Univerzitet u Beogradu
Elektrotehnički fakultet

Master teza

Parametrizacija Pokreta Rukom: Model Zasnovan na Primitivima

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APSTRAKT

Trenutno je prisutno veliko interesovanje za uvođenje robota u rehabilitaciju hemiplegičnih pacijenata (MIT Manus, Braccio di Ferro… [2]). Osnovna motivacija za to je povećanje vremena vežbanja pacijenata, kao i smanjenje troškova lečenja. Uprkos velikom napretku rehabilitacionih robota njihovi kontrolni algoritmi su još uvek daleko od savršenih. Naš cilj je razvoj metode koja bi omogućila kontrolu robota na način koji je sličan prirodnom pokretu.

U ovom dokumentu ćemo predstaviti metodu za automatsku parametrizaciju pokreta ruke koja se zasniva na znanju eksperata. Pokreti posmatrani u ovom radu su pokreti rukom „od tačke do tačke“. Ovaj metod je namenjen za prenos znanja u scenariju u kome prvo eksperti izvode pokret i time obučavaju robota, a zatim pacijenti uče pokret radeći ga uz pomoć obučenog robota. Eksperti su zdrave osobe koje su uvežbale posmatrani pokret.

U analizi kretanja posmatraćemo statičke i dinamičke parametre pokreta rukom (krajnje tačke). Razlog za to je što je metoda razvijena za manipulandume koji su u stanju da utiču samo na krajnju tačku (*end effrctors*). Pre demonstracije metode ili eksperimenata na kojima se ona zasniva opravdaćemo redukciju kontrole proksimalnog segmenta na kontrolu krajnje tačke u ovim pokretima [4,5,6,7,11].

Metoda za parametrizaciju pokreta predstavljena u ovoj studiji je zamišljena kao klasifikator koji će iskustvo pokreta prenositi robotu u prostoru trajektorije i brzine ruke. Ovaj klasifikator naglašava fiziološke osobine pokreta posmatranih u eksperimentima koje izvode zdrave osobe (eksperti). Metod namerno omogućava određeni stepen odstupanja od "savršenog" pokreta, jer čak i zdravi, vešti pokreti pokazuju varijansu i pripadaju stohastičkim procesima. Ovaj princip je od posebne vrednosti za kasniju upotrebu u terapiji gde su varijacije zbog lezije centralnog nervnog sistema neizbežne. U ovom dokumentu, ograničili smo prezentaciju samo na deo kojim se procenjuju karakteristike brzine.

U radu je uveden termin “probability tube”, koji predstavlja razvijeni klasifikator.

Iako je prezentovana metoda razvijana za ravanske pokrete ona se direktno može prevesti u trodimenzionalni prostor. Takođe se može i jednostavno nadgraditi tako da obuhvata dodatne parametre (aplikacija na robotima sa više stepeni slobode).

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Master thesis

Action Representation of Arm Movements: Primitives Based Model

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Contents

THE CHALLENGE

Current research in the rehabilitation of post stroke patients favors intensive, assisted exercise of the paretic arm. The use of haptic robots is one method which is receiving a lot of attention today; yet, the methods to control these robots are still far from perfect. Namely, the control that mimics biological control is still not defined. One possible method to derive the biological-like control law is to capture the knowledge by analyzing effective movements (movements performed by experts) in the space of sensors and use this data to build the action representation. Fig. 1 shows the principle that is envisioned for the future improved rehabilitation.

In parallel, it was demonstrated that providing feedback that is motivating increases the effectiveness of the therapy. One favorable method to increase the motivation is to use visual feedback (e.g., virtual reality, Wii games). For the use of this kind of feedback it is of interest to design an interface which will allow the development of action representation that is adequate for later direct implementation within the robot environment. In the first phase the research concentrates on relatively simple haptic robot which was designed for planar movements (MIT Manus, Braccio di Ferro [2], or similar), so the decision was made to look at the possible use of mechanical or electronic movement generator that will translate the planar movements of the hand into the required motions of the game or virtual reality controller. This task directly led to the design of a mechanical function generator (pantograph) and an electrically controlled movement generator. Based on the known redundancy of the arm structure the end point movement was anticipated to have stochastic nature; thus, the methods for action representation are assumed to use methods that are suitable for the analysis of stochastic processes.

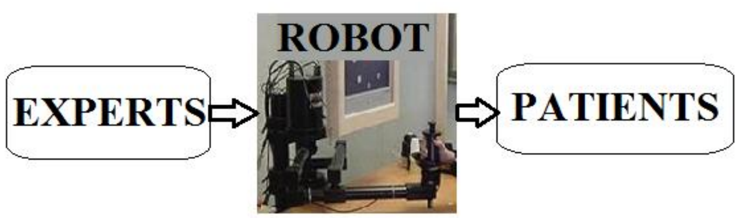

Figure 1 : The concept of the new modality for training of motor skills in individuals with sensorimotor disability

The elements that were the core of the research presented here are:

1. selection of the game that will be used as the feedback;
2. capturing of the data that can be used for action representation;
3. analysis of the movement in the sensors space; and
4. data fusion that leads to the action representation.

INTRODUCTION

Learning from an expert: Development of the interactive learning paradigm

To re-establish movement abilities a person with sensorimotor disability (patient) should be practicing and learning fundamental movement skills since the mastery developed does not come all at once. It is important to consider that patients do not have all the components of the sensorimotor systems that are available to healthy subjects. Therefore, the learning needs to go through a series of developmental stages, mostly through the training. The goal of the training should be to assist patient to move to the next most natural version of the skill he/she is learning, rather than pushing him/her to perform the skill the way a healthy subject would.

When a person is learning new motor skills after stroke caused by a cerebro-vascular accident (CVA) several processes are taking place: 1) the neural substrate is likely developing new connections (cortical plasticity), 2) the muscles that have not been used for some time are getting stronger, and 3) possibly some of the injury related reflex changes will deteriorate. In order to optimize the learning it is important to provide the patient with as many opportunities to explore all possible movements in a rich environment in a manner that is both safe and challenging. As the skill begins to emerge naturally, learning can be dramatically improved through opportunities for fun practice using lots of different equipment and materials.

We anticipate, based on the results of using electrical stimulation within a paradigm termed Functional Electrical Therapy (FET) (Popovic et al., 2003), that the optimum time to learn the skill after CVA is in the acute stage of the disability. At this time, assisting the patient through simple instruction and practice can improve learning, and pay great dividends. If the patient goes too long without learning a skill, then learning it may become more difficult. However, the sooner the patient starts to overcome the learning deficit the easier it will be for him/her to catch up and develop the skill and confidence needed to be fully active with their friends and peers. The specific problem after stroke is the development of compensatory strategies and neglect of the use of the affected arm due to more intense use of the nonparetic arm and hand.

Here we dedicate the attention to the “learn from an expert” scenario. In this scenario, the robot trainer would have learning capabilities and in particular it will be capable to build its internal representation of the motor task by mimicking expert human movement. This means that the expertise of healthy subject will be translated into the control of a robot. This was hypothesized to be doable by watching expert humans while repeating the same motor task by a representative set of sensors. The outcome of the learning process is a state space representation of skilled gestures created by the “biological” teacher, and the underlying control law. Once this representation is developed, then the control model can be built and used for the training in patients.

The first phase of the scenario requires that the teacher (healthy subject=expert) performs precisely defined motor task that can be later offered to the patient when being trained by the robot. The motor task should be challenging, interesting, and must allow grading the level of difficulty. For that reason we decided to include the Nintendo Wii platform which supports games characterized by a high degree of interactivity through the Wiimote game controller instrumented with accelerometers and gyroscope, and LED position tracker to detect the movement of the player. These games are highly motivating and imply the acquisition of complex sensorimotor skills. For this reason, they constitute an appropriate benchmark for the learning from an expert scenario, but also they could find an immediate application in the rehabilitation domain.

Game types. Nintendo Wii games can be roughly divided into two typologies: 1) competitive, in which the player has a competitor (other player or the Wii) with whom he/she directly interact and its actions are the results of such interaction. The examples are tennis, baseball, table tennis, boxing, etc; and 2) non/competitive, in which the player is exposed to a difficult task and needs to find a strategy to maximize performance. In this case, the player and his/her competitor (if any) do not interact directly. The task may be of targeting type, or may involve the control of an (unfamiliar) tool or device. The examples are bowling, golf, shooting, driving a vehicle/flying a plane, etc.

Transfer scenarios. The expert-non expert transfer scenarios could also be of two types: 1) sequential where the expert plays the game. Expert movements and other performance-relevant information are recorded, and used to set-up a scheme of assistance which captures his learned skill. Then a non-expert is exposed to the game while a robot provides physical assistance. Alternatively, the basic gestures are captured from expert recordings (e.g., forward and backward strokes in tennis). During non-expert performance, motor intentions are captured (e.g. intention to perform a forward, backward stroke). Intentions trigger specific schemes of assistance; and 2) parallel where the expert and the non-expert, or two non-experts play the game at the same time. In this case, suitable assistive forces are generated and applied to the non-expert player.

Interfaces for Wiimote. The Wiimote was developed to be held and manipulated by the hand/arm in the space. In this way the player generates accelerations and positions the controller with respect the projected image on the screen. The signals are recognized by the Wii console, and the play is made interactive. This directly suggests that the acquisition of skills is equivalent to capturing the movement of the Wiimote and the direct method is to link the robot and the Wiimote during the play.

Each robot is characterized by its peculiar workspace and by its number of degrees of freedom. The robot should have enough degrees of freedom to allow the player to perform the movements required by that particular game. As all games are controlled dynamically, by acceleration and angular rate signals, the robot workspace is much less of an issue (the same game can be successfully played through movements of very different amplitude). One possibility is to rotate the robot workspaces (e.g., mounting the robots vertically) or to modify the workspaces by using mechanical appendices (sticks, levers), to transform e.g. translations into rotations. The gadgets for the testing that we have so far developed are mechanisms that allow simple movements of the handle (device held by the hand that is part of the robot). These are mechanical systems that either include the Wiimote or control the Wiimote that is electrically driven generating Wiimote motion that momics the motion as when held in the hand (Fig .2).

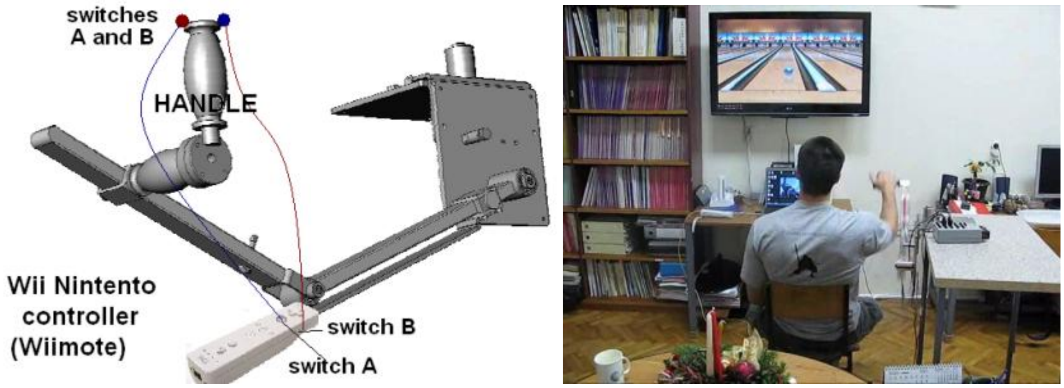

Figure 2 : The function generator (pantograph) for transformation of planar to rotational movements that is suitable for Wiimote and 2D robot (left panel), and the use of the system for data collection (right panel).

