Intention from Motion

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Abstract—In this paper, we propose Intention from Motion, a new paradigm for action prediction where, without using any contextual information, we can predict human intentions all originating from the same motor act, non specific of the following performed action. To this purpose, we have designed a new multi-modal dataset consisting of a set of motion capture marker 3D data and 2D video sequences where, by only analysing very similar movements in both training and test phases, we are able to predict the underlying intention, i.e., the future, never observed, action. We also present an extensive three-fold experimental evaluation as a baseline, customizing state-of-the-art techniques for 3D and 2D data analysis, and proposing fusion methods to combine the two types of available data. This work constitutes a proof of concept for this new paradigm as we empirically prove the affordability of predicting intentions by analysing motion patterns and without considering any additional contextual cues.

I. INTRODUCTION

ACTION AND ACTIVITY recognition are surely intriguing and most active areas in computer vision. The task here typically consists in the classification of a fully observed action or activity. More recently, the community has also started to investigate a variant, extending the paradigm to the “early” activity recognition, which aims at recognizing an action before it is fully disclosed. Early activity recognition is sometimes improperly confused with action prediction, improperly because such works are not really predicting an action, but rather they are actually classifying an action from its beginning, i.e., they identify an action from the observation of the onset of that same action. The actual action prediction problem consists instead in the classification of future actions considering all the events occurring up to a certain instant. As a different paradigm, here we aim at introducing a brand new challenging action prediction problem consisting in the prediction of human intentions, defined as the overarching goal embedded in an action sequence.

In Fig. 1 we show the different paradigms for action and activity analysis and our proposed new concept for intention prediction. The novelty stands from the fact that intentions cannot easily be predicted using discriminant previous information extracted from a certain anticipative data stream since, unlike the other paradigms, such data displays the same class of motor act which can be performed with different intentions. Despite this, in general, the prediction of intentions still remains a manageable, yet rather complex problem, as we will show.

Previous attempts in classifying future or unfinished actions utilize developing motion patterns which are specific of the subsequent actions, since they contain some cues that undoubtedly help the recognition. For instance, if the goal is understanding whether two people are going to shake their hands or to give a high-five, by just looking at the first part of their interaction, a low wrist height can be an evidence of a handshaking [2], [3]. Further, another important aspect of the entire activity recognition problem is that the current techniques are mainly exploiting the scene context to support the classification ([4], [5], [1], [6], [7], [8], [1], [9], [10], and [11]), i.e., the objects present in the scene and the knowledge about the actions associated to them are cues that can be utilized to help in making a correct inference of the ongoing action to be recognized. However, although this information could help, it can be insufficient to solve the task or, worse, the context may not always be available or easily recognizable, being also misleading when the scene is too noisy or cluttered [2]. In any case, an important source of information to disambiguate intention can be provided by the kinematics of the movement [13].

In fact, recent findings from behavioural neuroscience indicate that how a motor act is performed (e.g., grasping an object) is not solely determined by biomechanical constraints imposed by the object’s extrinsic and intrinsic properties with which one is interacting but it depends on the agents intention (e.g., to pass vs. to use the object [14], [15]). Since the same cerebral areas are used in both motor planning and intentions understanding [15], this suggests the fascinating possibility that predicting intentions is viable from kinematics only.

In this paper, we aim at introducing Intention from Motion (IFM), a brand new action prediction problem, performed in the worst-case scenario, where two challenging aspects largely differentiate it from the current literature.

• Grounding from the assumption that the same class of motor acts can be performed with different intentions [9], we want to analyse the movement onset of an apparently unrelated action (actually embedding the intention from the very beginning), the same for all intentions, capturing those subtle motion patterns which anticipates the future action.

• Unlike the main existing literature, we want to avoid the exploitation of any hints derived by the context, solely focusing on the kinematics of the movement.
Fig. 1. Four different paradigms in human action/activity analysis. (a) Action/activity recognition: each sequence is fully observed to infer the class label (“running” for the top sequence up to “high-five” for the bottom). (b) Early activity recognition: only a few initial frames per action/activity are observed and the goal is the early classification from these incomplete observations. (c) Action prediction: future actions are predicted analysing all past events which, in general, can be very different across different classes. For instance, in the top sequence a standing up activity leads to predict a “kissing”, while, in the bottom, a conversation between a group of friends anticipates a “high-five”. (d) Intention prediction: a novel paradigm where unobserved future action are anticipated from the same class of motor act, all extremely similar in appearance, no matter which different ending will occur.

To this end, we propose a new dataset as a test-bed to investigate the feasibility of inferring intention from motion so as to provide a proof of concept for this task. A set of experiments was designed in which subjects were asked to grasp a bottle, in order to either 1) pour some water into a glass, 2) pass the bottle to a co-experimenter, 3) drink from it, or 4) place the bottle into a box. The dataset is composed by a) 3D trajectories of 20 motion capture (VICON) markers outfitted over the hand of the participants and b) optical video sequences lasting about one second, with an occlusive camera view in which only the arm and the bottle are visible. The goal is to classify the intentions associated with the observed grasping-a-bottle movement, i.e. to predict the agent’s intention.

Even if the literature presents some methods aimed at specifically tackling the prediction of future actions [3], [17], [2], [18], [7], the experiments therein included are typically performed on standard action recognition datasets, just adapted to the new task, and often considering the start of the same action, which of course facilitates the prediction.

On the contrary, our new dataset is explicitly designed for intention prediction, a problem never considered before in computer vision in the terms we posed. It is also important to note that, despite the apparent simplicity of the experiments, this scenario constitutes an actual proof of concept which can be further extended to actual applications. Indeed, an object, namely a knife, can be grabbed with very different intentions, e.g., cropping an apple or attacking a person. In more into-the-wild applications, it would be extremely valuable to infer whether a subject who is standing in front of a bank counter and grabbing something from the pocket, will pick his wallet and deposit money or, instead, will extract a gun and attempt a robbery. Further, in crowd behaviour analysis, it would be paramount to detect whether the apparently casual motion patterns of an individual/group of people can forerun a fight or, in social robotics, to provide a robot of the capability to read human intentions in order to figure out her action, hence providing to the subject the feeling of a more realistic engagement. Evidently, in all these cases, the discrimination must rely on the kinematics exclusively, the context being uninformative.

To sum up, this work is characterized by the following main contributions.

(a) We introduce the new problem of Intention from Motion. That is, from the same observable “neutral” motor act - used in both training and test phases - we classify the underlying intention using solely the motion information, without using any contextual cue.

(b) We propose a 3D & 2D dataset, specifically aimed at the prediction of human intentions. This dataset is designed in a principled way by defining four intentions (Pouring, Passing, Drinking, Placing) performed by independent naive subjects, which are all forerun from the very similar initial grasping-a-bottle movement, while avoiding bias which can affect the subsequent performance analysis. To the best of our knowledge, this is the first time a dataset has been explicitly designed for intention prediction.

(c) We tested several state-of-the-art action recognition algorithms to provide a baseline performance for this dataset. As for the 3D data, we applied some state-of-the-art kinematics features, also working directly on the raw data by combining Dynamic Time Warping [19] and graph Laplacian [20], while exploiting a (kernelized version of) a covariance-based descriptor to model the joints temporal

\footnote{The dataset is available upon request (andrea.zunino@iit.it).}
inter-relationships. As for the video sequences, we applied Dense Trajectories algorithm \cite{21} and compared several hand-crafted features. We also presented some initial attempts to customize deep-learned features for our task, either applying 3D convolution on video sequences or extracting 3D frame-based representations.

