Assessing unconstrained surgical cuttings in VR using CNNs

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1 INTRODUCTION
In the recent years, industry and academia [8] have massively adopted Virtual Reality (VR) applications to train students and personnel. Despite the effort, only limited systems involve procedures for assessing user progress inside the immersive environment, that either evaluate only trivial tasks or require a huge amount of time by the reviewers [6]. On the other hand, the need for real-time automated evaluation of user’s actions is constantly increasing. State-of-the-art methods for similar tasks either require the development of complicated task specific computer vision algorithms [10] or support very simple tasks [4].

This work proposes a deep learning based system, that is able to assess, in real-time, user actions within a VR training scenario. The method enables the rapid development of trained assessment functions, since it utilizes data augmentation to minimize the amount of labelled data that need to be collected. Furthermore, by using transfer learning, these assessment functions can be reconfigured to support similar tasks, thus reducing even more the amount of training data. In this paper, we present the results of our method for the task of tearing a deformable 3D model [3].

Different machine and deep learning algorithms [1, 7] were considered and compared (see Table 1). Ultimately, our proposed model is a Convolutional Neural Network (CNN), trained on a dataset created with a data augmentation technique [2].

2 OUR APPROACH
Data Collection: The input datasets, generated by multiple execution of the training tasks, are labelled by a score, specified by the task designer, in our case a surgeon. These datasets contain per-frame captured transformation data (translation & rotation) of the active virtual tool (e.g. a scalpel), forming its trajectory and representing the user gesture on each action.

Data Sampling and Augmentation: Since the execution of an action is user dependent, the required task completion times vary and the generated trajectory lengths \( M \) are non-uniform. To amend this, random samples are taken, creating \( N \)-length trajectories that can be fed to the CNN. The remaining data of the long trajectory are sampled to create more \( N \)-length trajectories, augmenting the dataset. This technique significantly increases the number of the training data and therefore enhances the training process.

Neural Network (NN) Architecture: Since low training and inference times are preferred, a lightweight model, able to provide high-accuracy results, was created. This was achieved by using a 15-layer CNN, which consisted of 4 sets of two Convolutional, two ReLU, and a Batch Normalization layer, along with 3 final layers, a Global Average Pooling, a Flatten and a Dense layer, which formed the classifier. Each of the 4 sets produces an output of higher dimensionality. Thus, as the input is passed down deeper in the network, more complex patterns in the trajectory are found.

Training: After being collected and sampled, the data are split randomly in training, validation and testing sets. The training set is used to train the NN, while the validation set is used to find the best hyper-parameters and prevent over-fitting. Lastly, the testing set is used to evaluate the model’s accuracy. The NN was trained using the Adam optimizer with a learning rate of \( 10^{-4} \), the sparse categorical cross entropy loss function, with 100 epochs and a batch size of 16.

Inference: The trained NN model is then imported in the user’s actions assessment module of the VR application. As before, these

![Figure 1: The trained Convolutional Neural Network assesses the cutting action performed on a deformable 3D model.](image-url)
actions are captured and sampled into smaller length trajectories, which are fed into the model. The user’s score is produced instantly with no overhead on the application’s performance.

**Retraining:** The proposed NN can be easily adapted for similar tasks, utilizing transfer learning. In this respect, the first layers of the NN are frozen while the deepest ones are retrained using a small amount of new training data. This procedure reduces training time and the required amount of the collected data, and provides high accurate results, since the model’s first layers represent more generic patterns, that are common to similar actions.

**Scoring System:** The user’s actions are evaluated with a score in the range of 0 – 10. However, the NN regards scores 0 – 5 (6 classes), which requires less training data. The model outputs the probabilities $p(i)$ of a trajectory belonging to each of the 6 classes. Ultimately, the score $S_{tr}(k)$ for a single trajectory $k$ (in range 0 – 10) and the final score $S_{tot}$ for the entire action are obtained by evaluating

$$S_{tr}(k) = 2 \sum_{i=0}^{5} i \cdot p(i) \quad \text{and} \quad S_{tot} = \frac{1}{K} \sum_{k=0}^{K} S_{tr}(k).$$

### Table 1: Table comparing the accuracy of traditional ML techniques and the proposed CNN (last column) for different number of classes.

| No. of Classes | Logistic Regression | KNN | SVM | CNN |
|----------------|---------------------|-----|-----|-----|
| 2              | 100%                | 100%| 100%| 100%|
| 3              | 100%                | 100%| 100%| 100%|
| 6              | 39%                 | 66% | 83% | 95% |

Figure 2: The confusion matrix of the convolutional neural network for the 6 classes.