Experiment scenarios

The possible scenarios that are considered with this system include: 1) competitive game, sequential transfer; 2) non-competitive game, sequential transfer; 3) competitive game, parallel transfer; and 4) non-competitive game, parallel transfer. This relates to the following games that can be used for the training of non-experienced subjects (patients): bowling (3D robot such as Omega, Falcon with the reduced workspace) or 2D robot (e.g. BdF) arranged vertically; tennis (3D with the reduced workspace or 2D robot with the rotational degrees of freedom added mechanically); table tennis (3D wrist robot with the limited workspace); flight simulator (2D robot, with the mechanically added rotations).

Implementation details

The competitive-sequential scenario requires: 1) recording of basic movement gestures (i.e. in tennis: serve, backward and forward strokes) from expert movements; 2) on-line prediction of motor intentions in trainee (H3D software); 3) assistance module for each basic movement gesture (could be just a simple position controller, driven by the corresponding expert gesture).

The Non-competitive-sequential scenario requires: 1) module for detection of time of release, position and velocity at release during successful expert movements; 2) approximation of the position-velocity mapping corresponding to successful hits from expert data; and 3) assistance module which pushes trainee hand toward a position-velocity couple that is compatible with success, based on the above mapping.

It is important to state that while competition is important, it is learning to compete that should be the focus – not winning. It has been reported that for best long-term results 70% of time in the sport should be spent in practice, with only 30% of the time spent on competition. This is the time to develop and refine all fundamental movement skills, and learn overall sport skills. By this time patient have developed clear ideas about the skills they like and in which they feel they have success, and this should be encouraged. The focus should be on exercising at least 2-3 skills in different seasons. Focusing only on one skill for longer times should be discouraged. Optimize training and competition ratios and follow a 60:40 % training to competition ratio. Too much competition wastes valuable training time and conversely, not enough inhibits the practice of technical/tactical and decision-making skills.

Based on the initial testing [9] the decision was made to reduce the complexity in the initial phase of the development of the action representation to somewhat more simple motor task. Having in mind that the first phase of research is mostly focused on planar robots (Braccio di Ferro, MIT Manus [2]…) and that pointing and point to point arm movements are quite thoroughly described in literature [4,5,6,7,11] we have decided to start from there. The presented method will be the basis for action representation of planar pointing and point to point movements. This method for action representation, called "probability tube", is a classifier capable of estimating the quality of movement, based on data gathered from expert's knowledge.

The method

In this document we will present a method for automatic action representation of point to point hand movements based on knowledge gathered in experts' trials. This method is intended for sequential transfer scenario, because action representation is based on data sets containing several trials.

In the analysis of pointing movement we will only observe static and dynamic parameters of hand (endpoint - EP) movements. This is done since the method is developed for manipulandums which are able to affect only the endpoint. Before starting any demonstration of the method or the experiments on which it is based we will justify the reduction of the proximal segment control in these movements to endpoint control.

Method for action representation of movements presented in this study is envisioned as a classifier that will capture the experience of the movement by observing the trajectory and velocity of the hand. This classifier emphasizes biological-like movements observed in trials performed by healthy individuals (experts). The method intentionally allows certain degree of deviation from "perfect" movements, since healthy skilled movements show variance and belong to stochastic processes. This principle is of specific value for later use in therapy where the variations due to the central nervous system lesions are unavoidable. In this document, we limit the presentation only to the part that estimates characteristics of velocity.

We introduce here a term "probability tube", which is actually the classifier.

This presentation relates to only planar movements; yet, it can be directly translated to 3D, and it can also be generalized to incorporate additional parameters (application with robots with more degrees of freedom).

ENDPOINT CONTROL

There is an approximately linear relation between elbow muscle torque and shoulder muscle torque when people are free to choose the path of their hand to point at a target in front of them (e.g., Gottlieb et al. (1996), M. Popovic et al. (2002)).

Linear covariance of shoulder torque and elbow torque is seen in natural pointing movements, but not when people point in a less comfortable way. This suggests that the linear relation serves movement economy by linking the timing of torque pulses. In the pointing movements that Gottlieb et al. (1996) studied, torque profiles typically exhibit a biphasic form. A linear relation between two biphasic torque profiles results from a strict temporal coupling of the torque pulses. Since deviations from linearity sometimes are observed, this relation cannot be simply a hard-wired biomechanical artifact of a moving linked system. Rather linearity may be a natural organizing principle for decreasing the degrees of freedom at the level of muscle torques, at least for those movement tasks that can be accomplished under such a constraint.

Such correlation in pointing and reaching movements can be spotted even in infants. It is present and well defined before they develop any other adult-like strategy in these movements as shown by Zaal et al. (1999). Their results suggest that the principle of linear synergy is a fundamental property of the human neuromotor system from early in life and is likely not learned as a means to constrain the kinematics of the hand into the forms seen in adult reaching. They stipulate that the principle is not responsible for the straightness of the hand path nor for the unimodal bell-shaped velocity profile. Concluding that the following the principle of linear synergy does not simply lead to the kinematics we well know in adult reaching. Rather, successful reaching for a target must be sculpted into the temporal structure of the torque patterns from this preference of the system to apportion dynamic torque proportionately and synchronously between shoulder and elbow. The principle acts as a constraint in the high-dimensional space of kinematic and dynamic possibilities, thereby reducing the degrees of freedom of the problem of learning to control the arm for purposeful activity (Bernstein, 1967).

Being that movements included in this study have no constraints and are performed by healthy individuals in a natural way, it is possible to assume that such correlation between elbow and shoulder torques is present in all of the movements. Thus we can conclude that this type of parameter reduction is justified for the purposes of movement representation.

With that concern settled, we can proceed with forming the action representation method.

THE EXPERIMENT

Given that the entire process of forming, testing and validating the “probability tube”[1] is based on experimental data, we have created a more complex, wide-ranging experiment which can be performed routinely in standard clinical conditions. Having the clinical use in mind the entire setup of the experiment is specially designed in order to be robust and easy to use.

Experiment used in this research consists of two parts. The purpose of the first part is to generate a knowledge base of well defined movements which is then used to create adequate “maps” for robot guided assistance. The second part of the experiment is used to validate the method by testing its generalization on similar; yet, different movements. The setup is shown Fig. 3. All references to coordinate system and the movement layout will be in respect to notations introduced in this figure. All performed movements emphasize extension.

In both parts of the experiment, while performing tasks, all of the subjects were strapped to a rigid chair with comfortable set of belts that goes around shoulders and across the chest of the subject, preventing trunk movement.

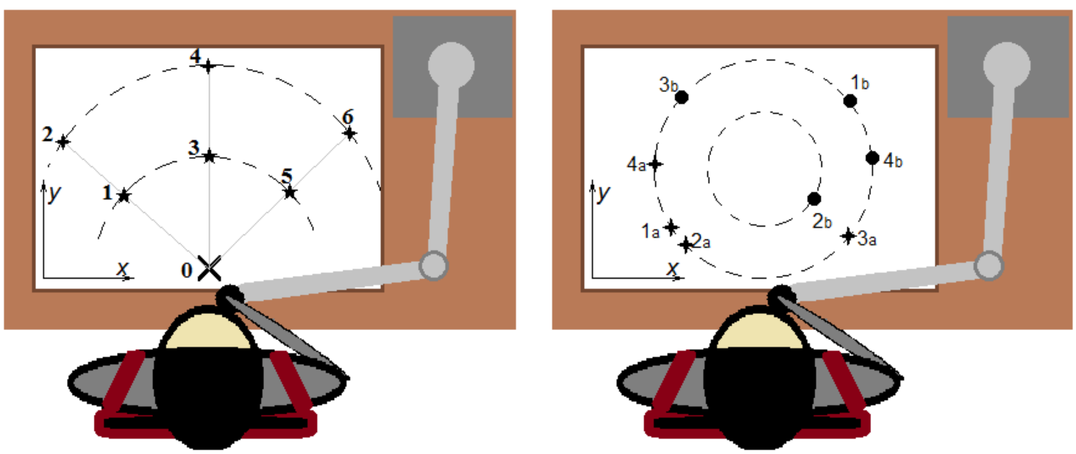

Figure 3 –Part of the experiment where subject performs pointing movements (left panel), and part of the experiment where subject performs point to point movements (right panel)

The first part of the experiment is comprised of six radial point to point movements. These six movements could also be anticipated as pointing movement. The movements can be described as long and short, and they are performed in three directions (Fig. 3, left panel). The initial point of movements is 0, marked at the central line of subjects’ body at approximately 40% of his/her ability to reach. Long movements are from the initial point to 90% of the maximum reach in the given direction, while short movements are 50% of the long movements.

[1] “Probability tube” is one possible type of action representation that can be used for transfer of expertise for the control of the robot.

The experiment includes four set of trials. Two first sets are normal (self-paced) and fast movements with the pantograph. In fast movement subjects were asked to move the hand at about 90% of their maximum ability with the given task. The second two sets follow the same protocol, but they are performed without the pantograph (Fig. 4). This setup was included to allow the influence of the pantograph (disturbance of the free hand movement). We made every effort to minimize the friction between the mouse and the handle in the experiments without the pantograph.

In order to seemingly randomize tasks the order of movements was: 1, 4, 6, 5, 3, 2. Subjects performed the tasks for 10 times.

This experiment provides us with information about the radial point to point movements performed in three different directions, two different lengths and two different speeds. This allows us to generate the representation and later test the generality of representation in point to point movement that are not radial.

The second part of the experiment has four movements, as shown in Fig. 3b. These point to point movements were performed with pantograph (normal speed and fast), similar to the first part. The purpose of this part was to verify the representation generated in the first part, and to assess whether such representation can be further generalized on other movements.

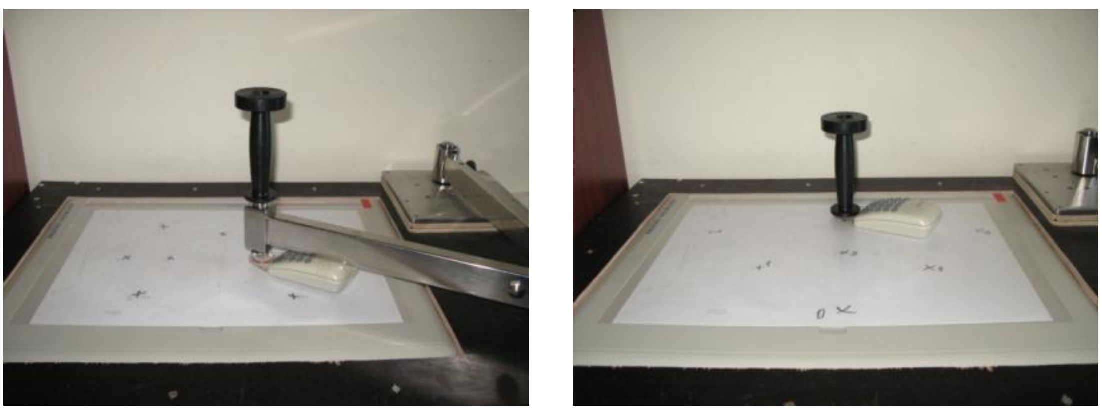

Figure 4 – The experimental setup with pantograph (left panel) and without pantograph (right panel)

Subjects

Nine subjects (three females and six males, age 20 to 24, all right-handed) participated in the experiments. All subjects were able bodied individuals with no known neurological or orthopedic deficit. All subjects signed the informed consent approved by the local ethics committee.

