The 18th IEEE International Symposium on
Robot and Human Interactive Communication
Toyama, Japan, Sept. 27-Oct. 2, 2009

Digital Representation of Skills for Human-Robot Interaction

Carlo Alberto Avizzano, Emanuele Ruffaldi, Massimo Bergamasco
PERCRO, Center of Excellence for Information and Communication Engineering
Scuola Superiore Sant'Anna, Pisa, Italy

Abstract— **The present paper deals with a system architecture and a digital format to support the acquisition, storage and transfer of human skills. Virtual Environments and Haptic interfaces will be addressed as target platforms for the capturing and rendering of skills.**

There are several methodologies for approaching definition and modelling of skills, and the present work will focus on a specific approach that merges evidences from human sciences with present approaches in intelligent robotics and machine learning.

This work presents a supporting tool that enables researchers to model, analyse and control the skill transfer process. In addition this work will provide an overview of a skill transfer framework, and information related to the models of skill representation that are being employed.

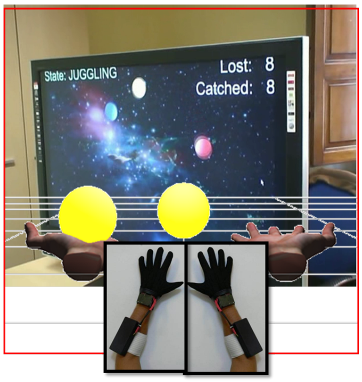

Fig. 1. Training component in the Juggling application

I. INTRODUCTION

The use of computer as a means for learning begun in the middle of 60s. At that time the term of Computer-Assisted Instruction (CAI) has been coined in order to address programs that were based on "question and answer" tutoring approaches [1].

The advent of computer based multimedia and Internet has deeply changed such an approach in the following 40 year period. Today with the term e-Learning we address complete interactive, online training programs that allow remote trainee to undertake distance learning accordingly to well designed pedagogical approaches.

Accordingly to Gagne[2] five instructional areas can be found in instructional design literature:

1) Intellectual / procedural knowledge;
2) Cognitive relational abilities;
3) Symbolic and declarative knowledge;
4) Motor skills in performing physical tasks;
5) Attitudinal skills;

While other areas can be taught by means of classic CAI approaches, motor skills can only be transferred with complex human interfaces that allow user to be immersed into digital environment and apprehend from the interaction with the interface.

The term enactive knowledge [3] underlies this kind of learning process while the Enactive Society [4] promotes the development of immersive virtual environment for the manipulation of this knowledge.

In the past years several approaches have been proposed to employ robot and haptic devices in training. Yokokoji[5] proposed an integrated system named "What you see is what you feel (WYSIWYF)". WYSIWYF records sensorimotor actions from experts and plays them back to unexperienced used using D-Base recording of compliance information and a specialized impedance controller that forces the users to follow exemplary data. A similar approach that allows generalization was introduced by Sano [6] in 1999 in order to model the experts data into a set of Neural Networks.

Recently the issue of training is being supported even more by attempt to use machine learning and automated techniques to capture and represent the quality of motion of human gestures.

Buss in 2008 [7] extended the copy and playback strategy with a more complex trainer/trainee semi-teleoperated architecture, that allowed the trainer to intervene on the trainee perception by means of an hybrid controller that mixes up environmental and trainer stimuli to present the trainee feedback. The use of K-Means clustering also allowed to support the training in case of force replication.

Calinon [8] in 2006 has proposed an integrated architecture which can help robot to behave like human by means of a training by showing. The proposed system extract relevant features from the observation of samples and is able to generalize to different contexts. The Calinon's system relies on a probabilistic description defined in a support space (determined with Principal Component Analysis). The behavioral description is then designed with a mixture of density function (Gaussian and Bernoulli) which describes the spatio-temporal correlation across different modalities and cognitive relationship in observation action. The ability to generalize motion is demanded to the use of a Gaussian Mixture Regression.