\(\text{(d)}\) As to widely analyse the proposed dataset, we highlight the main challenges that have to be faced in predicting intentions from motion, namely consisting in 1) assessing whether/which some portion of the reach-to-grasp is more/less rich in predictive cues, 2) inspecting the additional effort required to devise intention-predictive patterns in a subject-invariant way and 3) designing fusion techniques to fully take advantage of the multi-modality.

The rest of the paper is structured as follows. In Section \textbf{II}, we report some previous works from the literature dealing either with early activity recognition or action prediction. Section \textbf{III} introduces our dataset and the experimental setting. Subsequently, we extensively describe the analysis accomplished on the 3D data in Section \textbf{V}, and on the 2D video sequences in Section \textbf{VI}. Section \textbf{VII} presents our broad analysis of the proposed dataset, presenting the related challenges. Finally, Section \textbf{VIII} draws the conclusions and sketches the future work.

\section{Related Work}

In this Section, we briefly report the most relevant works from the existing literature, which either deals with action prediction or early activity recognition.

Ryo et al.\cite{17} devised a system to infer the ongoing activity by only analysing its \textit{onset}, i.e., its beginning. This is done with a dynamic programming method to match an extension of classical bag-of-features representation which allows to capture the topical correlation of descriptors. Hoai and De la Torre \cite{18} designed MMED, Max-Margin Early-event Detectors to address the problem to understand a specific human emotion after it starts but before it ends. They trained a structured output support vector machine \cite{22} on the whole accomplished emotion development and, during testing phase, they managed to classify fear rather than disgust when they are about to occur. Yu et al.\cite{23} propose a generalization of Spatio-Temporal Interest Point \cite{24} to categorize actions from their beginning. The inter-dependencies between different spatial location are implemented into a probabilistic graphical model fed by histogram features. Cao et al.\cite{4} split a complete action into temporal segments which are further represented by means of sparse coding, so that actions are recognizable from incomplete data. Ryoo et al.\cite{25} tackle early activity recognition from egocentric videos: the task is detecting the so-called \textit{onset signature}, a bunch of kinematic evidence which has strong predictive properties about the last part of the observed action. Some works have attempted to investigate how much of the whole action is necessary to perform a classification: Davis and Tyagi \cite{26} adopt a generative probabilistic framework to deal with the uncertainty due to limited amount of data, while Schindler and Van Gool \cite{27} try to answer the aforementioned question using a similarity measure between the statical and the motion information extracted from videos. Soran et al.\cite{28} devise a notification system for daily activities where, for instance, the detection of an ongoing milk boiling alerts the human user. Xu et al.\cite{29} subdivide the beginning of a video into a bunch of snippets, and the final ending is predictable through a ranking model which simulates Internet query auto-completion. Li et al.\cite{30} use a random tree to model all the kinematics up to a certain instant to constrain the predicted action to be the more likely on the basis of the past ones (e.g., predicting “grab an object” if “reach an object” is detected). Huang et al.\cite{31} face activity forecasting for human interactions: the acts of an agent induce a cost topology over the space of reactive poses where the response of the co-agent can be retrieved. Lan and Savarese \cite{3} developed the so-called \textit{hierarchical movemes}, a new representation to model human actions at multiple levels of granularity, which was integrated in a max-margin learning framework for action prediction. Vondrick and Torralba \cite{2} uses a deep neural network trained over 600 hours of videos. During training the net exploits videos to learn to predict the representation of frames in the future and the last fully connected layer allows to perform classification over different future endings.

One common aspect of both (early) activity recognition and action prediction is that contextual information is frequently used to perform the classification. Indeed, once the objects present in a scene are detected, the object-object or object-person relationship can be modelled by several probabilistic architectures (e.g., graphical models \cite{1}, \cite{5}, \cite{32} or topic models \cite{33}, \cite{3}). Among the works which directly model the context inside the algorithms, some of them deal with the prediction of future trajectories of moving objects (vehicles or pedestrian) \cite{34}, \cite{7}, \cite{35}, \cite{6} by estimating the spatial areas over which such objects will most likely pass with respect to those which are excluded by this passage (e.g., car circulations over sidewalks \cite{7}).

In this paper, unlike all the aforementioned works, we are not classifying actions from their very first beginning, but we aim at predicting \textit{intention from motion}, a brand new challenge in action prediction consisting in recognizing (i.e., anticipating) different intentions which finalize the same class of motor act, distilling from it the discriminative motion patterns characterizing the specific intention, while fully neglecting any contextual information.

\section{The Dataset}

Seventeen naive volunteers were seated beside a \(110 \times 100\) cm table resting on it elbow, wrist and hand inside a fixed tape-marked starting point. A glass bottle was positioned on the table at a distance of about \(46\) cm and participants were asked to grasp it in order to perform one of the following 4 different intentions.

1) \textbf{Pouring} some water into a small glass (diameter 5 cm; height 8.5 cm) positioned on the left side of the bottle, at 25 cm from it.

2) \textbf{Passing} the bottle to a co-experimenter seating opposite the table.

3) \textbf{Drinking} some water from the bottle.
Intention 1: Pouring

Intention 2: Passing

Intention 3: Drinking

Intention 4: Placing

Fig. 2. An exemplar footage of the proposed dataset referring to each of the four intentions: Pouring, Passing, Drinking and Placing. As stressed in the paper, it is clearly visible how the grasping onset is extremely similar across the different classes and the constrained experimental conditions force us to perform activity prediction in the worst-case scenario where no clues can be drawn from the context and no trivial kinematic patterns are available.

4) Placing the bottle in a cardboard $17 \times 17 \times 12.5$ box positioned on the same table, 25 cm distant.

After a preliminary session, in which participants are familiarized with the execution, each subject performed 20 trials per intention. The experimenter visually monitored each trial to ensure exact compliance of these requirements. In order to homogenize the dataset, we completely removed trials judged imprecise. Thus, the final dataset includes 1098 trial (253 for pouring, 262 for passing, 300 for drinking and 283 for placing) and, for each of them, both 3D and video data have been collected. 3D marker trajectories and video sequences are acquired from the moment when the hand starts from a stable fixed position up to the reaching of the object, and both are exactly trimmed at the instant when the hand grasps the bottle, removing the following part. Our controlled setting constitutes an actual worst-case scenario since fixing the parameters for all the trials across subjects (e.g., table size, position and size of the box, position of the co-experimenter, etc.), especially the starting hand position and the bottle location, we put ourself in neutral conditions, removing possible subjective biases which might affect the classification performance (e.g., some intentions might be better discriminated if starting hand position would have been left free). Moreover, any other more complex activity forerunning an intention might provide further discriminant information for the prediction of the future action, with respect to a single, simple, arm movement.

3D kinematic data. Near-infrared 100 Hz VICON system was used to track the hand kinematics. Nine cameras were placed in the experimental room and each participant’s right hand was outfitted with 20 lightweight retro-reflective
hemispheric markers. After data collection, each trial was individually inspected for correct marker identification and then run through a low-pass Butterworth filter with a 6 Hz cutoff. Globally, each trial is represented with a set of 3D points describing the trajectory covered by every single marker during execution phase. The $x, y, z$ marker coordinates only consider the reach-to-grasp phase, the following movement is totally discarded. Indeed, the acquisition of each trial is automatically ruled by a thresholding of the wrist velocity $v(t)$ at time $t$, acquired by the corresponding marker. Being $\varepsilon = 20$ mm/s, at the first instant $t_0$ when $v(t_0) > \varepsilon$, the acquisition starts and it is stopped at time $t_f$, when the wrist velocity $v(t_f) < \varepsilon$.