Instrumentation

Since this experiment is intended to be regularly used in rehabilitation facilities it was very important that the setup is simple, easy to use and resistant to failure. For this reason we decided to base all of our measurements on commercially used devices: CalComp Drawing Board III, and custom made LabVIEW virtual instrument.

Recording of data in this experiment is done with CalComp Drawing Board III, shown in Fig. 4. This sensory system records the absolute position of the *mouse* in coordinate system originating in the lower left corner of the board. Data transfer to PC was done directly from Drawing Board III using serial port.

The sampling rate of the board is set on 100Hz. This is high enough to record all of the voluntary movements performed by healthy individual as well as all pathological movements that can be expected in hemiplegic patients that are characterized with the spectrum that is below 10 Hz. 100 Hz was selected since the probability tube is in the velocity space, and the velocities are calculated by numerical derivation.

Spatial resolution of Drawing Board is 40 samples per mm.

Data acquisition was performed in custom made LabVIEW 2010 virtual instrument. This virtual instrument simultaneously records data from CalComp Drawing Board III and other sensors (accelerometers, gyroscopes, goniometers).

Each task in a trial is recorded separately in order to facilitate later data analysis.

Besides reliable data acquisition special attention was paid to creation of user interface. User interface, shown in Fig. 5 informs the operator and the subject which movement is next (both in number and target position), how many movements is left, and is the recording on. It also allows following of the key parameters in movement to the operator, enabling him/her to detect any irregularities in subject's performance.

There is a screen with data acquisition interface which is shown to subjects while they perform the task. It is the same screen as the one that operator can see, without key parameter data, which could temper with subject's performance.

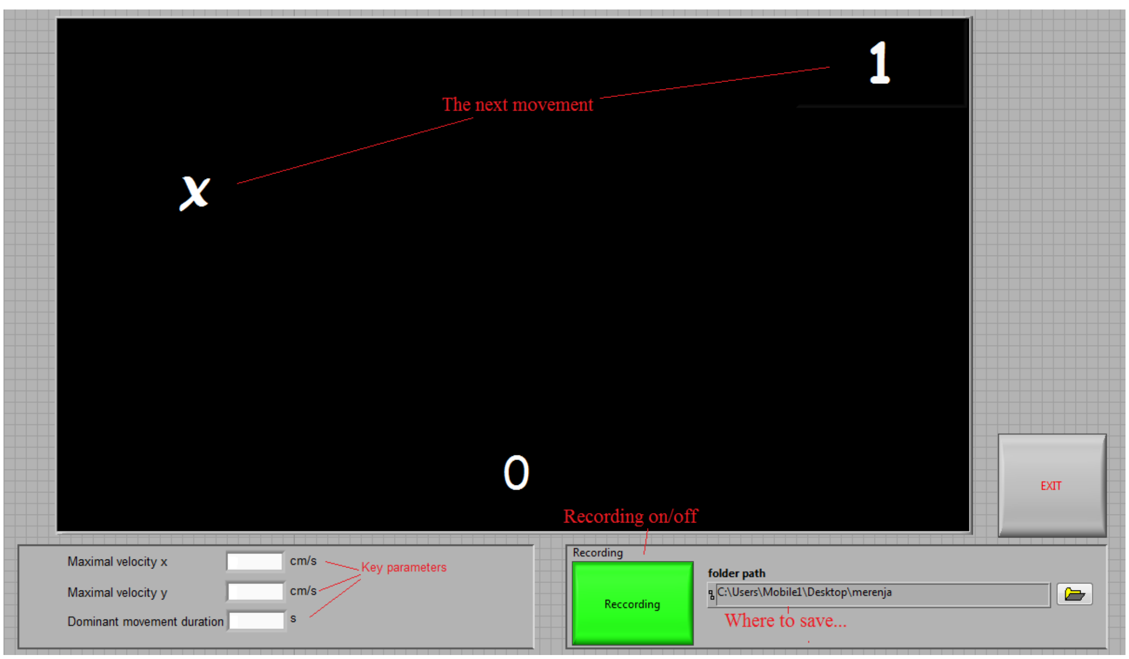

Figure 5 – The screen shown to the operator during the experiment. The screen shown to the subject is the same, without the box in the lower left corner.

Offline data analysis was done in MATLAB 2009a.

The pantograph used in this experiment is a mechanical rig with two cylindrical joints, as shown in Fig. 2 and 3. It has no friction and low inertia. The more detailed description of the pantograph is given in [9].

We are using the pantograph as an assistive tool in our experiments intended to simulate restrictions imposed by planar robots. With this tool it is generally possible to deliberately introduce some resistive forces for purposes of motor control training. When that is not done, as here is the case, the pantograph shouldn't interfere with normal movements.

As mentioned in the experiment description all movements in the first part were performed both with and without the pantograph. The purpose of this was to determine the perturbation that the pantograph introduces and eliminated complex computations related to the mechanics. For that we decided to use black-box model with three key parameters, trajectory, velocity and acceleration, of the handle in these two types of trials. The main reason follows the fact that the mechanics of the pantograph introduces a highly position of the end point, velocity of the end point, and angular accelerations and rates of the pantograph dependent load even when considering zero friction. Namely, the mechanical effect of the pantograph with two rigid bodies can be analyzed by using the law of momentum. The sketch of the system in the horizontal plane is:

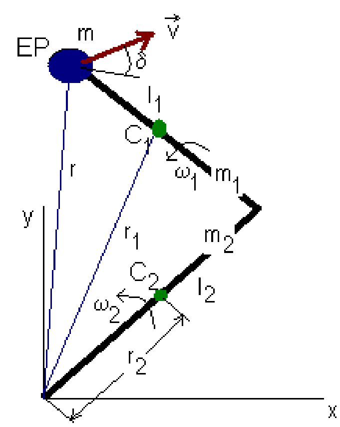

Figure 6 – I_1 and I_2 are inertia moments for the center of mass of pantograph rods. C_1 and C_2 are centers of mass, EP is the end point (handle); m, m_1, and m_2 are masses respectively. ω_1 and ω_2 are absolute angular velocities of the pantograph bars. r, r_1 and r_2 are distances to the center of masses with respect the reference point.

The equation that describes the mechanics of the pantograph in the horizontal plane comes from the law of momentum

$$M = \frac{dL_z}{dt}$$

where Lz it the kinetic moment of the system with respect the z axis.

$$L_z = mrv\cos\delta + I_1\omega_1 + m_1 r_1{}^2\omega_1 + I_2\omega_2 + m_2 r_2{}^2\omega_2$$

Therefore, the momentum that needs to be generated by the hand is

$$M = F_T r = \frac{d(mrv\cos\delta + I_1\omega_1 + m_1 r_1{}^2\omega_1 + I_2\omega_2 + m_2 r_2{}^2\omega_2)}{dt}$$

The F_T is the tangential force that it is required to compensate for the inertia.

In the Fig. 7a and 7b trajectories of one trial of the first part of the experiment with and without the pantograph are given. Only the dominant[2] part of movements is shown. These are randomly chosen trials that represent majority of trials with parameters within normal limits performed in this experiment. All tasks shown in both figures are from the same trial.

Velocities of one task with and without pantograph are shown in the Fig. 7c and 7d. As previously only the dominant part of each movement is shown. All trials are from the same subject.

Accelerations of the same task (same trials) are shown in Fig. 7e and 7f.

The differences in trajectory between trials with and without the pantograph are inside the limits of within-subject variability.

Both with and without the pantograph velocity has distinct bell-shaped pattern. There are no statistically significant differences between velocity patterns in these two groups of trials.

The only difference between the two groups can be noticed in the acceleration. Acceleration in trials performed without the pantograph has additional higher frequency component superimposed on what would be the expected acceleration in this type of movement. This can be noticed in Fig. 7b. where acceleration curves appear less smooth. The reason for this is existence of friction between the CalComp Drawing Board III and mouse in trials without the pantograph.

One other phenomenon is noticed in trials without the pantograph. The overshot that usually appears in trials with pantograph, and is later corrected with submovements, is much smaller or even absent in trials without the pantograph. This is a consequence of a well known control principle. By introducing a dumping force, in this case friction, control of the actuator becomes easier. It is also possible that additional sensory information (tactile) is helping subjects assess the position of their hand during the movement, but that is not the subject of this study.

[2] Dominant part of the movement will be defined and explained later in the text

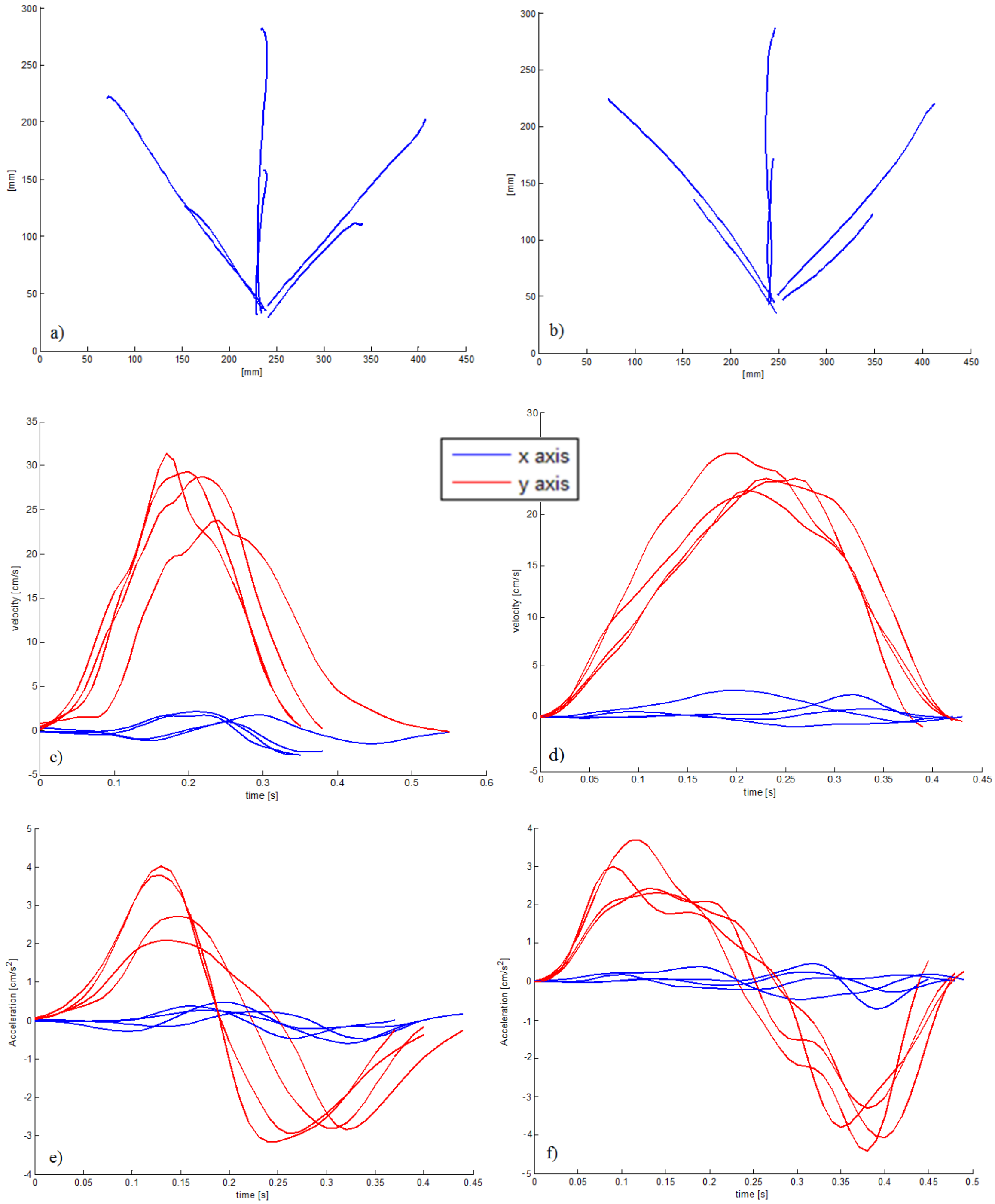

Figure 7 – Trajectory, velocity and acceleration for trials with pantograph (left side) and trials without the pantograph (right side)