However the research produced so far do not address the issue to manage and support a representation framework

978-1-4244-5081-7/09/$26.00 ©2009 IEEE

which enables to analyze the human skills as belonging to an extensive digital representation. In this work we shall review some of the modelling efforts available so far and correlated them into a unique framework which allow us to design and support experiments for the capturing and transfer of skills.

In contrast with what available so far, our approach is focused on a human centered design which correlates elements of the digital modelling with evidence and background used in human science. This is mainly motivated since out objective is to wrap the knowledge related to human skills for the training of other humans, and to design multimodal system to achieve such a training.

In the following of this paper we will address the framework design principles we adopted in order to make such complex systems more understandable; the relationships with body sensori-motor properties and related cognitive states; the methodology that will be adopted to capture and model experts styles; the strategies under development for training. The implementation of the overall structure will also be described on a practical system to test and transfer skill related to juggling.

II. The Unified Framework

A sensorimotor skill is difficult to be described. The modeling of a specific act of doing represents a challenge in some fields of research such as cognitive science, psychology, robotics, bio-mechanics and other behaviour-related studies. Any description requires an in depth correlation amongst the action performed and the user perception[9]. In addition both of them should take into account different factors:

- Identification and definition of the user environment interaction: the amount of information to model a proper skill interaction, both in terms of observable items and controllable actions, is supposed to rely on a reduced set of information than those measurable in the environment;
- Identification and classification of styles: relevant skills can successfully be achieved through different and relevant expert styles. Modeled skills should cope with the variability of actions along the limit cycles that the rhythmic repetition identifies.
- Implementing training, requires the setup of particular control strategies that feedback styles information trough the simulation embedded. In order to provide training online, new specific interactive tools are required.

A. Environment Interaction

Scientific literature reports several models to represent the interaction of an agent in an environment. In our approach we searched for a representation that can easily be extended to cope with the above points. The chosen model was introduced by Warren [10] and is summarily represented in 2. Warren allowed three separate dynamical descriptions to identify the environment and the user response. In addition relationships of perception and action are modeled separately.

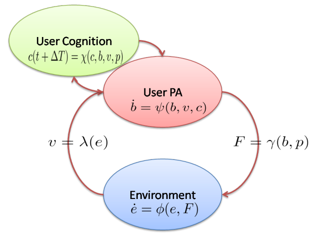

Fig. 2. Extended Warren model

In this model the behavior of an agent in general is being modeled in terms of exchanges of information the agent itself and the Environment, each described as a dynamical system. The Environment has an internal state ‘e’ and a descriptive function ‘ϕ’ that are mapped onto the agent through an observation function λ. Similarly the internal state of the user ‘b’ evolves with the ‘ψ’ function and is mapped in the environment with a set of forces via the ’γ’ function. Here two vectors of parameters guide the cognitive response (c) in performing the skill and constraint the physical limitation (p) in terms of fitness and physical abilities. Additionally the parameters ’c’ are time varied by the evolution of the user cognition, here represented as a regular discrete time update function ‘χ’.

Even if the Warren model is quite limited in terms of insight for the internal functions: ‘ψ, λ, χ, γ’, as we shall see it offer the opportunity to enhance the interaction model towards a digital mediated interaction which handles separately the factors identified for the Unified Framework.

It is here particularly relevant that in an approach using multimodal interfaces we can replace completely (or partially) the real environment with a virtual environment whose behavior and dynamics is defined by code and completely known to the designer.

The introduction of a virtual environment therefore allow us to have a knowledge not only of the ϕ function but also for λ and γ. The user behavioral functions (ψ and χ) still unknown.

B. Capture of Styles

Capture of style is more than capture of expert data. From the preliminary experiments of Johansson[11] more than 30 year ago, which demonstrated that information on gestures and style can be encoded in a reduced set of variables, in the past decade a lot of efforts have been performed to classify and identify human motion from observation. Nowadays, styles can be identified and modeled in detail. For instance, when considering walking the biological motion, the tracking of a reduced representation of the human pose[12] can be decomposed into phases and clustered into different styles. For instance one identification analysis on styles of walking that allows abstracting from normalization is presented by Troje[13].