2D video sequences. Movements were also filmed from a lateral viewpoint using a fixed digital video camera (Sony Handycam 3-D) placed at about 120 cm from hand start position. The view angle is directed perpendicularly to the agent’s midline, in order to ensure that the hand and the bottle were fully visible from the beginning up to the end of the movement. It is worth noting that the video camera was positioned in a way that neither the box (Placing), nor the glass (Pouring), nor the co-experimenter (Passing) were filmed. Adobe Premiere Pro CS6 was used to edit the video in .mp4 format with disabled audio, 25 fps and $1280 \times 800$ pixel resolution. In order to format video sequences in an identical way to 3D data, each video clip was cut off at the exact moment when the bottle is grasped, discarding everything happening afterwards. To better understanding how demanding the task is, note that the actual acquired video sequences encoding the grasping last for about one fourth of the future action we want to predict: see Figure 2 Consequently all the sequences result about 30 frames long.

In all the experiments reported in this paper, either dealing with 3D or 2D data, we consider all the possible pairwise comparisons between intentions and the all-class one. We select one-subject-out testing procedure, that is, we compute seventeen accuracies, training our system on all the subjects except the one we are testing, then we averaged all the accuracies to get the final classification results.

IV. Human Performance in IfM

As a preliminary analysis to check how human beings can predict intentions, we tested the human capabilities on Pouring vs. Placing and Pouring vs. Drinking throughout the following experimental apparatus. We asked each of 18 participants to watch 400 videos of reach-to-grasp movements and predict if the task is, note that the actual acquired video sequences encoding the grasping last for about one fourth of the future action we want to predict: see Figure 2 Consequently all the sequences result about 30 frames long.

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Averaging all the human accuracies in the Pouring vs. Placing test, we get 68% of accuracy. Afterward, we move to the second test (Pouring vs. Drinking) and we repeated the same procedure for a different set of 18 participants. In Pouring vs. Drinking, accuracy decreases to 58% (-10%). These results are statistically significant and suggest that human observers are able to exploit kinematics to predict intentions. However, although the human brain can read in a grasping some motion pattern which anticipates four different intentions, we can anticipate that computer vision methods will prove to be more valuable outperforming human predictive ability.

V. 3D motion analysis

Several techniques have been proposed for action recognition from 3D data. Bag-of-words histogram representation [37], [38], eigen-joints [39], Gauss-Markov process [40], actionlets [41], Lie algebra embedding [42], covariance descriptors [43], hidden Markov models [44], subspace view-invariant metrics [45] or occupancy patterns [46], [47] to name a few. Nevertheless, to the best of our knowledge, no attempt has been performed to address the problem of action prediction from 3D data. Thus, in this Section we will face the IfM problem by analyzing the markers trajectories. To this aim, we either extract standard kinematic features (Section V-A), customize Dynamic Time Warping (Section V-B) and apply a representation based on kernelized covariance (Section V-C).

A. Kinematic features

A recent social cognitive work [48] argued that intentions become “visible” in the apparent motion flow and understanding other’s intentions cannot be divorced from the discrimination of essential kinematics. Thus, we exploited 3D kinematic features (KF) for IfM. Following [49], we computed wrist velocity, the module of the velocity of the wrist marker, wrist height, the $z$-component of the wrist marker, wrist horizontal trajectory defined as the $x$-component of the wrist marker and grip aperture, i.e. the distance thumb-index tips markers. Such features were referred to the reference system of the motion capture system, $F_{\text{global}}$ [49]. A better characterization of the dynamics can be provided using a local reference system centered on the hand, $F_{\text{local}}$ [15]. In this way, we computed relative $x, y, z$ coordinates of thumb, index, thumb-index plane and the radius-phalanx. These variables provide the information about either the adduction/abduction movement of the thumb and index fingers or the rotation of the hand dorsum. Thus, they ensure robustness towards finger flexion/extension or wrist rotation that can vary significantly from one trial to another [15]. The 4 features from $F_{\text{global}}$ and the 12 from $F_{\text{local}}$ gives a total amount of 16 kinematic features, namely $F_K$. Acquisition time $[t_0, t_f]$ (see Section II] is scaled into $[0, 1]$ and data are sub-sampled with step 0.01. Consequently, for each of our 16 kinematic features, we have 100 equispaced values describing the evolution of such features during the reach-to-grasp movement.

In Table I we report the classification results, using a linear support vector machine (SVM), considering $F_{\text{local}}$ and $F_{\text{global}}$ [49] individually, then concatenating all the features from the
two groups $[15]$. In the three cases, we used a feature vector of 1200, 400 and 1600 components respectively. As expected, when we combine $F_{\text{local}}$ and $F_{\text{global}}$, the performance generally improves. Our results show that KF are able to obtain classification performances with a substantial improvement over the random guess level: using $F_K$, an average +26.25% improvement over the random guess level on the pairwise comparisons and +20.13% on the all-class case. Relying on the kinematic interpretability of KF, we conclude that the actual dynamic of the grasping encodes some motion patterns which go beyond the fulfilment of the action itself and can concretely anticipate the underlying intention.

B. Dynamic Time Warping for fBM

After the investigation of KF extracted from the markers 3D data, we directly exploit them by means of Dynamic Time Warping (DTW) $[19]$, a well-known technique to find the optimal temporal alignment between two sequences $[50]$. It is used in a wide range of applications: automatic speech recognition $[51]$, handwriting and online signature matching $[52]$, gesture recognition $[53]$, data mining and time series clustering $[54]$, as well as video surveillance $[55]$. 

In this paper, we used DTW to capture the mutual inter-dependencies between the position of the markers in different trials, in order to better model time evolution and thus predict intentions. Precisely, DTW measures the similarity between two marker trajectories $\mathbf{u} = [\mathbf{x}(1), \ldots, \mathbf{x}(M)]$ and $\mathbf{u}^\prime = [\mathbf{x}(1), \ldots, \mathbf{x}(N)]$, for any $M, N \in \mathbb{Z}^+$. $\mathbf{x}(i)$ denotes the coordinates of the $i$-th marker at time $i$. $\mathbf{p}_h(i)$ and $\mathbf{p}_h(i)$ are the (potentially different) trajectory lengths and, for any $i = 1, \ldots, M$ and $j = 1, \ldots, N$, we have $\mathbf{x}(i), \mathbf{x}(j) \in \mathbb{R}^3$. Precisely, $\mathbf{x}(i) = [p_1(i), \ldots, p_20(i)]$ and $\mathbf{p}_h(i) = [x_h(i), y_h(i), z_h(i)] \in \mathbb{R}^3$ denotes the coordinates of the $h$-th marker at time $i$. Similarly, $\mathbf{x}(j) = [p_1(j), \ldots, p_20(j)]$ and $\mathbf{p}_h(j) = [x_h(j), y_h(j), z_h(j)]$. To compare $\mathbf{x}(i), \mathbf{x}(j)$, we have defined the distance

$$d(\mathbf{x}(i), \mathbf{x}(j)) = \frac{1}{2} \sum_{h=1}^{20} \| \mathbf{p}_h(i) - \mathbf{p}_h(j) \|_2$$

(1)

where $\| \cdot \|_2$ is the Euclidean norm. As a measure to quantify the similarity between $\mathbf{u}$ and $\mathbf{u}^\prime$, $\Delta(\mathbf{u}, \mathbf{u}^\prime) = \min \left\{ \sum_{i=1}^L d(\mathbf{x}(i), \mathbf{x}(j)) \right\}$ computes the minimum over all the paths $[(i_1, j_1), \ldots, (i_L, j_L)]$ of length $L$ which optimally warp $\mathbf{u}$ and $\mathbf{u}^\prime$ $[19]$. Thus, computing $\Delta$ for all pairs of sequences from our dataset, we get the $1098 \times 1098$ similarity matrix $\mathbf{S}_{\text{DTW}}$.