DATA ANALYSIS

Once the data is recorded and we have trajectories, velocities and accelerations of hand for all movements we can begin data analysis which will eventually result in action representation of recorded movements.

Data recorded for each movement is analyzed in three steps.

In the first step we determine phases of the movement and extract the one that is of interest to us. Once we have limited each movement to the phase of interest we can precede to the second step.

The second step is the only one different in the process of trajectory and velocity estimation. In this step we manipulate the way observed parameter is presented in order to get consistent presentation in most of the trials. This is demonstrated on the example of velocity.

The final step is making the "probability tube" itself. Being that this is the key to the entire process it will be described in a separate chapter.

Phases of the movement

In this type of movements we can usually determine three different phases. First phase is preparation, in this phase small movements can be recorded, while the subject is anticipating the command to start moving. The second phase is the dominant movement (DM), which is the part of the movement in which the hand is moving towards the goal with the bell-shaped velocity [4]. The final part of the movement is made out of corrective submovements. It is believed that these submovements occur in order to compensate the error made in DM, but there could be some other reasons for this phenomenon [4].

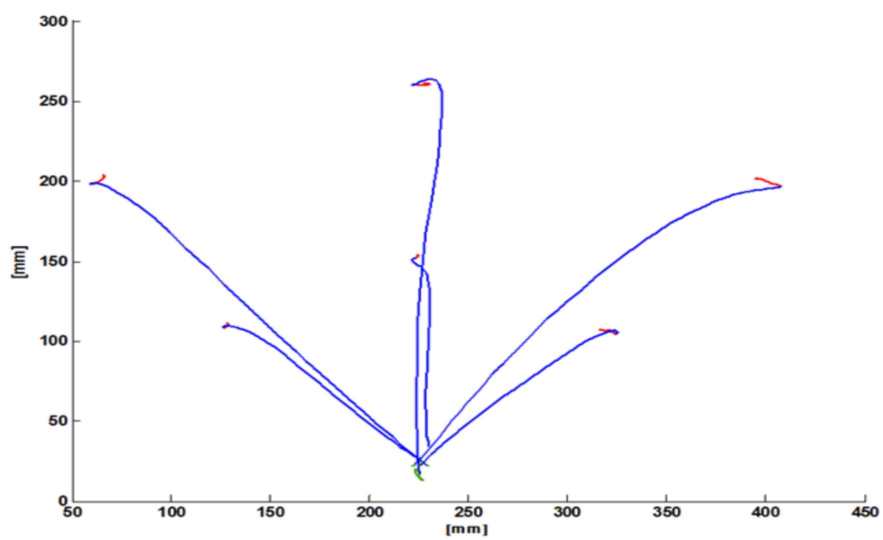

Figure 8 – Trajectories of one trial of the first part in the experiment. Blue part of the trajectory is the one classified as dominant movement. Initial part (green) is recordings before the onset of the movement. The final part (red) is submovement used to correct the positional error

One trial of the first part of the experiment is shown in Fig. 8. These are trajectories of one normal trial with pantograph. Each phase is presented in different color.

These phases are determined by observing dynamical parameters of the movement, velocity and acceleration. The onset of the movement, point between the first and the second phase, is determined as the moment when velocity reaches 5% of maximal velocity recorded for that movement. The end of DM is determined at the moment of first acceleration zero crossing from negative to positive, as suggested in [4]. In Fig. 9 we can see an example of movement phase classification. In this document we will present a method for action representation of dominant part in pointing movement.

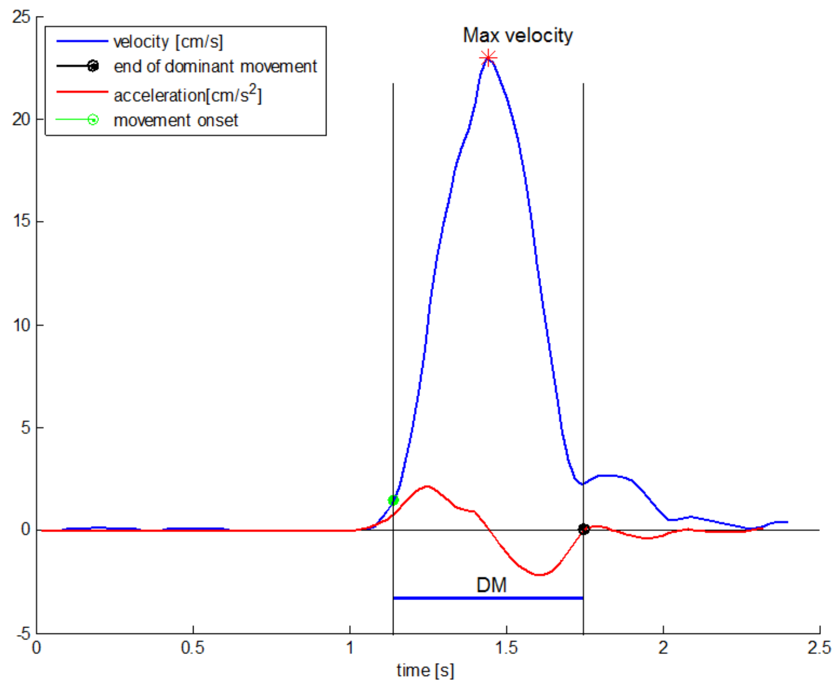

Figure 9 – Dominant movement (DM) is between movement onset(green o), which is considered when velocity reaches 5% of max and first acceleration zero crossing from negative to positive (black o), as suggested in [4]

Parameter presentation

It was already mentioned that in this document we will demonstrate the concept of the "probability tube" for velocity. The only difference in the proposed process of action representation for velocity and trajectory is in this step. This is the step in which data is prepared for the "probability tube", which itself is a universal method that can classify any type of data, provided that it is properly prepared. Here we will show what it means to prepare data for the "probability tube", and also introduce a novel way of perceiving velocity.

Velocity of hand during the movement is a vector. In order to present it in a clear way we can decompose it to *x* and *y* components, respecting the notation introduced in Fig. 3. Velocity components for several trials of the same task, for one subject, are presented in Fig. 10. Since this is 0-4 movement *y* component is dominant, and it contains most of the information. Velocity graphs in all trials are familiar bell shaped curves. Never the less, we can see that due to slight variations in velocity over time there is a large dissipation on the graph, which results in different shapes of component curves. The subject who performed these trials is a healthy, able bodied individual, and the trials were performed under supervision of the author, where all key parameters were regularly monitored. Having that in mind, we can assume that the inconsistencies that appear here are not due to irregular performance of the subject, but rather come from the way data is presented.

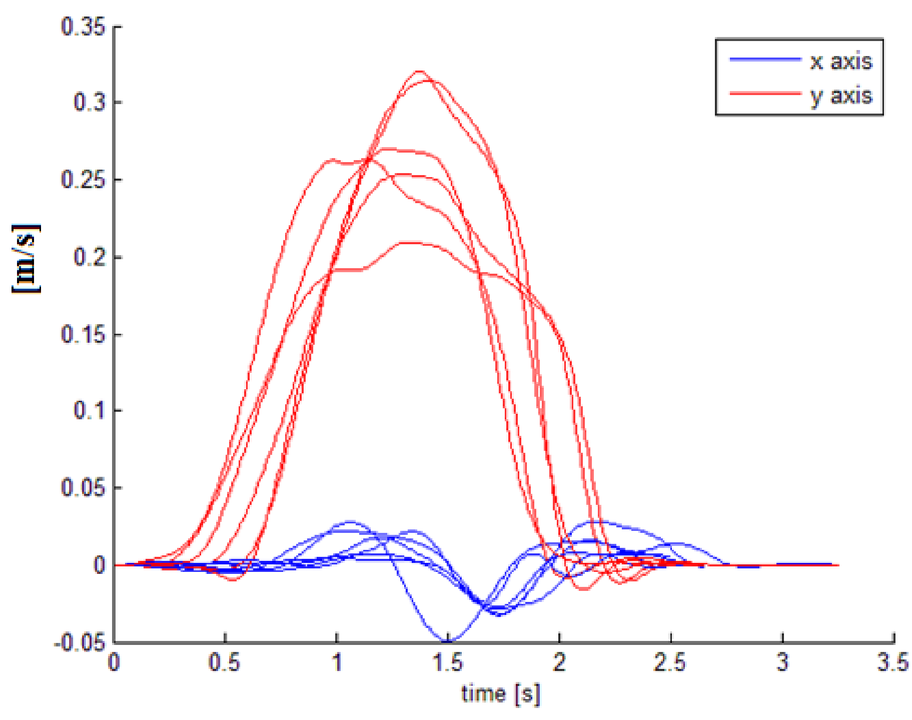

Figure 10 – **EP velocity of the dominant movement.** We show several trials from one subject while performing movements 0 to 4 during in the setup with the pantograph.

Different approach of presenting velocity components is given in Fig. 7. The same velocity components are presented, but in respect to position along the trajectory, rather than time. We can notice that there is a well established shape of velocity curves appearing in these movements.

This is done in order to eliminate the variability of the bell shaped velocity with respect the time (amplitude and duration). This process should be considered as the normalization and it leads to transformation of the presentation of velocity *vs.* time to the velocity *vs.* distance, and later velocity *vs.* trajectory phase.