One common approach to model and classify styles in computer vision is to associate them accordingly to what are called motion signatures [14], a sort of motion invariants that may be determined on signals by sort of processing of captured data. Pattern simplification techniques, such as PCA[15], and pattern recognition are commonly employed in the determination of the action style.

Our approach distinguishes itself from existing ones in the fact that the recognition is not completely demanded to automated tools but relies on a set of action sub-skills and guided style information provided by human scientists and experts in the application field. To understand how here information is modeled and stored we premise the levels of representation that will be employed: within the framework. In particular we distinguish data accordingly to four different levels: Variables, Features, Sub-Skills and Skills.

Relevant Variables: only part of the raw data collected during the interaction is stored and employed. The amount of information is enough to code the relevant inputs that defines an action but neglects all those elements considered not to affect the expression of the skill. This is achieved by creating a metric which is dependent on the results achieved in the target space more than focused on the user motion space. Each selection is therefore depending from an in depth analysis of the task and the consequence that an action may have on final results. This selection is typically performed with experienced trainers (masters) who cooperate in the variable design. For instance style and posture in grasping may be relevant in surgery operation and could be neglected in power actions.

Features: are extracted from variables by following the indications discussed with experts' trainers. The introduction of the features in the computing process allow us to have a better targeted process that makes distinction between style components and better focuses on the styles properties that are considered of primary importance by trainers. In opposition to what it could resemble at a first sight features do not simplify the representation of the task, they increase the dimension of the representation vector and introduce more elements to be inspected. In the other side features greatly simplify and improve the analysis of the performances. Each feature is designed in order to have particular mapping with analysis tools (the 'performance indicators') that highlight the quality of execution of a particular phase of the skill. Two types of features are considered here: sensori-motor features (SMF) and discrete-event features (DEF) that outline the presence of particular states of interaction during the operation in the virtual environment;

Digital sub-skills: the introduction of DEF and SMF concepts in the mathematical modeling allows us to provide an operational guideline to the above Warren's model. In particular we expect that the above feature may catch a list of relevant points that could be observed in the user physical and cognitive spaces ($\{b\}, \{c\}$) and in their characteristic evolutionary function (χ_u, ψ_u). Hence using features we expect to have a methodology to qualitatively sample the hidden dynamics in the points the trainers consider to be of high relevance for the performing of action. This approach has been structured by introducing the concept of sub-skills. In total 14 different categories of sub-skills[16] have been introduced in order to measure different properties, organizing them between motor (8) and cognitive (6) sub-skills. The selection process of the sub-skills starts from a preliminary hierarchical analysis of the target task and a mapping from every sub-task into a set of sub-skills that from expert knowledge are relevant for the purpose of the investigation. Sampling of the above mentioned relevant points is gathered indirectly by means of what have been called "performance indicators". During exercises, each low level multidimensional point, mapped through the performance indicators, produces a statistical distribution that will be here defined as a"sharp";

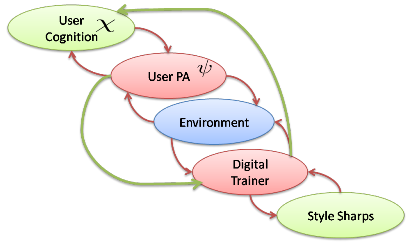

Fig. 3. Digital Trainer extension: implements trainer and expert knowledge as an embedded feedback into VR training applications.

Digital skills: the introduction of the digital sub-skills allows at once to correlate trainers and typical motor science indicators with the analytical model employed for the representation of the skill. This is performed by decomposing the user skills into the relevant sub-skills that are required for the specific task, then defining performance tools that measure the distance among performers. This approach allows us to redefine the digital signature of an expert style as the set of "sharps" that a specific expert sign into the system when repeating a task with a given style. The use of "sharps" allows us to create a mathematical description for given styles and to define a notion of style distance as the joint probability that a given set of points belongs to a "sharp":

$$d^x_{C_\#} = P(x \in C_\#)$$

C. Digital Training

The Warren approach can be further extended towards a new model that fully support for a Digital Trainer. The most relevant properties of the Digital Trainer is that it allow the user to Learn by Doing, by gathering task information from the direct interaction with the Environment and not from commands from the Trainer.