In a first experiment, we exploited the matrix $\mathbf{S}_{\text{DTW}}$ to perform a $K$-nearest neighbours ($K$-nn) classification, where the label of any testing sample is obtained after a majority voting among the labels of the $K$ training examples which are the closer in the sense of $\Delta$. With the exception of Pouring vs. Placing, the performances of $K$-nn using $\mathbf{S}_{\text{DTW}}$ are poorer than SVM fed with KF. This constitutes an evidence of the extreme similarity of grasping movements across different intentions. Indeed, only watching the closest trials in the sense of $\Delta$, one can only infer which trials are the more similar across subjects, which is not enough to predict intentions.

In order to get a more discriminative information, we computed the normalized graph Laplacian $\mathbf{L}$ $[20]$ using $\mathbf{S}_{\text{DTW}}$ as adjacency matrix. $\mathbf{L}$ is a classical tool to model the topology of a graph and, in our case, can better provide geometrical insights about the global configuration of the trials across subjects and intentions. As an original application of graph Laplacian, here, the matrix $\mathbf{L}$ actually transforms $\mathbf{S}_{\text{DTW}}$ into a kernel, which has been used to train an SVM, and leads to the results reported in Table I. The increase in performances are due to the properties of graph Laplacian: $\mathbf{L}$ attested to be robust towards the misleading differences related to the apparent similarities of the grasping, so that the discriminating motion patterns can better be retrieved.

C. Intention from motion with kernelized covariance

In this Section, we inspected the sampling covariance estimator - briefly, covariance - in predicting human intentions from motion.

In the literature, the usage of covariance for classification tasks has been intensively studied $[56], [57], [58], [59], [60], [61]$. Since the work of $[56]$ which proposed covariance as a local patch descriptor, such idea was applied to many different applications such as face recognition $[57]$ image and texture classification $[58]$ or person identification $[59]$ to name a few. The scored performance of covariance eventually enhanced after moving from the finite to the infinite dimensional case: such a change exploited the theory of Riemannian metrics on the manifold of positive definite matrices $[60], [61]$.

| 3D results           | Linear SVM fed with KF | $\mathbf{S}_{\text{DTW}}$ matrix | Hierarchy $[56]$ |
|----------------------|------------------------|----------------------------------|------------------|
|                      | $F_{\text{local}}$ (%) | $F_{\text{global}}$ (%)         | $F_K$ (%)        |
| Pouring vs. Placing  | 79.70                  | 86.10                            | 84.32            |
| Pouring vs. Drinking | 72.15                  | 70.36                            | 76.48            |
| Pouring vs. Passing  | 76.55                  | 67.39                            | 82.81            |
| Passing vs. Drinking | 63.10                  | 68.05                            | 70.75            |
| Passing vs. Placing  | 62.60                  | 64.38                            | 69.44            |
| Drinking vs. Placing | 64.40                  | 71.41                            | 73.72            |
| All-class            | 45.08                  | 48.01                            | 55.13            |

TABLE I

RESULTS FROM 3D DATA. FOR THE KINEMATIC FEATURES, A LINEAR $C = 10$ SVM IS FED WITH $F_{\text{local}}$ AND $F_{\text{global}}$ GROUPS OF FEATURES, AS WELL AS WITH THEIR COMBINATION $F_K$. FOR THE $\mathbf{S}_{\text{DTW}}$ MATRIX, IT HAS BEEN PERFORMED EITHER A $K$ NEAREST NEIGHBOURS CLASSIFICATION ($K = 5$) AND, ONCE APPLIED THE GRAPH LAPLACIAN $\mathbf{L}$, IT HAS BEEN USED AS KERNEL FOR AN SVM. FINALLY THE HIERARCHICAL TEMPORAL PYRAMIDAL OF $[55]$ HAS BEEN USED IN THE CONFIGURATION $L = 3$ WITH OVERLAP, AND BUILD IT USING BOTH COVARIANCE (COV) AND KER-COV ALTERNATIVELY.
Moving to the field of action recognition from motion capture systems, covariance allows to model the mutual variation in time of any pair of joints. Additionally, since each single action acquisition can have a (slight) different duration, covariance is convenient since invariant with respect to it. Thus, many works were actually based on such kind of representation: for instance, \cite{62} applied such idea for spatial and temporal derivatives for gesture recognition and \cite{30} proposed a hierarchical model composed by a L-layered temporal pyramid of covariance descriptors. Recently, \cite{63} set the state-of-the-art performance on action recognition from motion capture data: since trial-specific Gram matrix were interpreted to generalize the linear relationships codified by covariance, a bipartite low/high level kernel pipeline is proposed to move from the encoding of single instance to the measurement of (dis)similarity across trials.

However, as a main limitation of covariance representation, the latter can only capture linear mutual relationships \cite{64} which, clearly, can not be always the richest in discrimination. It should be therefore valuable to replace them by other, discriminative, general interdependences: such a problem was precisely addressed by \cite{65}. Therein, such problem was solved through a rigorous mathematical pipeline by kernelized covariance (ker-COV). Formally, covariance is

$$\hat{S}_\phi = \frac{1}{N-1} \sum_{i=1}^{N} (\phi(x(i)) - \mu_\phi)(\phi(x(i)) - \mu_\phi)^\top,$$

where $\mu_\phi = \frac{1}{N} \sum_{i=1}^{N} \phi(x(i))$ is the average of the data $x(1), \ldots, x(N)$ transformed by the feature map $\phi$, which allows $\hat{S}_\phi$ to model non-linear relationships. Usually, the feature space produced $\phi$ has higher dimension than the original data space and, thus, explicit usage of $\phi$ can be very expensive for both computing and storage. Thus, \cite{65} showed that \eqref{2} can be efficiently computed in terms of the kernel $k$ only, actually recovering the applicability of the kernel trick for covariance. In this way, the classical covariance is actually retrieved as a particular case and the kernelization can appreciate more general discriminants in the data. Moreover, such generalization is also versatile since it can be applied in existing covariance-based pipelines, with no additional required adaptation since it is enough to choose which kernel function $k$ should be used (according to the theory in \cite{65}, it must be a Taylor series kernel). Eventually, $k$ has some parameters which are selected by cross validation: this is what we did with $\sigma > 0$ to define the exponential-dot-product kernel $k(x, z) = \exp(-\frac{(x-z)^\top}{\sigma})$ used in this Section.