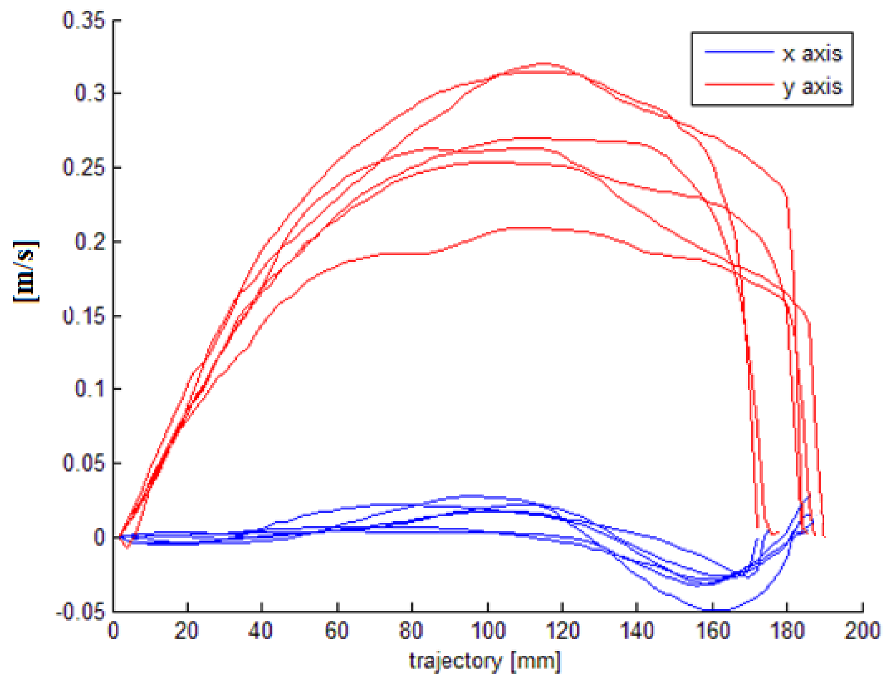

Figure 11 – **EP velocity of the dominant movement.** We show the same movements as in Fig. 10. Both components of velocity are presented in respect to position. In this way the representation is partly normalized.

The transformation process is the following: The trajectory in divided in segments (1 or 2 mm, depending on movement length), and then for each of these segments the EP velocity is calculated as the mean velocity for all samples within this segment. The algorithm for calculating the normalized EP velocity (Fig. 12) is:

1. In order to divide the trajectory to 1 or 2mm parts we chose a starting point. At the beginning the starting point is first sample.
2. The loop is created that will go through following steps for each sample
3. We assume that the current sample can be the end of the current small part
4. We calculate the length of trajectory between the beginning and the current point, if that length is more then 1(2)mm then

5. Velocity at that part of movement is mean of all velocity samples between beginning and end
6. New part begins at the last point of current part
7. Calculated velocity is added to positional velocity array

8. If the condition from point 4. is not met we take next sample and repeat the procedure starting from 3.

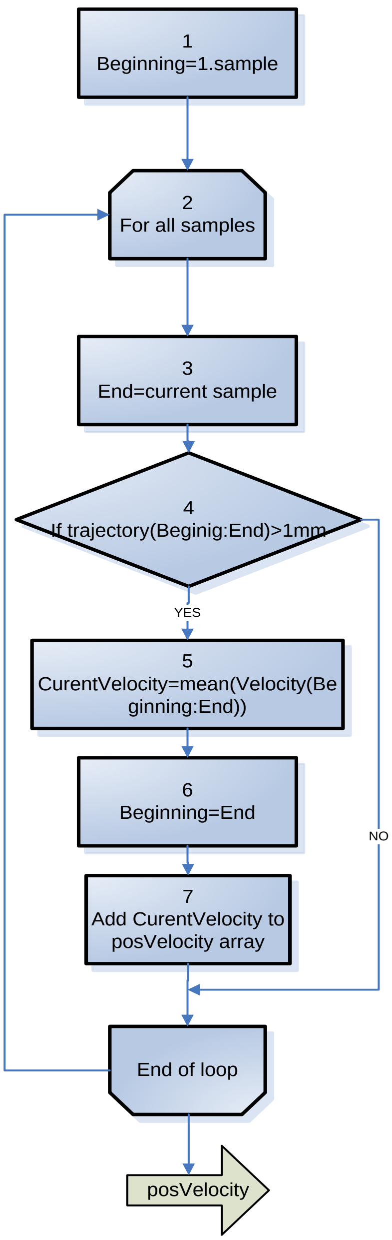

Figure 12 – Algorithm for calculating the normalized EP velocity

From the Fig. 11. we can notice that there are slight variations in the length of trajectory. Since differences are less than 5%, we assumed that they have little effect on movement strategy, and decided to disregard them.

In order to overcome this source of variation we can normalize trajectories, and observe velocity with respect to the trajectory, but in relative, not absolute terms. This allows us to compare parameters at certain percent of the movement, rather than at certain distance from the start. This is not only justified, but even favorable since movement strategies are generally not formed by the cm but by movement phase [7]. Data presented in this way is given in the Fig. 13.

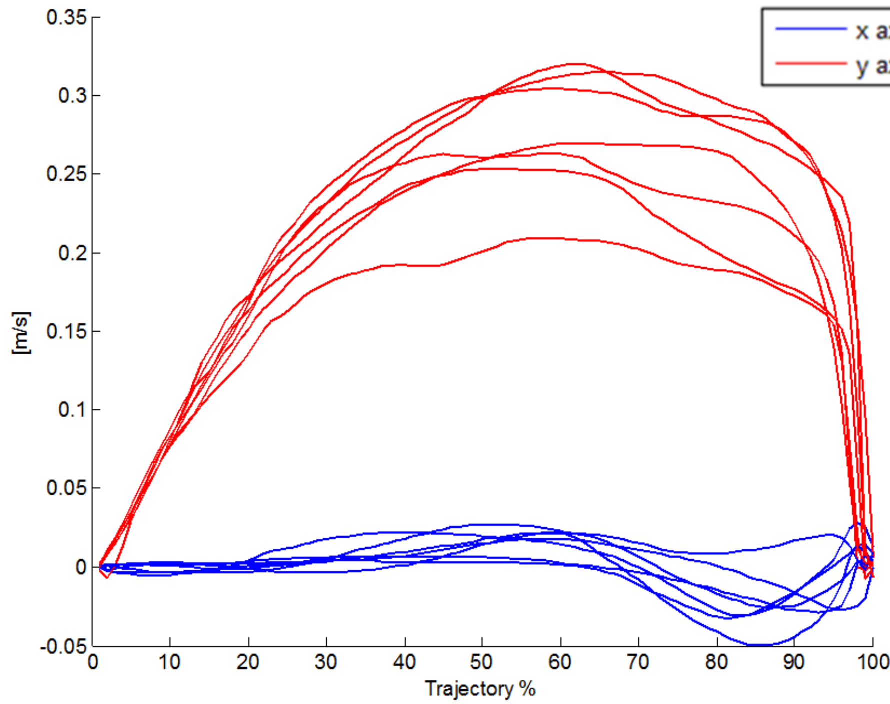

Figure 13 – EP velocity in DM presented in percent instead the length of the trajectory (Fig. 12).

Once the data is presented in this way it is possible to analyze the parameters describing the expert assumed movements. Besides having a bell-shaped velocity the curve for all subjects tends to remain almost the same along first 15 to 20% of the movement. The variance progressively rises up to about 80%. Finally, the variance is slowly decreased. After 95% of the movement the velocity rapidly falls to 0. These findings are in accordance with the results presented in [6, 7, and 11].

The existence of such clear pattern that fits all trials allows us to compose a method for automatic action representation of planar point to point movements based on expert's knowledge gathering.

THE "PROBABILITY TUBE"

The method for action representation presented in this document is called "probability tube". Even though the entire method bears the name "probability tube" forming of the tube itself is just the last step of the entire process. In this chapter "probability tube" will refer to this step, not the entire method.

The presented method is general for automatic action representation of planar point to point movements based on expert's knowledge gathering. In the other hand the "probability tube" is a classification tool that can be used for representation of any parameter as long as data sets are harmonious enough.

The entire process of making the "probability tube" is given as flow chart in Fig 13. This algorithm will be described on the example of intensity of velocity vector.

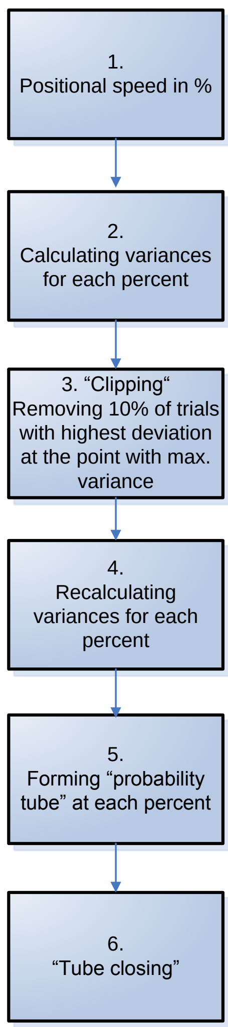

Figure 14 – Algorithm for synthesis of the "probability tube"

Each of the steps given in the Fig. 14 will be explained. All visible changes to data will be demonstrated in figures shown along the explanation of the step in which they occur.

1. **EP velocity in % –** Input data for this algorithm in this example is positional velocity from all subjects that are participating in the training process. Calculating positional velocity is described in the algorithm shown in Fig. 15.

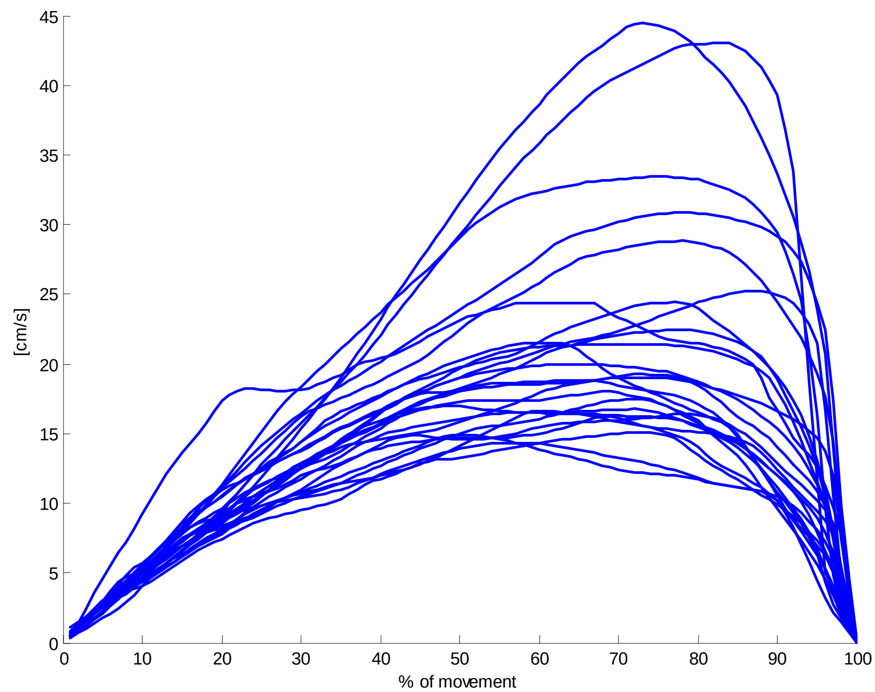

Fig. 15 – EP velocity in dominant movement in percent. Here, trials for the 0-1 movement from several subjects are presented. These trials will be used for synthesis of the example of the action representation.