### 3 RESULTS & DISCUSSION

Figure 1 shows the scores calculated by the DL model for two different cuts performed by a user on a deformable 3D model. The action graded with 10 during training was collinear and of greater length to the one that scored 8. In Table 1, a comparison of the accuracy of different models is presented for various number of classes. In the case of 2 or 3 classes, all models perform correctly, however, when 6 classes are used, only our proposed CNN method achieves an acceptable performance. In Figure 2, the confusion matrix of the trained model depicts that, for most classes, the true labels coincide with the predicted ones. The only exception is the third label which sometimes is predicted falsely as the second one, due to the fact that the specific classes have very similar trajectories, making it difficult for the model to distinguish among them. As this error could also be made by a human, the results are considered satisfying. However, we plan to mitigate that issue by performing semi-supervised learning [9] using unlabelled data collected by users executing cutting actions using the MAGES SDK [5]. With such training data, the model will learn to better distinguish among different trajectories, allowing the classifier to achieve better performance for all classes.

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### REFERENCES

[1] Angus Dempster, François Petitjean, and Geoffrey I. Webb. 2020. ROCKET: Exceptionally Fast and Accurate Time Series Classification Using Random Convolutional Kernels. Data Mining and Knowledge Discovery 34, 5 (Sept. 2020), 1454–1495. https://doi.org/10.1007/s10618-020-00701-z arXiv:1910.13051

[2] Brian Kenji Iwana and Seiichi Uchida. 2020. Time Series Data Augmentation for Neural Networks by Time Warping with a Discriminative Teacher. arXiv:2004.08780 [cs, stat] (April 2020). arXiv:2004.08780 [cs, stat]

[3] Manos Kamarianakis and George Papagiannakis. 2021. An All-in-One Geometric Algorithm for Cutting, Tearing, and Drilling Deformable Models. Advances in Applied Clifford Algebras 31 (Jul 2021), 58.

[4] Vasilios Lahanas, Constantinou Loukas, Nikolaos Smallis, and Evangelos Georgiou. 2015. A novel augmented reality simulator for skills assessment in minimal invasive surgery. Surg. Endosc. 29, 8 (Aug 2015), 2224–2234.

[5] George Papagiannakis, Paul Zikas, Nick Lydatakis, Steve Katesro, Mike Kentros, Efstratios Geronikolakis, Manos Kamarianakis, Ioanna Karterouli, and Giannis Evangelos. 2020. MAGES 3.0: Tying the Knot of Medical VR. In ACM SIGGRAPH 2020 Immersive Pavilion. Association for Computing Machinery, Article 6, 2 pages.

[6] Erica Southgate. 2020. Using Screen Capture Video to Understand Learning in Virtual Reality. In 2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW). 418–421. https://doi.org/10.1109/VRW50115.2020.00089

[7] Zhigang Wang, Weizhong Yan, and Tim Oates. 2016. Time Series Classification from Scratch with Deep Neural Networks: A Strong Baseline. arXiv:1611.06455 [cs, stat] (Dec. 2016). arXiv:1611.06455 [cs, stat]

[8] Biao Xie, Huimin Liu, Rawan Alghofaili, Yongqi Zhang, Flavio Destri Lobo, Changyang Li, Wanwan Li, Haikun Huang, Mesut Aldere, Chritos Mossa, and Lap-Fai Yu. 2021. A Review on Virtual Reality Skill Training Applications. Frontiers in Virtual Reality 2 (2021). https://doi.org/10.3389/frvir.2021.645153

[9] Xiaogang Yang, Zixing Song, Irwin King, and Zenglin Xu. 2021. A Survey on Deep Semi-supervised Learning. https://doi.org/10.48550/ARXIV.2103.08550

[10] Aneqiz Qia, Yachna Sharma, Vinay Bettadapura, Eric L. Sarin, Thomas Ploetz, Mark A Clements, and Irfan Essa. 2016. Automated video-based assessment of surgical skills for training and evaluation in medical schools. Int. J. Comput. Assist. Radiol. Surg. 11, 9 (Sept. 2016), 1623–1636.