0.2 work efficiently. The model begins to overfit without dropout as a regularizer. I also tested with an MNIST model which was less efficient than the LSTM.

After we were able to process the data, a recommender system was used to properly recommend different moves to the fencer and coach. In this model, we analyzed data through three types of analysis: real-time, near-real-time, and batch analysis. The next step was to filter the data to provide a realistic recommendation to the fencer in real-time. Rather than implementing content-based filtering, collaborative filtering proved to be much more effective with a memory-based filter too.



Our next step was to gain results for the model's accuracy and adjust various weights accordingly.



From our findings, we were able to see that the accuracy of our model was not as expected but still high enough to not be a nuisance to fencers and coaches. To further improve on the accuracy and reduction of loss, we hope to spend more time adjusting weights and possibly trying out more types of fencing moves to see if the number of inputs would change the number of outputs.

Many other fundamental aspects of our theoretical program are still in development, limiting its current application. However, following further development of motion capturing data as well as even more detailed neural networks, the program should be able to improve and eventually provide pinpoint accurate output data. What we have suggested is essentially a skeletal framework of an analytical deep learning program that can be used for many sports, and in our case fencing.

Final product

The program is open-sourced and is encouraged for all fencers to take advantage of. The link to our program will all be attached in the following google drive. Fencers and the general public is encouraged to advance the product and results from this project further.

Future challenges

- Creating motion tracking systems with better accuracy
- Extracting only necessary information from video clips, and being able to deal with low-quality clips that may be hard to work with.
- Branching further in the deep learning neural net to allow for more complex analysis such as how well a fencer is performing, whether or not they are experiencing fatigue, etc.

Conclusion

In the end, we were able to utilize artificial intelligence to provide detailed feedback to a fencer through a video upload. Our project used an artificial intelligence program capable of analyzing fencers through deep learning. For our artificial intelligence, we trained it to specifically study foil/epee. Our system relies on utilizing motion capture technology to input data into our AI and applying deep learning technology to analyze successful moves and those that are less successful in terms of probability. IoTs have already been developed that allow for whole-body motion capture, so we utilized many of the related works to aid us further. We were able to incorporate data from a variety of sources such as Youtube videos and fencing clips taken by individual fencers with consent, so we created fencer skeletons and extracted motion data from such sources. We categorized moves as strong or weak against certain people by examining the effectiveness over a certain amount of touches, and other factors such as how difficult the move itself is to do. Our program is capable of suggesting to an athlete the moves that he/she should take to win against a certain opponent.

References

1. Asia, S. (2019, October 30). *En garde! Wearable IoT and AI keep fencers on point*. Microsoft Stories Asia. https://news.microsoft.com/apac/features/en-garde-wearable-iot-and-ai-keep-fencers-on-point/

2. Benkohn. (2021, March 5). *Virtual Saber Aid*. Medium. https://medium.com/swlh/virtual-saber-aid-ece8c13b9a4d

3. Doug. (2018, June 7). *fencing-the-new-it-sport-for-kids*. Kidzu. https://kidzu.co/sports-athletics/fencing/fencing-the-new-it-sport-for-kids/

4. Malawski, F., & Kwolek, B. (2018). Recognition of action dynamics in fencing using multimodal cues. *Image and Vision Computing*, 75, 1–10. https://doi.org/10.1016/j.imavis.2018.04.005

5. Michaelsen, A. N., & Cleland, C. L. (2019). Kinematic determinants of scoring success in the fencing flick: Logistic and linear multiple regression analysis. *PLOS ONE*, 14(9), e0222075. https://doi.org/10.1371/journal.pone.0222075

6. Mo, J. (2021, August 16). *Pose Estimation and Preprocessing for an AI Fencing Referee*. Medium. https://thejasonmo.medium.com/pose-estimation-and-preprocessing-for-an-ai-fencing-referee-e63515a55dbd

7. sholtodouglas, & CodLiver, C. (2018, November 20). *GitHub - sholtodouglas/fencing-AI: Using deep learning to referee fencing*. GitHub. https://github.com/sholtodouglas/fencing-AI

8. Sugano, K., Ochi, K., Sone, R., Manabe, D., Ai, K., Ishibashi, M., & Hanai, Y. (2021, September 13). *Fencing tracking and visualization system*. Rhizomatiks. https://research.rhizomatiks.com/s/works/fencing_tracking/

9. *Sword Types*. (2009). Uni-Kiel.de. https://www.tf.uni-kiel.de/matwis/amat/iss/kap_1/basics/b1_1_3.html