2. **Calculating variances for each percent –** at every percent a sample of each trial is taken and an array is formed. Variance of one of the arrays formed in this way presents the variance of velocity at the percent corresponding to the array.

3. **"Clipping" –** as shown in Fig. 15 there is a possibility that some trials will be significantly different than others. These trials are exceptions to the rule, and should be treated as such. That is why from all arrays calculated in the previous step we take the one with the highest variance. In that array we eliminate the worst one. This process is repeated until 10% of trials is "clipped".

This way the variance of the entire structure is diminished. The biggest effect is at the part where variance was highest. On the other hand the data set is not too impoverished even if the excluded trials weren't all abnormal.

We chose median rather than mean, because it is not affected by extremely deviated trials. The change in median after the "clipping" is always the same, while in mean it can vary depending on clipped trials.

The data set after "clipping" is shown in Fig. 16.

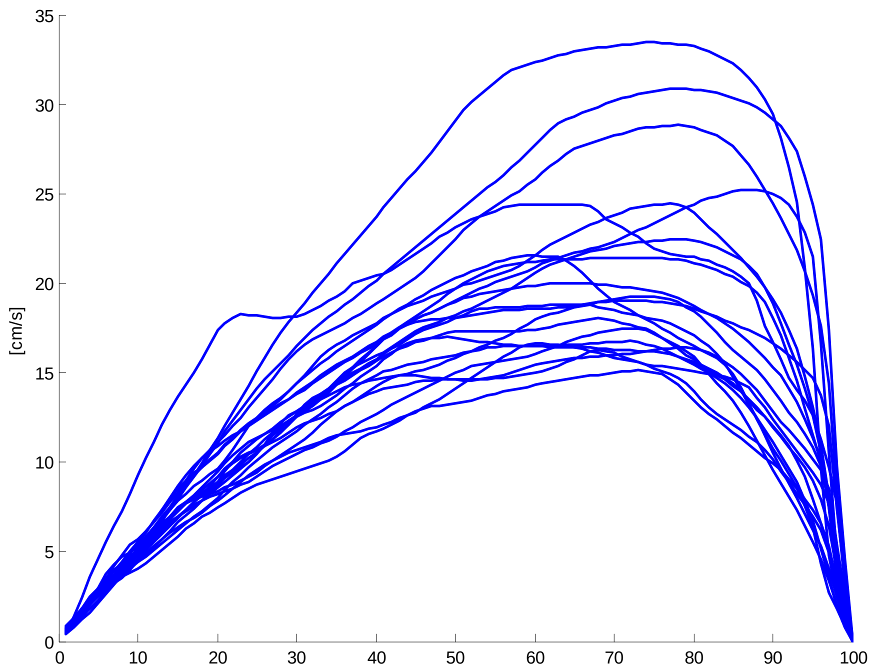

Figure 16. – "Clipped" data. Of all trials 10% of trials with worst variance are "clipped" from the set, leaving data with significantly better statistical properties.

4. **Recalculating variances for each percent** – after the "clipping" we repeat the procedure from step 2.

5. **Forming "probability tube" at each percent** – The "probability tube" formed in this step for the example is shown in Fig. 16. The tube allows deviation from the "ideal" values, but in a way that is founded in expert's trials. In parts where trials are harmonious it should be narrow, with over all high probability, while in parts with high variance it should be wide with ranging probability.

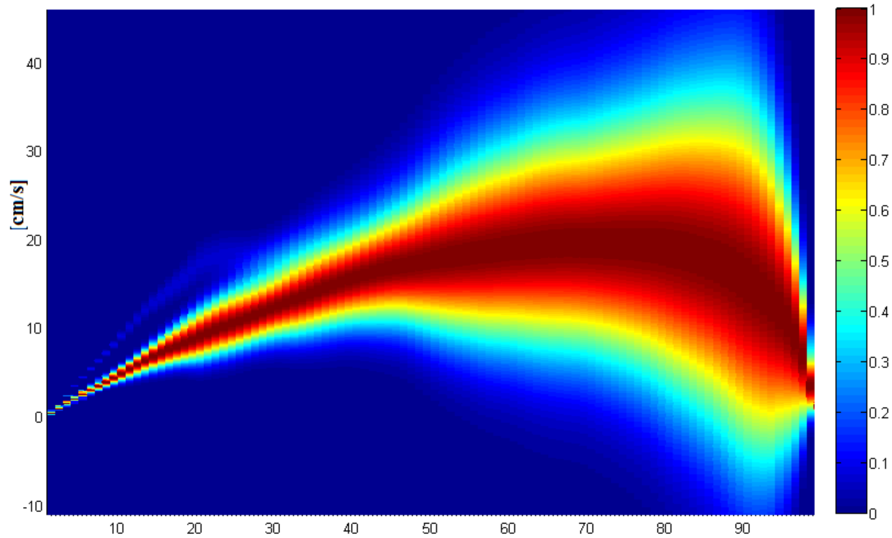

Figure 17. – Primary "probability tube" for EP velocity. This is the result of statistical analysis in which probability of velocity in each percent of the movement is calculated as superposition of Gaussian curves formed for velocity of each trial at that percent. At one percent all Gaussian curves have same variance, variance of velocity at that percent, and they are centered on specific velocity curves.

This step is the key point in the algorithm. There for it is presented by a flow chart given in Fig. 17. The process is done in two steps.

5.1. First step is a loop that performs two operations for all trials at the given percent

5.1.a Calculate the Gaussian curve centered at the point of the current percent of the current trial, with standard deviation equal to the variance of array at the current percent.

5.1.b Add this curve to other curves calculated for this percent. This way we get superposition of all Gaussian curves belonging to this slice of the "probability tube".

5.2. Once the superposition of all curves is calculated we normalize the slice to values between 0-1.

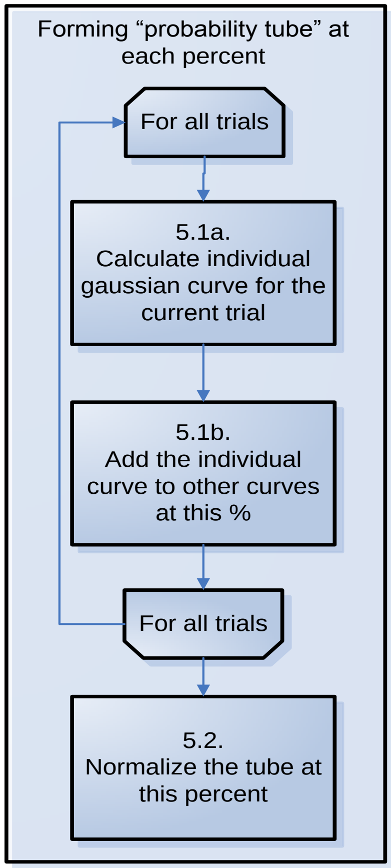

Figure 18 – ***Algorithm for making the "probability tube" at each percent***

The last step is necessary because of the huge differences in variance of the parameter at the beginning, and the middle part of the movement, described in the chapter introduction. Before the normalization peak values at the beginning can be several tens of times larger than peak values in the middle part. This is logical, and correct, but it is not convenient for purposes probability presentation.

We are trying to figure out what is the probability that the observed parameter will take certain value at the certain percent of the movement. There for it makes sense to normalize each percent for the sake of better presentation. It is necessary to say that these are no longer probabilities in the absolute sense, but rather relative values for each slice, where the range from 0 to 1 is arbitrarily chosen.

6. **"Tube closing"** – the primary "probability tube" is made solely based on statistical analysis of expert's data gathered in experiments. As such it has some faults that can be pointed out in the example shown in Fig. 17. At the beginning of the movement due to strong clustering of the velocity curves the tube is very narrow and steep characterized with very little or no variation. On the other hand the part between 70% and 90% is very wide. The reason for this

is high variance of the EP velocity during this part of the movement. This effect of the variance can be big enough to lead in errors in the representation. In the given example, we can notice that the representation allows negative velocities in the last 20% of the movement even though this is physically impossible. In order to eliminate these problems we have developed a method for automatically adjusting the tube, inspired by morphological operations used in image processing. The result of "tube closing" applied on the tube in our example is shown in Fig. 19.

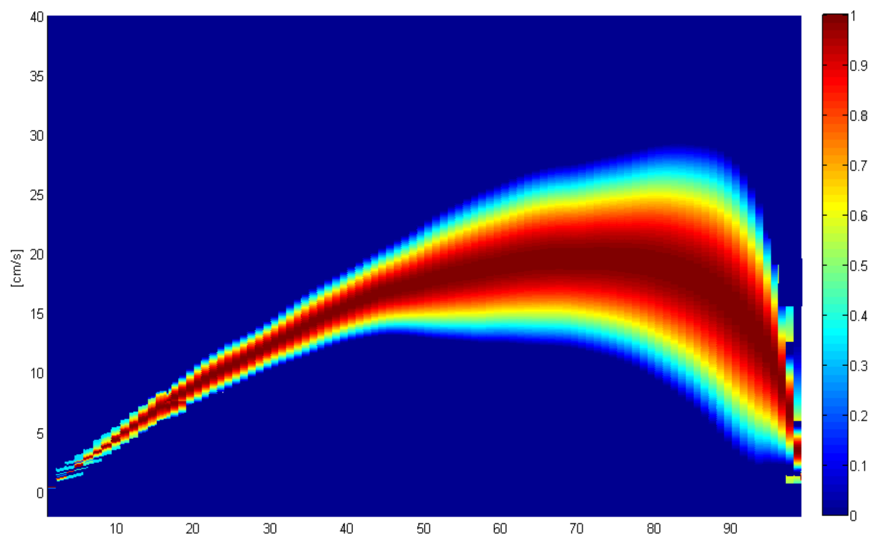

Figure 19 – The "probability tube" for EP velocity after "tube closing".

"Tube closing" is a three step process. The first step is to raise probability of parts of the tube with steep slopes, similar to dilatation in image processing. Step two is to "shave off" the parts of the tube with low probability. This step is corresponding to image erosion. The final step is rescaling the tube back to range between 0 and 1. This algorithm is given in the flowchart in Fig. 20. and thoroughly described.

6.1. For every point of the tube which has probability higher than ε (ε >0) rise the probability to decrease the slope. The probability is raised proportionally to the difference between the probability of the point and its most probable direct neighbor, but in such way that it favors the points on steeper slopes. Formula used for this is:

$$increas = (p_{maxNeig\ hbot} - p_{curent})20^{\frac{-0.7p_{curent}}{p_{maxNeig\ hbot}}}$$

Values of parameters in this formula are heuristically obtained

6.2. After the first step only parts of the tube with low value are the ones within slices with high variance, far away from the center of the tube. These are exactly the parts which we want to remove. Due to preparation done in the previous step we can removing these trials comes down to removing all trials with value lower than the threshold. The threshold used in the example is 0.7; this is a heuristically obtained value.

6.3. Finally the tube that comes out of the second step is normalized to values ranging from 0 to 1.

The final appearance of the tube has been given in the Fig. 19. In this figure we can see that by its appearance the tube really does resemble the data that it should represent. In order to examine the quality of this representation we will perform a comprehensive investigation of representations characteristics, as well as the method itself.