In a first instance the digital trainer can be added to the interactive environment in the same manner a typical trainer interact with a trainee. He is another subject operating in the same environment, and therefore possesses it own observation and action linkages toward the same environment. Here the behaviour of the trainer dynamics (ψ_{DT}) has a completely different role from the user one. Trainer feedback should complement user action with a proper feedback that enhance or accelerate the learning capacity. The use of the style models here is used to measure the distance (as explained before) from reference models and compute reaction models that helps the user to undertake the proper corrective action.

The digital trainer however can have much more possibilities that a standard trainer to undertake an in depth communication with the trainee due to the following motivations:

- the observation of the subject are not simply based on the observation of user action in the environment and can be enhanced with real-time biometric measurements (EEG, EMG, ECG, Oxygen consumption, Eye Tracking,...) that provide a more accurate discrimination of condition that determine user response;
- the action of the trainer on the environment are not limited to a physical interaction, but being a digital entity in a digital environment, can affect deeply the behaviour of the environment. It is of a particular value the capability for the trainer to control some real-time parameters of the environments simulation and status rendering;
- the trainer feedback can also bypass environment mediated communication and control specific rendering devices (vibrotactile, haptic, sound, terminals,...) that reflects trainer information directly to the user perception.

III. Implementation

The implementation of this framework has been performed by means of three different modules: a skills repository system, a computational framework, and an interactive VE. All these components are required and communicates each other during the setup of digital training exercises.

A. *The skills repository system*

The repository system is a Database architecture based on SQlite [17]. The choice of SQlite as a reference DBase was explicitly done in order to embed the data capture and to maintain the data collection into a unique structure. SQlite has in this operation some unique features in terms of performances, portability, deploy languages and manipulation tools that makes it the best platform to employ. However as for all Database engines, it is freely manipulable from users and requires some additional constraints in order to maintain the information clearly ordered. This feature has been employed on the SQlite by means of an access interface called "DataKit" that helps to organize information in the store and retrieval operations (see figure 4).

DataKit provide the user with clear functionalities to store, tag and retrieve data from the repository. For instance, when considering the experiments, the DataKit structure allows to record the relevant variables with a coherent set of information (meta-tags) that uniquely identifies both experiment details and the setup conditions that have been associated with the environment configuration and the training protocol. This operation is of particular values since training requires the access to data logs across sessions in order to compare progresses and effects of specific environments, protocols, accelerators and digital trainers. The use of the metatags helps the recover and process of information in this sense,

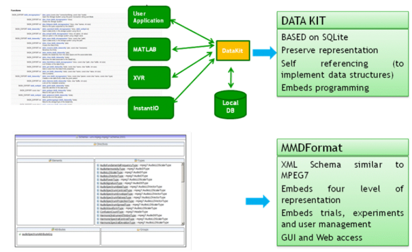

Fig. 4. SQlite DataKit: allows interoperable application from different VR technologies to share and to interoperate with a common set of information representation

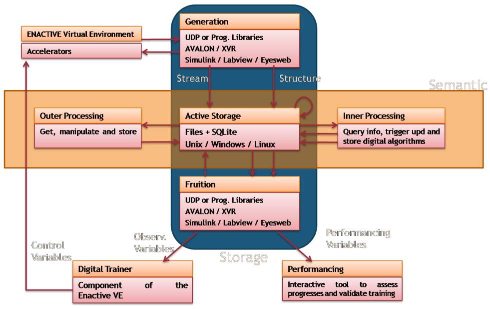

Fig. 5. SQlite DataKit: allows interoperable application from different VR technologies to share and to interoperate with a common set of information representation

by allowing the protocol designer to call back and process the whole information related to a common protocol, setup or sub-skill, and to compare differences among expert style performances and user progresses.

