

# How humans and artificial classifiers decode grasping movements through kinematic information

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## Introduction

- Humans use sensorimotor information to understand others' actions (Rizzolatti & Sinigaglia, 2010, 2016), beyond visual recognition of the observed movements (Calvo-Merino et al., 2006)
- Recent studies described the computational basis of action recognition through kinematic information (Cavallo et al., 2016; Montobbio et al., 2022), but no studies manipulated how this varies over time.
- In our study, we used machine learning techniques to describe how kinematic information is used in recognition of grasping movements when variable portions of actions are shown.

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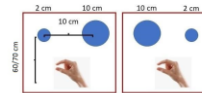
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## Methods

### 1. Stimuli acquisition

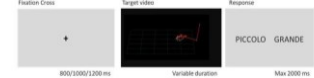
Two experimenters were asked to reach and grasp two objects (a small ball and a large ball)  
 160 videos were recorded. Kinematic features (grip aperture and velocity of wrists) were extracted for each video at 10%, 20%, 30% and 40% of movement. Sixteen final videos were selected.

Two 2\*2\*4 RM ANOVA (size\*agent\*time) with grip aperture and wrist velocity as dependent variables were performed.



### 2. Human recognition of grasping actions

Thirty participants (mean age 22.87 ± 0.7; 20 females), all right-handed, were enrolled to the present online study. Participants were asked to discriminate between grasping large or small object by looking at the 10%, 20%, 30% and 40% of the whole movement.



Three 2\*4 RM ANOVA (size\*time) with recall, precision and reaction times (RT) as dependent variables were computed.

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

### 3. Decision tree

Decision Tree was run to test if the algorithm could accurately predict participants' responses on the basis of the kinematic information for each time of movement (10%, 20%, 30%, 40%).

Our dependent variable was participants' responses (small or large) at 10%, 20%, 30% and 40% and our predictors were grip aperture and wrist velocity.

### 4. Classifier

Kinematic data was classified using a classic method known as Support Vector Machine (SVM). We used an RBF kernel with other parameters set as default values.

Visual data was classified using a CNN-RNN Neural Network architecture.

We evaluated our models using 10-folds cross-validation on the 160 videos on recall and precision.

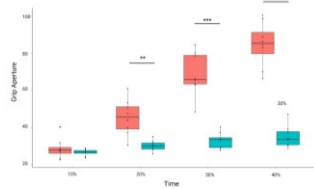
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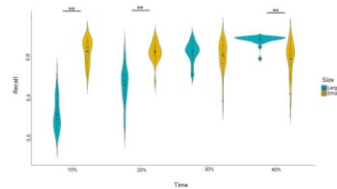
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## Results

### 1. Stimuli acquisition



### 2. Human recognition of grasping actions



### 3. Decision tree

|                   | 10%     | 20%          | 30%          | 40%          |
|-------------------|---------|--------------|--------------|--------------|
| Correct responses |         |              |              |              |
| small             | 100%    | 89%          | 89.9%        | 94.6         |
| large             | 0%      | 52%          | 75.2%        | 81.3%        |
| overall           | 81%     | 76.5%        | 82.3%        | 87%          |
| Predictors        | a10, a0 | a20, a0, a10 | a30, a0, a20 | a30, v30, a0 |

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### 4. Classifier

|       | Recall |      |      |      | Precision |      |      |      |
|-------|--------|------|------|------|-----------|------|------|------|
|       | 10%    | 20%  | 30%  | 40%  | 10%       | 20%  | 30%  | 40%  |
| Human |        |      |      |      |           |      |      |      |
| small | 0.84   | 0.83 | 0.80 | 0.78 | 0.82      | 0.64 | 0.84 | 0.94 |
| large | 0.21   | 0.50 | 0.81 | 0.82 | 0.62      | 0.78 | 0.82 | 0.82 |
| SVM   |        |      |      |      |           |      |      |      |
| small | 0.91   | 0.9  | 0.98 | 0.98 | 0.66      | 0.86 | 0.92 | 0.94 |
| large | 0.49   | 0.83 | 0.88 | 0.93 | 0.74      | 0.90 | 0.98 | 0.98 |

## Discussion

- Decision tree could accurately predict human behaviour using kinematic information (grip aperture).
- SVM classifier using kinematic information to classify grasping actions shows similar patterns of performance compared to human recognition.
- Further analyses with CNN-RNN Neural Network architecture will highlight performance based on visual recognition of movements.

## References

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