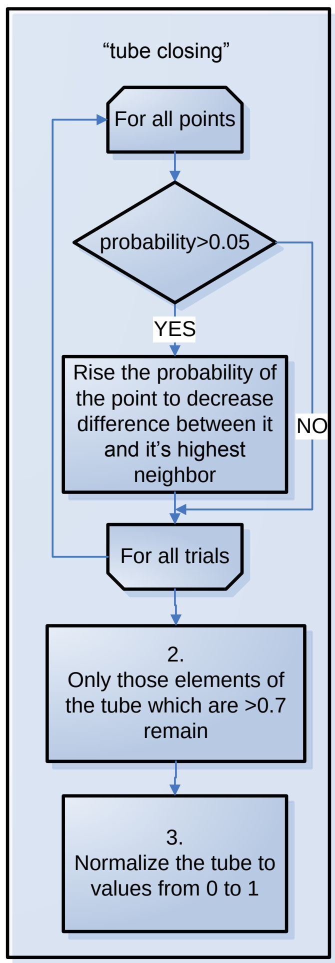

Figure 20 – Algorithm for the "tube closing"

VALIDATION OF THE REPRESENTATION

There are two aspects to the validation of the “probability tube” method. First we will investigate how well is the data represented by the “probability tube”, and then we will determine if the “probability tube” method meets all of the specifications that this method should have.

Data representation

This is a method for gathering expert’s knowledge and its results are based only on expert’s trials. There for quality of the final estimation is heavily affected by quality of the data gathered during the trials. The probability tube from the example given in previous chapter is shown in Fig. 21, along the “clipped” data that it should represent.

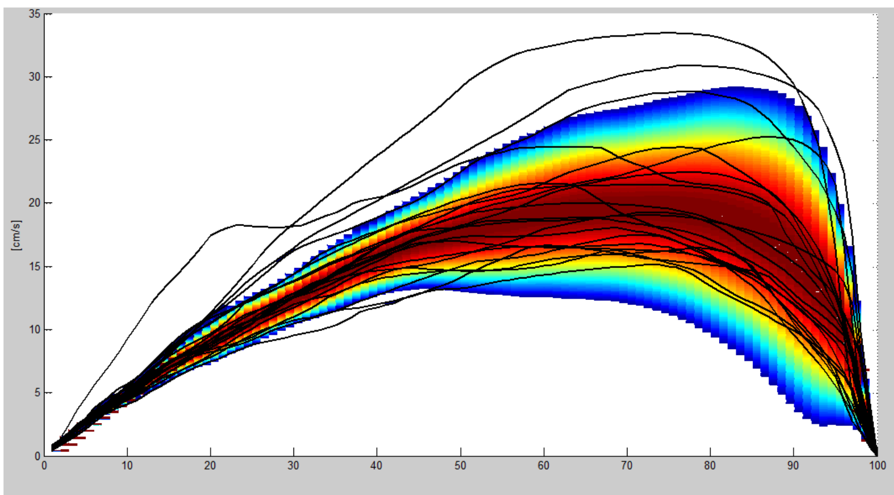

Figure 21. – The “probability tube” and trials. This is the “probability tube” calculated for the first movement, shown together with the trials of that movement.

In this figure we can see that most of the trials are in the tube, but some of them aren’t, or at least not during the entire movement. The amount of trials enclosed by the tube is one measure of quality of the tube as representation tool.

In order to quantify successfulness of data representation achieved by “probability tube” we have calculated histograms of trials in respect to value of “probability tube” assigned to these trials. In Table 1 such histograms are shown. Histograms are divided in ten equidistant pieces, ranging from 0 to 1.

In this table besides the data for the movement represented in Fig. 21 all other movements are quantified. Positional velocities for these movements, numerated in respect to Fig. 3 (left), along with their probability tubes are presented in Figures 22 to 26.

movement	Percent of trials belonging to certain part of the tube									
	0-0.1	0.1-0.2	02.-0.3	0.3-0.4	0.4-0.5	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1
1	**20,33**	**3,82**	**4,89**	**4,69**	**5,03**	**6,30**	**6,04**	**8,12**	**9,59**	**31,19**
2	**11,74**	**2,58**	**3,52**	**3,52**	**6,57**	**4,46**	**5,63**	**21,36**	**15,96**	**24,65**
3	**9,58**	**1,97**	**1,60**	**3,66**	**5,07**	**6,29**	**8,73**	**13,33**	**16,53**	**33,24**
4	**18,08**	**2,93**	**4,93**	**3,99**	**5,75**	**8,33**	**7,75**	**8,92**	**8,45**	**30,87**
5	**26,91**	**2,22**	**2,89**	**2,52**	**3,71**	**5,93**	**8,15**	**9,34**	**12,16**	**26,17**
6	**1,41**	**2,41**	**2,41**	**4,63**	**8,25**	**12,88**	**12,88**	**18,91**	**21,93**	**14,29**

Table 1. – Histogram of all trials in respect to parts of “probability tube” that they belong to, calculated for each task of the first experiment.

In Table 1~~.~~ we can notice that more than 80% of all trials are inside the “probability tube” for all tasks except the fifth movement. This movement will be discussed later in text.

Most of the trials (more than 50%) in each task are concentrated at the center of the tube, in the region with probability higher than 0.6.

This data suggests that “probability tube” is a viable model for action representation, in order to confirm this claim we will perform a detailed analysis of each probability tube in respect to their data sets.

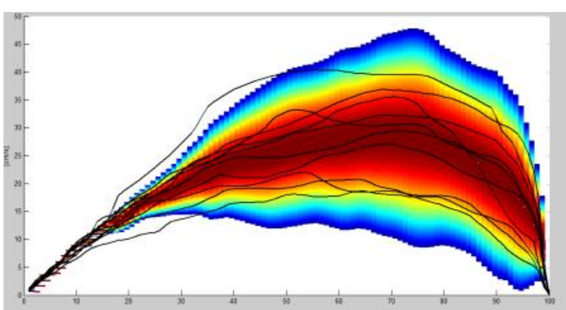

Figure 22. –This is the “probability tube” calculated for the second movement, shown together with the trials of that movement.

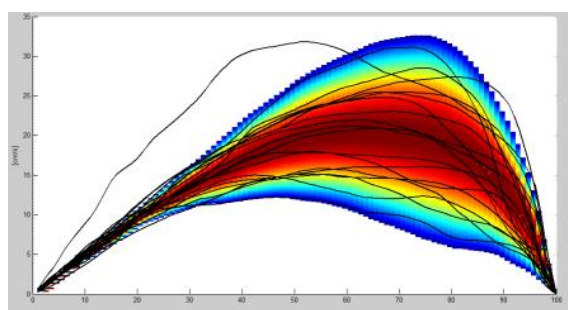

Figure 23. –This is the “probability tube” calculated for the third movement, shown together with the trials of that movement.

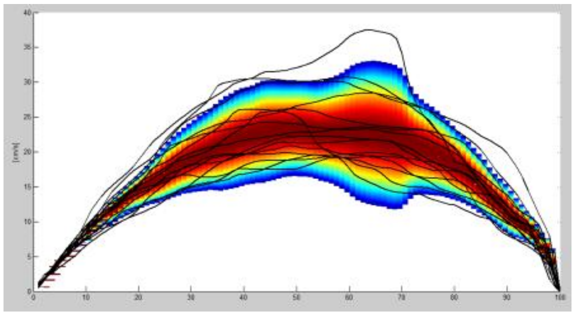

Figure 24. –This is the “probability tube” calculated for the fourth movement, shown together with the trials of that movement.

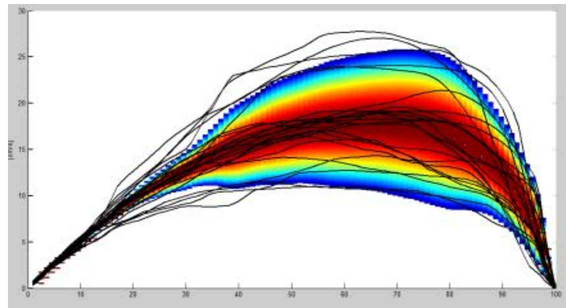

Figure 25. –This is the “probability tube” calculated for the fifth movement, shown together with the trials of that movement.

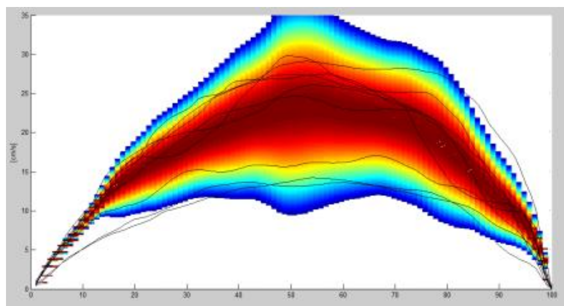

Figure 26. –This is the “probability tube” calculated for the sixth movement, shown together with the trials of that movement.

By examining Fig. 21 we can notice that there are two trials which are out of the tube for the better part of the movement. This can be interpreted in two ways. First direction of thinking is that the tube is not general enough. In that case heuristically obtained parameters in the “tube closing” should be revised in order to accomplish better fitting. Other interpretation could be that these two trials actually present a different strategy, and that the “probability tube”, which is essentially a classifier, excluded them from the strategy as “the odd one out”.

These are key questions and their further investigation will lead to validation of the “probability tube”. In Fig. 21. to 26. we have presented “probability tubes” calculated for positional velocity of all movements in the first part of the experiment. In synthesis of these tubes the same set of parameters was used as in the example. This way we can perform an objective study, which will test quality of data representation.

In these figures, as well as in Table 1, we can notice that the “probability tube” never encloses all of the trials. We can notice two different cases where this happens.

The first case is where we have intermittent occurrences of trials “sticking out” of the tube, as in Fig. 22, 23 and 24. This can be caused by irregular trials performed differently because the subject was distracted or testing a different strategy. Since in essence the “probability tube” is a classifier these trials are mostly removed, and have little or no weight, as shown in Fig. 19. In the other hand some trials are not covered by the tube, even though they clearly belong to the dominant strategy. This can be seen in Fig. 22 and 23 between 10% and 30%. This could suggest that heuristically obtained parameters are not ideal for these movements. This problem will be addressed in the last chapter.

The other case is the appearance of an entire "lock" of trials around the edge of the tube. This suggests existence of a strategy which is not in accordance with predominant strategy. It is expected to have such inconsistencies in experiments with several subjects. Since this is also an expert's strategy it would not be correct to completely disregard it. This is why the tube is done in the way which will give some weight to this other strategy, allowing it to expand the tube in its direction. The worst case scenario for this is shown in Fig. 26. Here we can see two distinct strategies, both having too few trials to become decisively dominant. In that case the tube becomes very wide and its value as a classifier significantly decreases.

One way to overcome this is to introduce additional step in tube synthesis, which would check for existence of alternative strategies within a movement before the tube itself is formed, and then in case of their existence allow forming of independent tubes which would later be merged. This problem will be addressed in our future work.

Testing initial hypothesis

After inspecting "probability tubes" formed for all movements of the first experiment we can give a comprehensive analysis of the representation.

In the introduction we have stipulated that the developed method is a universal method for automatic action representation of planar arm movements based on experts' movements. One by one we will test and analyze all of these properties.

The first premise that is going to be checked is **"this method is automatic"**.