As done in \cite{65}, we plugged in the new kernelization in \cite{66}, replacing the low level kernels to encode separately each action instance, while all the rest was not modified. For instance, we used the default parameter selection of the code publicly released by the authors.\footnote{In comparison with the results reported in Table \ref{table:results}, STIP approach shows lower performance than DT adopting the same BoF encoding with 1000 visual words, HOG and HOF features score 38.62% and 37.45% respectively.} In this way ker-COV + \cite{63} scored 58.92% and, if compared with the original method proposed in \cite{63}, it is higher than either covariance representation (COV-RP, 48.93%), polynomial kernel (Ker-RP-POL, 52.67%) or Gaussian radial basis kernel usage (Ker-RP-RBF, 56.12%). Nevertheless, the registered performance is about 4\% below in comparison with $S_{DTW}$ (Section \ref{VI-B}). Possibly, the reason for this suboptimal performance of ker-COV + \cite{63} is due to the fact that \cite{63} does not address a fine modelling of the temporal evolution within each trial, since such information is collapsed into the matrix encoding. This is not ideal for our dataset which actually forces us to capture the smallest anticipating cues in the kinematics of the grasping. As a more time-sensitive approach to combine with ker-COV, \cite{36} proposed a L-layered temporal pyramid. To investigate its effectiveness in IfM, we adopted such model ($L = 3$) with both covariance (as originally done in \cite{36}) and ker-COV.

The results of such an approach are presented in Table \ref{table:results} with the only exception of Drinking vs. Placing where the best approach still remains $S_{DTW}$ (codified with graph Laplacian for SVM classification), the scored performance makes ker-COV the best 3D encoding in the all-class comparison and the remaining pairwise ones. Eventually, this has to be read as a strong evidence that a proper level of granularity in the temporal analysis of the kinematics can effectively predict intentions from motion.

\section{Analysis of 2D Video Sequences}

In this Section we present the classification results obtained from the video processing. In Section \ref{VI-A} we will test the local features \cite{66}, originally devised for action recognition, as a baseline for intention prediction, while, in Section \ref{VI-B} we will show preliminary investigations adopting Convolutional Neural Networks (CNNs) features.

\subsection{Local spatio-temporal features for IfM}

The class of approaches, named in \cite{66} as local, extracts from an input video some interest points (IPs), detecting remarkable variations in both space and time, and associate each of them to a volume from which features are computed. Among the most effective methods, STIP \cite{24} and dense trajectories (DT) \cite{67} use a sparse or dense approach, respectively, to extract IPs. For STIP \cite{24}, a convolution with a Gaussian filter is used, while for DT \cite{67}, at different scales, a dense grid of points is initialized and each of them is tracked using optical flow. Subsequently, spatio-temporal volumes are generated by stacking the $N \times N$ spatial neighbours centered in all the $L$ points in any tracked trajectory. The volume is warped in order to follow the related trajectory and it is subdivided in a $n_x \times n_y \times n_z$ grid of cuboids. From each one, the following features are computed: Histograms of Oriented Gradients (HOG) \cite{68}, Histograms of Optical Flow (HOF) \cite{69}, Motion Boundary Histograms \cite{70} in both $x$ and $y$ directions (MBHx and MBHy), trajectory shape descriptor (TSD) \cite{21} and Histograms of Oriented Trackelets (HOT) \cite{71}. As suggested by the literature \cite{21}, DT is more efficient compared to STIP\footnote{http://lear.inrialpes.fr/software/}. Precisely, using publicly available DT code\footnote{http://www.uow.edu.au/~leiw/} we adopted default parameters choice $N = 32$, $n_x =$
$n_y = 2$ and we set $L = 5$ and $n_t = 1$ to better deal with our extremely short footages. We obtained the results reported in Table I where we analysed in a separated fashion all the single features, while also testing three different high-level encodings: $\ell^1$ normalized bag-of-features histograms (BoF) \cite{22}, square-root normalized Fisher Vector (FV) \cite{73}, and Vectors of Locally Aggregated Descriptors (VLAD) \cite{74}. For BoF, changing the number of visual words did not bring any remarkable improvement, thus, we fixed it to 1000 and built a dictionary which was also used for VLAD. Instead, for FV, we employed a Gaussian mixture model with 256 components (as in \cite{75}).

| DT results | HOG (%) | HOF (%) | TSD (%) | MBHx (%) | MBHy (%) | HOT (%) |
|------------|---------|---------|---------|----------|----------|---------|
| Pouring vs. Placing | BoF 85.28 | BoF 85.75 | BoF 83.23 | BoF 85.56 | BoF 84.64 | BoF 83.64 |
| Pouring vs. Drinking | BoF 70.63 | BoF 77.21 | BoF 72.66 | BoF 70.78 | BoF 74.15 | BoF 64.81 |
| Pouring vs. Passing | BoF 71.77 | BoF 67.41 | BoF 72.17 | BoF 72.55 | BoF 68.33 | BoF 72.22 |
| Passing vs. Drinking | BoF 66.67 | BoF 65.49 | BoF 65.34 | BoF 71.21 | BoF 64.65 | BoF 69.10 |
| Drinking vs. Passing | BoF 65.55 | BoF 76.84 | BoF 56.00 | BoF 66.86 | BoF 66.00 | BoF 63.75 |
| Drinking vs. Placing | BoF 70.66 | BoF 75.60 | BoF 68.77 | BoF 73.19 | BoF 71.60 | BoF 70.44 |
| All-class | BoF 48.16 | BoF 48.05 | BoF 45.01 | BoF 47.71 | BoF 45.80 | BoF 46.33 |

Globally, FV and VLAD often outperform BoF encoding and VLAD improves FV 25 times out of all the 42 comparisons in Table I. Albeit HOT gives the lowest performances, in this case BoF is better than FV and VLAD. Among all the considered features, in most of the cases, HOF descriptors reach the best classification scores, giving an additional evidence that predicting intentions is affordable by only considering the kinematics. However, the DTW-based classification results are higher than all the DT features and this justifies how the use of 3D measurements of the markers trajectories leads to superior performances with respect to hand-crafted visual features. It is worth to note that such results remarkably improved the performance of a human observer which faces IfM by analysing the video sequences (58% on Pouring vs. Drinking and 68% on Pouring vs. Placing).

### B. CNN features for IfM

Far from providing an exhaustive validation of deep learning methods in the existing literature, we deem valuable to present preliminary attempts to check how features learned by CNNs behave in respect to IfM problem.

Since we deal with video sequences, we started our analysis with a recent architecture using three-dimensional convolutional networks (3D ConvNets) \cite{76}. The approach proposed in \cite{76} jointly exploited the spatial and temporal information provided by a video sequence extracting spatio-temporal features from a stack of frames. First of all, a video is split into 16 frame long clips (with custom overlap between two consecutive clips), then these clips are passed to the network to extract fc6 features from each bunch of frames \cite{76}. All fc6 activations are averaged over the clips and then a final L2-normalization is performed to obtain a compact C3D video descriptor. Since C3D can be used as a feature extractor for several video analysis tasks, we adopted the same pipeline for our intention prediction purpose. We divided each video sequence in three 16 frame long clips but instead of averaging all the fc6 features, we simply concatenated all the three descriptors (for each video the final C3D is a $3 \times 4096$ dimensional vector). We finally trained linear SVMs over C3D features. As clips given in input to the architecture, we have considered stacks of raw frames (I), and also stacks of images representing the optical flow (OF) magnitude computed between pairs of the original frames. In the second and third columns of Table I we report the accuracies. Comparing the two different inputs, C3D with OF-based images is better respect to consider raw frames for the clips of the videos.
This demonstrates that OF-based images are able to better capture the motion information focusing on the kinematics only of the movements. Nevertheless, the best features among the local DT still outperform the C3D approach in all the comparisons, e.g. HOF descriptor encoded with VLAD scores 58.23% (Table III) while C3D with OF-based images only 52.14% (Table III). This is probably due to the fact that the classes of action, which 3D ConvNet was originally trained on, have very different motion dynamics between each other and such pre-trained network can not easily distinguish between our very similar grasping movements.