Class Type	Data	Algorithms
Variables	Yes	-
Features	Yes	Extracting Algoritms
Sub-Skills	-	Performancing Tools
Expert styles	Sharps	Relevant point extractors
Skills	Structure	Learning curves

TABLE I

Classes of data stored in the repository system

Raw Variable data are only the entry point of the services offered by the repository system, they store the results gathered from experimental session, but do not highlight the semantic knowledge that is encoded in them. The repository systems offer therefore additional level of information storage in order to embed in the repository features, sharps, sub-skills and skills structure together with relevant algorithms that are required to manipulate this information.

This is achieved by allowing that the low level information originally acquired from experiments can be processed and restored in the system by a set of internal and external toolboxes. Meta-tags during the processing operation are preserved and enhanced in order to maintain a clear list of dependencies on how the information has been produced.

Figure 5 highlights how the repository system is expected to be updated by means of the internal and external processing unit. The Enactive Virtual Environment is the interactive environment the user in operating in, this environment sends variables information to the repository by regular streaming of data. Such information is archived in the repository by storing both the streaming information and the structural metadata that have been explained above. At this step three kinds of operation are feasible: other processing, inner processing and fruition. In outer processing mode, an external program will provide to handle the data information to create higher level of representation (as in table I). Inner processing mode is similar but exploit the functionality of the DataKit to execute mathematical algorithms stored inside the database. Finally fruition operations allow to retrieve information for analysing the progress of training and/or provide the "Digital Trainer" feedback to the virtual environment.

B. The computing framework

Processing of information related to skills requires to merge, to interoperate and to setup a lot of different types of algorithms, from Principal Component Analysis (PCA) to Dynamic Time Warping (DTW), from Hidden Markov Models (HMM) to K-means. Being most of them already available on from elsewhere, We considered to be a nonsense develop them from the scratch or in a new environment. For this reason one of the relevant choice of the framework was to demand and rely the computing activities to a common computational program that already makes available most of these algorithms (the MATLAB ©program).

A porting of the DataKit interface was therefore provided toward this environment and the internal Simulink schematic designer. In such a way it is possible at anytime to connect the repository, manipulate data and store them back accordingly the philosophy of the outer processing.

However, given the complexity of the data handled by the framework some changes to the methodologies to access and handle data have been required. Different types of S-Function blocks have been developed in order to recover data from the repository (stream and sharps Sources Blocks), Store data back while preserving meta-tags hierarchy (stream and sharp Sinks Blocks), Visualize information (performances Display Blocks), Connect to virtual environment devices (IO Connector Blocks) and access to the transformation algorithms.

These schematics run and interact with the external training environment. For performance issues most of the blocks therefore do not run at any arbitrary frequency but share a triggering mechanism that allow them to share data only when update are required and/or available.

In addition some blocks require to share representation information that is more complex that the streaming data embedded in the connectors. In such a case the connector only share a pointer to the information description that will be handled properly by the visualization and computing blocks. For further details we demand to [18].

C. The Virtual Environment

Any virtual environment that implements the use of the Digital Repository as defined above can be used with the presented framework. Within the context of the SKILLS-IP the following environments will be supported: XVR [19], OpenSG and X3D with Avalon Instant Reality [20].

The virtual environment integration however requires that the VE should allow the repository system to interoperate environment accelerators. Within the framework of a training protocol, a training accelerator defines how one or more specific VE technologies can be used in order to: Reduce the Training/learning time and/or Improve the skill performances. It is expected that accelerators do not alter the basic sensori-motor information exchanged during task execution, but provides a richer set of information the user can exploit to converge better or faster to the desired style. Accelerators should take as input information the target style (in terms of sharps) and the relevant points (computed from features) hit by the trainee, and define a feedback strategy to correct the motion.

Several types of accelerators are presently under investigation they include: vibrotactile stimulation, control of task timings, cognitive highlights, sound based synchronization (metronome), haptic guidance and different kind of visual guidance.