As it is already mentioned there is no need for any intervention by the operator during the synthesis of the "probability tube". In the section **the "probability tube"** each step of this process was described. From here we can see that nowhere in the entire process is it necessary to get involved. The only detail which is not in the spirit of full automation is the existence of heuristically derived parameters.

Next premise is **"this method is based on expert's knowledge"**.

This means that besides the data obtained in trials of the experiment no other information is fed into the system, nor does it contain any a priori knowledge. Once again, looking back on the algorithm of the process, we can notice that there are no assumptions made about the characteristics of the data. The only thing observed and used here are statistical properties of gathered data. Even in the "tube closing" step where some a priori knowledge[3] was available, it was not used. Instead the results were obtained by manipulation of data and its statistical properties.

[3] For all tasks variance of first 15 and last 5% of the movement was low, representation shouldn't have negative values, velocity should be bell shaped…

The final premise, which is the paramount for this method, is **“this method is universal”** within limits.

The ability of this method to successfully estimate parameters of different pointing movements that start from the same point near the subject’s sternum, and spread out in different directions and lengths was tested in the first experiment. Results of this experiment are explained in the previous chapter and demonstrated in Fig. 21~~.~~ to 25, where velocities of all six movements and their “probability tube” presentations are shown.

We have already shown that the synthesis of “probability tube” is completely automatic as well as that it doesn’t need any prior knowledge about the properties of the estimated parameter. Both of these properties are prerequisites for universality.

From the description of the method we know that it was made in a way that is not favoring any specific planar point to point movement. It should be able to estimate parameters needed for action representation of all planar point to point movements, just as well as pointing movements performed in the first part of the experiment. To prove that it will we have tried to estimate positional velocity of movements performed in the second part of the experiment.

In Fig. 27 the first movement of the second part of the experiment is given. Image on the left is the trajectory of one trial of the movement. A red arrow is added to the graph demonstrating the movement direction. Right image is the probability tube formed for the first movement.

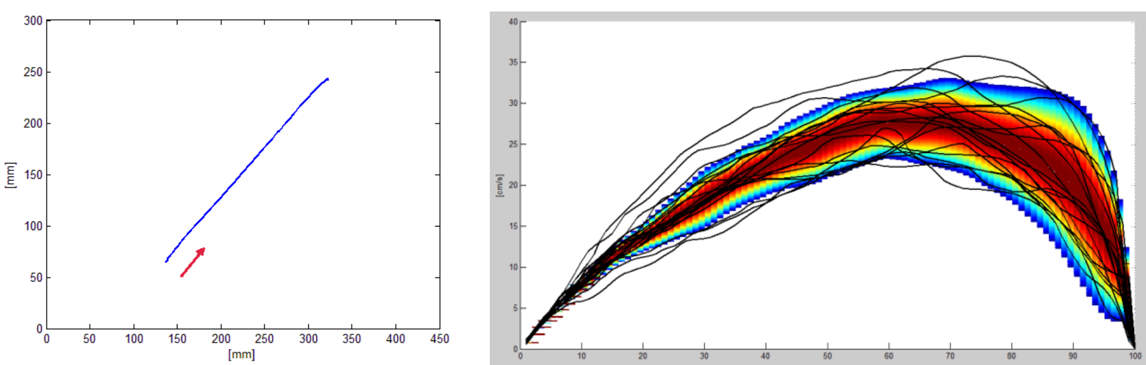

Figure 27. – The first movement of the second part of the experiment. In the left panel trajectory of the movement is given. The “probability tube” for EP velocity is shown in the right panel.

Other three movements performed in this experiment are presented in Fig 28, 29 and 30. in the same way as the first movement.

Just like in the first experiment histograms were calculated for every movement shown in these figures. Results are given in Table 2.

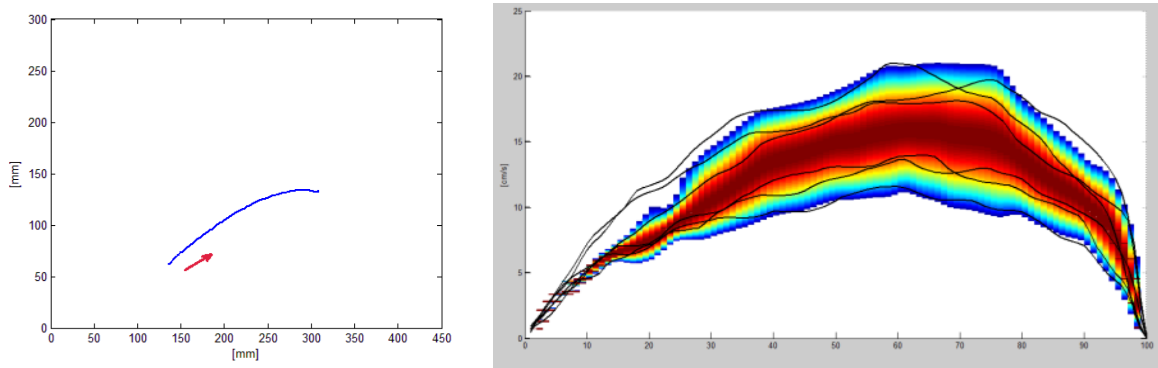

Figure 28. – The second movement of the second part of the experiment. In the left panel trajectory of the movement is given. The “probability tube” for EP velocity is shown in the right panel.

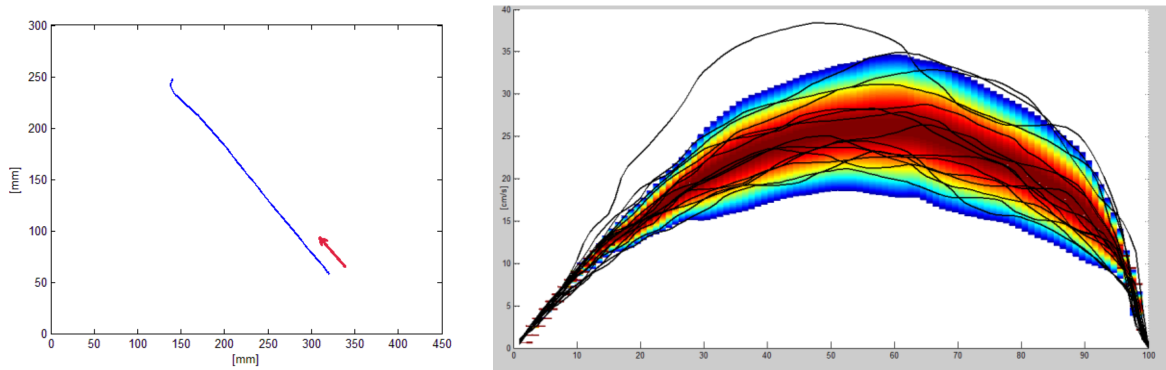

Figure 29. – The third movement of the second part of the experiment. In the left panel trajectory of the movement is given. The “probability tube” for EP velocity is shown in the right panel

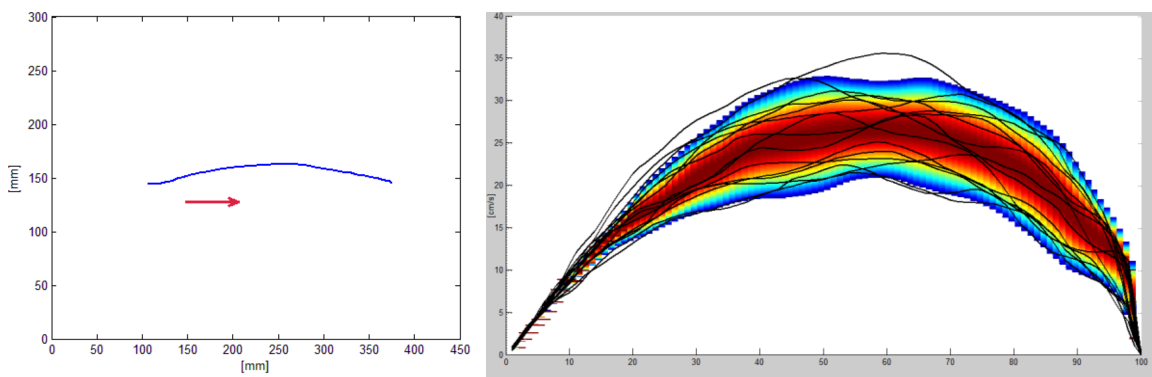

Figure 30. – The third movement of the second part of the experiment. In the left panel trajectory of the movement is given. The “probability tube” for EP velocity is shown in the right panel.

movement	Percent of trials belonging to certain part of the tube									
	0-0.1	0.1-0.2	02.-0.3	0.3-0.4	0.4-0.5	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1
1	**14,83**	**0,99**	**1,16**	**1,74**	**2,24**	**5,22**	**6,55**	**6,96**	**15,58**	**44,74**
2	**15,26**	**6,10**	**7,04**	**4,46**	**1,88**	**5,16**	**9,62**	**20,89**	**23,00**	**6,57**
3	**10,87**	**1,91**	**2,62**	**5,13**	**6,24**	**5,03**	**6,44**	**10,76**	**19,32**	**31,69**
4	**13,38**	**4,53**	**5,84**	**5,13**	**8,05**	**8,75**	**13,98**	**11,57**	**9,76**	**19,01**

Table 2. – Histogram of all trials in respect of parts of "probability tube" they belong to, calculated for each task of the second experiment.

Results shown in last four figures demonstrate that even with different movements the "probability tube" calculated for positional velocity successfully encloses more that 80% of the trials, as confirmed in Table 2. From this table we can also see that for all but the last movement, most of the trails are concentrated at aria with probability higher than 0.7.

With this final test passed we can say that this method really is a universal method for automatic action representation of planar point to point movements based on expert's knowledge gathering.

CONCLUSION AND FUTURE WORK

In this document a new method for planar, point to point, arm movement representation was presented. We have demonstrated a method for normalization that is essential for representation. The representation obtained with presented method is based on expert's knowledge gathered while they were performing the desired movement. The entire process is automatic.

Having such tool allows us to complete the learning scheme presented in introduction. At this stage we are limited to planar movements, but there are Wii games that are inherently played in this way. By choosing an appropriate Wii game (e.g., Frisbee throwing), and forming "probability tube" representation based on expert performance scheme of assistive forces for the robot can be generated for every stage of patient's recovery. In this way it would be possible for the clinician to create personalized training program for each patient without any complicated calculations and parameter adjustments.

In order to improve the performance of "probability tube" in our future work we will attend to some of the questions raised in this document.

First of all we will develop a procedure that will check for existence of alternative strategies within a movement before the tube itself is formed, and then in case of their existence allow forming of independent tubes which would later be merged.

We will extend the method to represent trajectory of the movement, as well as EP (hand) velocity. The ground work for this process is already done, since the "probability tube" is general enough to represent trajectory. The reason why this was not incorporated in this document is because in our analysis of trajectories in point to point movements we have noticed that subjects tend to deviate from the straight line. This is something already known and described in literature, but the thing which surprised us was that the side towards which they deviate is not constant. Since there is probability that the subject will stray to either left or right we would need to represent both cases, most probably by partitioning the tube at one point, and then uniting the partitions at later point.

One problem with this method that was mentioned several times comes from the heuristically derived parameters used in "tube closing". This heuristics could be eventually eliminated by a fully automatic method that uses stochastic model of these parameters.

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