Motivated by the well known transferability across different tasks of features learnt by a deep neural net (e.g., see [77]) and aiming at inferring subtle discriminative patterns from the appearance of our video sequences, we investigated all the available frames of the footages and exploited CNNs for a frame-wise representation [78, 79]. Precisely, as a first setup, we employed the AlexNet architecture [80], we extracted fc7 features from all single frames I and, consequently, we encoded each video with BoF as in [81] (Table III fourth column). In a second experiment we changed the previous pipeline performing a preliminary fine-tuning on the last fully connected layer to best fit the pre-trained model on our specific dataset. Since CNNs are the best known approach for image classification to date, the results in Table III (fourth and fifth columns) clearly state that a static analysis is not sufficient for IFM either adopting the pre-trained model or fine-tuning it over the frames of our dataset. Although performing the fine-tuning process, these fc7 descriptors are not always able to improve from random chance performance level (e.g., Passing vs. Drinking) and, sometimes, the performance shows a large drop if compared with dense trajectory features (e.g., about -20% Drinking vs. Placing).

Thus, in order to better capture the kinematics embedded in the grasping onsets, we fed AlexNet to process optical flow images, after another preliminary fine-tuning to match the new type of data. Indeed, feeding deep networks, pre-trained on ImageNet, with optical flow (OF) images was already shown to be effective in the literature. For instance, in [78], OF-based images are passed as input to fine-tuned GoogLeNet and AlexNet. Indeed, [78] noticed that fine-tuning a model designed for raw frames can help classifying optical flow images by allowing faster convergence than a random initialization of weights since the features which can discriminate, such as edges, are also effective for optical flow. In order to compute our OF images, inspired by [82], we combined into the three input channels the horizontal, vertical component and the magnitude of the optical flow field with a preliminary normalization in the range 0 ± 255. To obtain the descriptor for each trial, we performed the same BoF pipeline we used for raw frames. Since the latter configurations gives the best results (fifth column in Table III), we also consider the VLAD encoding on the fc7 features related to OF images, being consequently able to improve the all-class accuracy and to score a +5% on Passing vs. Drinking. As a final remark, inspecting the results reported in the last column of Table III, we notice that all the comparisons involving the Placing intention score very high (more than 94%), highlighting that distinguish the Placing class is almost trivial with this type of feature representations. Comparing the results obtained from the raw frames I with the OF ones, we get an additional evidence that all the grasping are very similar in appearance: indeed, by properly representing the motion of our reach-to-grasps, we managed to compute CNN descriptors which are the best video feature in the all-class case.

VII. UNDERSTANDING THE DATASET

In addition to tackle the prediction of unseen future actions all originating from the same motor act, the proposed dataset complicates the scenario with some additional challenges that have to be faced.

1) Although each grasping execution is extremely short in time and similar across different intentions, it is not clear whether there exists any temporal fragment when the discrimination within Pouring, Passing, Drinking and Placing is maximized.

2) In addition to retrieve the intention-anticipating motion cues from the same, apparently unrelated grasping onset, since the subject on which the system is tested is never seen in training, such cues have to be subject-invariant.

3) Multi-modality forces to find fusion approaches which can efficiently combine 3D markers kinematics and 2D video sequences.

| CNN results | C3D | Frame-based |
|-------------|-----|-------------|
|             | I   | OF          | I (fine-tuned) | OF (fine-tuned) |
| Pouring vs. Placing | 83.15 | 87.34 | 54.86 | 74.01 | 94.58 | 94.18 |
| Pouring vs. Drinking | 68.20 | 68.93 | 55.29 | 62.44 | 74.93 | 77.95 |
| Pouring vs. Passing | 69.42 | 65.02 | 49.93 | 60.28 | 75.89 | 74.20 |
| Passing vs. Drinking | 61.57 | 61.05 | 50.54 | 55.73 | 61.41 | 66.05 |
| Passing vs. Placing | 66.84 | 78.10 | 48.27 | 62.09 | 96.23 | 94.68 |
| Drinking vs. Placing | 68.30 | 76.67 | 51.36 | 58.69 | 95.87 | 96.18 |
| All-class | 45.51 | 52.14 | 25.85 | 37.03 | 64.55 | 65.64 |

TABLE III
ACCRUACIES OF C3D AND FRAME-BASED CNN FEATURES WITH SVM CLASSIFICATION (C = 10), FOR BoF AND VLAD WE SIZED OUR DICTIONARIES TO COUNT 1000 AND 50 WORDS RESPECTIVELY. AS BEFORE, FOR BoF WE ADOPTED A χ² KERNEL, WHILE A LINEAR ONE WAS EMPLOYED FOR VLAD.
Thus, as to provide a deeper understanding in all the aforementioned issues, in Section [VII-A] we will perform a fine temporal analysis of the 3D marker and 2D video data, in Section [VII-B] we will investigate the role of the subject in our one-subject-out testing pipeline and, finally, Section [VII-C] will set an experimental baseline to merge 3D and 2D data in an unique classification framework.

A. Snippet Analysis

In our dataset, the temporal length of all the grasping executions is extremely short, lasting 2-3 seconds only. Nevertheless, in this Section, we evaluate if some temporal fragments convey more discriminant information than others. To this aim, we perform a snippet analysis, according to the following pipeline. First, we consider the descriptors which obtained the best performance in our 3D and 2D analysis: kernelized covariance of 3D joints marker and CNN descriptors computed from OF images, respectively. We split the temporal duration of each trial in percentages by considering only the data (VICON marker or video frames) which have been acquired from the beginning of the grasping until the 10%, 20%, ..., 100% of its total length. Thus, the dictionary for VLAD encoding of CNN descriptors is specific of the considered part of the videos, while the temporal hierarchy of ker-COV features is applied to incremental portions of the grasps. Low percentages capture very few information (e.g., at 10%, for the shortest trial in the proposed dataset, only 13 markers acquisitions and 2 video frames only). With such an incremental time analysis we are able to check if there are some big jump in performance, meaning that the included time instants are extremely discriminative.

Tables [IV] and [V] report the results of the snippet analysis when ker-COV and VLAD-encoded deep features are used, respectively. For video data, in Table [V] the best scores are obtained considering percentages of the videos higher than 60% and, surprisingly, the best results is not registered when all the video is processed (e.g., Pouring vs. Placing is better discriminated at 70%) Additionally, CNN are able to capture discriminative information already from the very beginning of the movements (e.g. 85.80% in Passing vs. Drinking considering only a 10% of the frames in each video). Differently, snippet analysis with ker-COV does not remarkably exceed random chance level at 10%, 20% and 30%. In this case, all the best scores are performed considering the entire video footage. In particular, we notice a strong boost from the 90% to 100% percentages of the videos: the last 10% of the frames seems containing high information in the 3D part of the dataset. However the same boost is not confirmed in the 2D investigation and, clearly, this is due to the fact that comparing Table [V] with Table [V] is not fully reliable since the two feature representations exploit two different sources of data. In spite of this, we can anyway find a common trend, consisting in a general growth in accuracy when the data percentages considered get completed. Consequently, we can not find any portion of the reach-to-grasp execution that is completely useless for the prediction of intentions.