IV. A PRACTICAL EXAMPLE

A trainer for juggling skills has been setup. Learning to Juggle can easily be performed by practice and following the indication provided into several Internet sites. However for the sake of the experiment we would like to check if juggling skills could be learned in an instruction-less manner only practicing with the strategies described in this framework. There is no practical benefit in doing this for juggling except the fact that we assume to demonstrate the system being able automatically to convert training information from an empirical self learning to a system guided teaching.

Among possible tasks the three ball cascades style has been selected. Figure 1 shows the typical components employed in task operation: a couple of sensorized gloves monitors the motion of the user hands and the closure of the fingers. One additional sensor tracks the motion of the head to correlate equilibrium information. All these information, and the spatial positions of the three balls are gathered as variables.

Features extraction is based on relevant scientific literature they include zenith analysis, velocity vector of thrown, and timing of catches at a first analysis which demonstrated to be good indicators to correct typical defects of skills [21]. To further improve the quality of analysis and the motion envelopes that caused errors, Shannon index, principal Component Analysis [22] and other tools are being tested.

The MATLAB and Simulink repository design allowed us to integrate with the data store and retrieval with the mathematical model of the three ball cascade. The Figure 6

Four types of accelerators are presently under test: a velocity controller, which modulates the effect of the gravity acceleration accordingly to the user performances, a visual/sound synchronizer that highlights with sound and

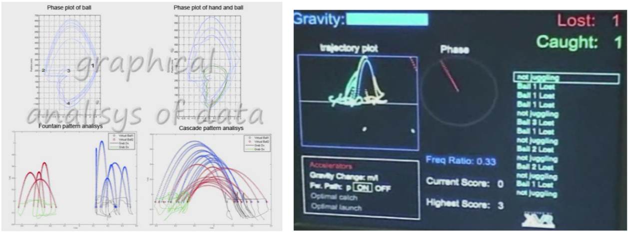

Fig. 6. Example of analysis performed by the system presenting the performance of the user, offline on the left, in real-time on the right. In particular in the right picture are being shown various elements used for generating the feedback in the virtual environment like bi-manual coordination (top center), errors of trajectories (top left), zenith points and sequencing errors (top right).

color effects the rhythm required for tossing and catching balls, a vibrotactile stimulator that enhances the catching sensation and allows better synchronization of audio stimuli and physical perception, and a trajectory envelope plotter that highlight the motion of the balls and facilitate plan of reaching operation.

V. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

The present paper has shown the current development at out center to design and test a common framework for the handling of multimodal training system. The framework designed is an hybrid approach between techniques coming from robotics and visual computation that prefer purely algorithmic solutions and those in use in motion and cognitive sciences that are strictly designed on cognitive and sensorimotor aspects.

The resulting framework allows conveying external expertise in the data manipulation and to manage data always with direct contextual interpretation. As a result, it is possible to design complete training system that exploit the analysis data to feed back training information to the users.

The framework described in this work has been designed within the activities of the SKILLS project. SKILLS takes into account five application domains for the setup of seven demonstrators: rowing, juggling, surgery, robotics rehabilitation, and industrial training.

B. Future Works

The practical example described therein only takes into account a preliminary design of the Juggling demonstrator. In the forthcoming period, this methodology will be implemented in all the above demonstrators and will be complemented with training protocols to assess the quality of on skill transfer in each of the identified domains. Further information will be soon available on the SKILLS project Website[23].

VI. ACKNOWLEDGMENTS

The authors gratefully acknowledge the contribution of European Community who co-supported the research herein described within the 6^{th} research framework program. The authors also acknowledge the partners of the SKILLS Consortium who positively contributed to build the framework herein described by their comments and observations.