B. The role of the subject: the personalized perspective

In all the experiments performed in this work, the adopted one-subject-out testing modality forces the classifier to predict the intention of a human actor which was never used in the training phase. Therefore, the classification task must rely on some intention-anticipating discriminant clues, which, at the same time, have to be shared across the subjects. As recently proved [83], the role of the subject has been frequently disregarded and sometimes underestimated for the task of action and activity recognition. Thus, in this Section, we want to investigate such a role in our new problem, namely, we want to check if the unknown identity of the subject who is acting complicates the prediction of his/her intentions. For this purpose, we applied the t-Distributed Stochastic Neighbor Embedding (t-SNE) technique [84], the state-of-the-art tool for dimensionality reduction in order to approximate high-dimensional feature encodings, so that our dataset can be visualized.

For this purpose, we adopted the kinematic features $F_K$ (Section [V]), since straightforwardly codifying the dynamics of the grasping in terms of differences and distances of marker positions. Therefore, we can produce a direct visualization of the data from a perspective of the lowest level encoding considered throughout our broad experimental baseline. The results are presented in Figure 3(a); where, it is evident the presence of several compact and distinct clusters. It is worth noting that t-SNE is an unsupervised technique which does not exploit neither the subject nor the intention information at all. However, as a post-processing step on the 2D points obtained from t-SNE, we plotted and colored them according to the subject performing each given trial, so obtaining the net result that each cluster precisely correspond to one specific subject, no matter which is the underlying intention. As a consequence, this suggests two important aspects of the dataset.

- Confirming the experimental findings of [83], all the instances of a given subject occupy a compact region in the feature space. Hence, intra-subject variability is quite negligible since the different trials of the same subjects are both close to each other and distant from the corresponding ones of a different actor.
- One-subject-out testing modality is actually challenging for our dataset since, before disclosing the underlying intention, the gap between subjects has to be bridged. Indeed, the low dimensional approximation provided by t-SNE suggests that, for instance, a Pouring trial of a given subject is closer to one of his/her Passing trials rather than to another Pouring of a different agent.

Despite the direct linkage between $F_K$ and the acquired grasping kinematics, such descriptor plays an extremely low level encoding of the data and, therefore, is not enough discriminant to capture all the subtle differences which anticipate the intention. Thus, it is natural to consider a more sophisticated feature representation, enriching the level of encoding aiming at both reducing the aforementioned gap and, possibly, clustering the data per intention. To do this, we applied t-SNE on the VLAD encoding on the deep features extracted from OF images. This allows to obtain the representation in Figure
Comparisons  |  10%  |  20%  |  30%  |  40%  |  50%  |  60%  |  70%  |  80%  |  90%  |  100% |
---|---|---|---|---|---|---|---|---|---|---|
Pouring vs. Placing  | 54.20  | 51.48  | 58.93  | 71.40  | 76.10  | 82.72  | 87.55  | 89.91  | 91.87  |  |
Pouring vs. Drinking  | 47.58  | 47.85  | 50.47  | 61.01  | 62.03  | 64.45  | 65.82  | 72.30  | 77.48  | 91.58  |
Pouring vs. Passing  | 50.67  | 50.75  | 53.22  | 53.98  | 57.57  | 59.62  | 67.18  | 71.97  | 77.16  | 87.64  |
Passing vs. Placing  | 53.49  | 54.20  | 59.44  | 61.67  | 62.03  | 64.93  | 63.01  | 67.84  | 74.06  | 91.24  |
Drinking vs. Placing  | 53.13  | 54.48  | 56.55  | 60.00  | 62.03  | 64.93  | 63.01  | 67.84  | 74.06  |  |
All-class  | 25.09  | 27.90  | 28.34  | 33.31  | 36.72  | 38.60  | 43.10  | 49.03  | 54.44  | 73.72  |

TABLE IV
ACCURACY PERCENTAGE FOR THE SNIPPET ANALYSIS USING KER-COV DESCRIPTOR.

Comparisons  |  10%  |  20%  |  30%  |  40%  |  50%  |  60%  |  70%  |  80%  |  90%  |  100% |
---|---|---|---|---|---|---|---|---|---|---|
Pouring vs. Placing  | 61.87  | 77.38  | 79.79  | 87.02  | 88.88  | 91.43  | 95.09  | 92.06  | 94.73  | 94.18  |
Pouring vs. Drinking  | 58.76  | 61.31  | 63.14  | 67.49  | 67.87  | 71.52  | 73.41  | 73.31  | 74.79  | 77.95  |
Pouring vs. Passing  | 61.91  | 57.82  | 62.57  | 66.00  | 65.25  | 65.47  | 66.79  | 69.98  | 77.13  | 74.20  |
Passing vs. Dring  | 56.67  | 61.25  | 59.91  | 62.85  | 60.01  | 67.78  | 65.25  | 64.63  | 66.05  |  |
Passing vs. Placing  | 85.80  | 90.93  | 95.65  | 96.19  | 97.73  | 95.82  | 96.33  | 96.28  | 98.75  | 94.68  |
Drinking vs. Placing  | 74.49  | 89.42  | 94.49  | 95.00  | 95.42  | 93.65  | 95.18  | 94.42  | 98.07  | 96.18  |
All-class  | 42.40  | 49.70  | 52.31  | 57.79  | 56.90  | 57.91  | 62.26  | 62.27  | 63.86  | 65.64  |

TABLE V
ACCURACY PERCENTAGE FOR THE SNIPPET ANALYSIS USING CNN FRAME-BASED DESCRIPTOR ENCODED WITH VLAD.

3(b) where each color represents a single intention. Clearly, the Placing intention is quite separated from the other ones (Pouring, Passing and Drinking). Quantitatively, such trend is readable by the fact that, in all the pairwise comparisons which involve Placing, such descriptor gave the highest performance in all our experimental baseline.

As a final remark to better evaluate the role played by the subject, it is interesting to apply to IfM the two-step pipeline proposed in [83]. Precisely, a preliminary identification of the subject is followed by a subject-specific action classification. The work [83] certified its effectiveness in the case where, similarly to us, intra-subject variability is low. In Table VI, we report the intention prediction performance in the all-class comparison, either using ker-COV or VLAD CNN features, since they are the most effective 3D and 2D ones, respectively. Both features produced an outstanding performance, both improving the best score obtained using one-subject-out in the 3D and 2D experimental baseline (precisely, 73.72% with ker-COV). This furthermore certifies the experimental conclusions of [83], where the one-subject-out testing modality ensures more generalization than classical ones, such as k-fold cross validation. Nevertheless, it is not easy to obtain high performance with this strategy and the two-stage pipeline greatly benefits from a personalized perspective.

|               | ker-COV       | CNN          |
|---------------|---------------|--------------|
| All-class     | 92.87 ± 0.97  | 85.66 ± 1.32 |

TABLE VI
TWO-Stage RECOGNITION PIPELINE ACCURACIES [83] APPLIED TO IfM IN THE ALL-CLASS CLASSIFICATION.
### C. Fusing 3D and 2D information

A unique aspect of our proposed dataset refers to its multimodal nature, namely providing both 3D markers trajectories and 2D video acquisitions of every reach-to-grasp onset. Thus, it is interesting to take advantage of such a dual source of information and to overcome the performance of simpler methods which only leverage on one type of data only. To this aim, in this Section, we present some baseline experiments as to combine all the inspected 3D and 2D feature representations in a unique descriptor, performing an (early fusion) of our data. Further, we investigate some basic late fusion modalities, where, at a higher level, we performed a combination of kernels, each of them representing each feature encoding separately. For a comprehensive analysis on fusion techniques, please refer to [85].

**a) Early fusion of feature vectors:** Throughout the experimental 3D and 2D baseline, several features have been envisaged: the 16 kinematic features $F_K$, the kernelized covariance ker-COV, the HOG, HOF, TSD, HOT, MBHx and MBHy histograms computed with dense trajectories and deep features extracted from raw frames/optical flow images using both C3D and AlexNet architectures. Globally, if one concatenates all such features in one single vector, its dimensionality is prohibitively high (namely, 579,786 components): actually, its usage leads support vector machines to suffer of the well known curse of dimensionality issue [86]. Then, in terms of performances, random guess is not exceeded (e.g., 22.81% in the all-class case). Hence, it is necessary to obtain more compact feature representation to actually let the classification gain from the dual source of information, thus improving the best single descriptors, when separately considered. In this Section, we do this in a two-fold manner, either performing PCA to reduce the dimensionality of the 579,786 feature vector or adopting information theory feature selection criteria [87] to select which are the most effective components in the whole 579,786 dimensional descriptors. For the former, a cross validation pipeline leaded us to project the data on the first 160 principal component which retain the 38% of their variance. For the latter, we exploited the Conditional Mutual Information Maximization (CMIM) criteria: each feature component is ranked according to which of them is able to better capture the variability in the class label, while also minimizing the redundancy with respect to previously selected component [87]. For the classification, we only used the 150 top-ranked components: Table VII shows the results, as well as a comparison with the performance scored by the best single descriptor (BSD) among all the ones presented in Section V and VI.

| Comparison        | BSD   | Early Fusion | Late Fusion |
|-------------------|-------|--------------|-------------|
|                   | PCA   | CMIM         | MSE         | ACC-r       |
| Pouring vs. Placing | 94.18 | 85.80        | 95.92       | 88.84       | 95.70       |
| Pouring vs. Drinking | 91.58 | 83.85        | 93.30       | 91.41       | 94.62       |
| Pouring vs. Passing | 84.47 | 79.88        | 90.47       | 85.85       | 90.04       |
| Passing vs. Drinking | 87.75 | 84.89        | 87.21       | 82.57       | 90.30       |
| Passing vs. Placing | 96.23 | 70.23        | 93.49       | 82.33       | 91.12       |
| Drinking vs. Placing | 96.18 | 82.63        | 93.68       | 90.97       | 96.87       |
| All-class         | 73.72 | 68.39        | 80.08       | 77.52       | 80.50       |

**TABLE VII**

**EARLY AND LATE FUSION RESULTS.**

Although PCA is able to attenuate the aforementioned curse of dimensionality problem, it scores inferior to the best single descriptor. This is possibly explainable by considering that reducing the dimension from the original 579,786 to 160 clearly impacts on the performance. However, despite a similar compression is done by CMIM criterion and sometimes the best score results are not improved, it is worth nothing that the all-class comparison performance jumps from 73.72% to 80.08%. Within the 150 selected components, 4% are taken from kinematic features, 18% from the deep features, 37% from the histogram features extracted by dense trajectory and the remaining 41% belongs to kernelized covariance. It says that all the inspected feature representations are discriminant per se, while also appreciating complementary aspects of the problem.

**b) Late fusion of kernels:** The considered early fusion techniques are not always able to improve the best single descriptor in all the comparisons (e.g., Drinking vs. Placing) and, as further issue, the DTW representation was not considered at that stage since not providing a direct feature representation. Thus, as to overcome all the aforementioned troubles, we applied a late fusion pipeline. Precisely, at the first stage, we compute a kernel to separately encode each different data encoding: a Gaussian RBF kernel was used for each kinematic feature, the Graph Laplacian was applied on the DTW similarity matrix, a Gaussian $\chi^2$ kernel for the bag-of-features histograms of frame-based CNN descriptors (one for the raw frames, one for the optical flow). Differently, we employed a linear kernel for kernelized covariance, the 6 histogram descriptors extracted with dense trajectories, C3D features (of both raw frames and OF images) and VLAD CNN descriptors on optical flow images. The resulting 29 kernels $K_1, \ldots, K_{29}$ are combined in a unique global kernel $K$ to feed SVM classification by using a weighted linear combination, according to the expression $K = \sum_{i=1}^{29} w_i K_i$, being $w_i \geq 0$ for every $i$. Actually, a proper selection for $w_i$ greatly impacts on the performance [85]: for instance, with a uniform combination $w_i = 1/29$, we registered a suboptimal performance of 57.26% in the all-class case. Thus, following some of the approaches reviewed in [85], we either use mean squared error- or accuracy-based criteria to select $w_1, \ldots, w_{29}$. We call the first approach MSE and, precisely, we choose $w_i \propto 1 - \frac{\varepsilon_i}{\sum_{j=1}^{29} \varepsilon_j}$, where $\varepsilon_i$ is the mean square error between ground truth and estimated labels, once the kernel $K_i$ is applied in a separated fashion. Second, we consider a pipeline (called ACC-r) where the final kernel $K$ averages the $\nu$ top kernels in the sense of their classification accuracy (here, $\nu = 3$). From the results (Table VII), it is easily checkable that, although MSE is sometimes able to score on par to BSD, the ACC-r pipeline is always able to improve the best single feature (with the only exception of Passing vs. Placing), and, in the all-class case, the final accuracy score is 80.50%. The latter is the highest result on such comparison in the whole
In this paper, we have proposed a novel approach to action prediction, namely the Intention from Motion paradigm, consisting in classifying intentions all starting with the same class of motor acts and without using contextual information. As a first attempt to face this challenging problem, we have proposed a new dataset specifically designed for our new action prediction setting. We have also presented an extensive experimental analysis to set a baseline on 3D kinematic data and 2D videos, as well as fusion methods have been proposed to show how both 2D and 3D information can improve classification performance. This study aims at providing the proof of concept for this new intention prediction task and, with this respect, the snippet analysis confirmed that there is no portion of the reach-to-grasp motion which is useless. Also, the presence of different subjects results in a characteristic noise which complicates the generalizability of the algorithm being at the same time an additional source of information to exploit as to boost the performance in a subject-aware setting. Moreover, the multi-modality of the dataset is a unique characteristic of our scenario, while the experimental setup allowed us to demonstrate that action prediction is feasible by only inspecting the kinematics while disregarding contextual information. Future perspective will focus on the acquisition of new datasets, increasing the number and the complexity of the considered intentions, to test IFM in more realistic scenarios. Overall, we firmly believe that our new Intention from Motion paradigm constitutes a breakthrough in action prediction, opening a new frontier for the computer vision community for many years to come.

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