REFERENCES

[1] "Computer-assisted instruction," Encyclopaedia Britannica, Website, March 2009. [Online]. Available: http://www.britannica.com/EBchecked/topic/130589/computer-assisted-instruction
[2] R. Gagne, W. Wager, K. Golas, J. Keller, and J. Russell, *Principles of instructional design*. Wiley Periodicals, Inc., A Wiley Company San Francisco, CA, 2005, vol. 44, no. 2.
[3] E. Gibson, *Principles of perceptual learning and development*. New York,USA: Prentice Hall, 1969.
[4] A. C. Alberto, "The enactive network of excellence," in *Proceedings of Haptex 06*. GENEVA – CH: MIRALab - University of Geneva, November 23 2006.
[5] Y. Yokokohji, R. Hollis, T. Kanade, K. Henmi, and T. Yoshikawa, "Toward machine mediated training of motor skills. skill transfer from human to human via virtual environment," *Robot and Human Communication, 1996., 5th IEEE International Workshop on*, pp. 32–37, 1996, http://www.ri.cmu.edu/pubs/pub_1713.html.
[6] A. Sano, H. Fujimoto, and K. Matsushita, "Machine mediated training based on coaching," in *1999. IEEE SMC'99 Conference Proceedings*, ser. ISBN: 0-7803-5731-0, vol. 2. 1999 IEEE International Conference on Systems, Man, and Cybernetics,, 1999, pp. 1070–1075.
[7] H. Esen, K. Yano, and M. Buss, "Force skill training with hybrid trainer model," in *Robot and Human Interactive Communication, RO-MAN*, no. ISBN: 978-1-4244-2212-8, August 2008, pp. 9–14.
[8] S. Calinon, F. Guenter, and A. Billard, "On learning, representing and generalizing a task in a humanoid robot," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 37, pp. 286–298, 2006.
[9] B. Bardy, D. Mottet, D. Gopher, C. A. Avizzano, E. Ruffaldi, E. Sanchez, and M. Bergamasco, "Introduction to the skills project and its theoretical framework," in *Proceedings of IDMME-Virtual Concept 2008*. BERLIN – DEU: Springer-Verlag, October, 8-10 2008.
[10] W. Warren, "The dynamics of perception and action," *Psychological Review*, vol. 113, no. 2, pp. 358–389, 2006.
[11] G. Johansson, "Visual perception of biological motion and a model for its analysis," *Perceiving events and objects*, 1973.
[12] A. Gritai, Y. Sheikh, and M. Shah, "On the use of anthropometry in the invariant analysis of human actions," in *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*, vol. 2, 2004.
[13] N. Troje, C. Westhoff, and M. Lavrov, "Person identification from biological motion: Effects of structural and kinematic cues," *Perception and Psychophysics*, vol. 67, no. 4, pp. 667–675, 2005.
[14] M. Vasilescu, "Human motion signatures: Analysis, synthesis, recognition," in *International Conference on Pattern Recognition*, vol. 16, 2002, pp. 456–460.
[15] J. Davis and H. Gao, "Recognizing human action efforts: An adaptive three-mode pca framework," in *Proceedings of IEEE International Conference on Computer Vision*, 2003, pp. 1463–1469.
[16] B. Bardy, C. Avizzano, D. Gopher, E. Ruffaldi, and M. Bergamasco, "The skills unified framework," June 2008, technical Report SKILLS Consortium.
[17] M. Owens, *The Definitive Guide to SQLite*. Apress, 2006, no. ISBN: 978-1-59059-673-9.
[18] C. A. Avizzano, E. Ruffaldi, and V. Lippi, "The multi modal data format, specifications and syntax," March 2009, sKILLS Consortium internal Report.
[19] E. Ruffaldi, "Haptic web, haptic rendering and interaction with xvr," in *XVR Workshop*, 2006, http://percro.sssup.it/pit/hapticweb.
[20] J. Behr, I. Fraunofer, and D. Reiners, "Don't be a wimp," in *SIGGRAPH 2008 Class Notes*, 2008, http://www. not-for-wimps. org.
[21] H. Austin. (1974) A computational view of the skill of juggling. [Online]. Available: https://dspace.mit.edu/handle/1721.1/6231
[22] A. Post, A. Daffertshofer, and P. Beek, "Principal components in three-ball cascade juggling," *Biological Cybernetics*, vol. 82, no. 2, pp. 143–152, 2000.
[23] B. Massimo. (2009) Skills ip. website. http://www.skills-ip.eu.