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► **To cite this version:**

Jenny Cifuentes-Quintero, Minh Tu Pham, Pierre Boulanger, Richard Moreau, Flavio Prieto. Towards a classification of surgical skills using affine velocity. IET Science Measurement and Technology, 2018, 12 (4), pp.548 - 553. 10.1049/iet-smt.2017.0373 . hal-01797351

**HAL Id: hal-01797351**

**<https://hal.science/hal-01797351v1>**

Submitted on 21 Oct 2024

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# Surgical Skill Classification using Affine Velocity

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**Abstract:** The aim of this study is to determine if navigation movements, used in surgical training, follow a particular power law which describes the relationship between the hand trajectory's curvature, torsion, and speed. Based on this approach, this paper proposes the affine velocity as an appropriate classification feature to solve the surgical movement recognition problem. Eight subjects with different surgical experience were involved in the experiments. They were asked to do two kind of movements that involve depth perception skills with their right arm. Using six video cameras and an instrumented laparoscope, the 3-D trajectory of the end effector was recorded for each participant. A power law was used to fit the data sets and the exponents that relate the torsion, curvature, and speed were calculated. The exponents involved and the affine velocity for each trajectory were then computed, using a multi-variable linear regression, and compared between participants. It is shown that fitting residual follows a normal distribution indicating no regression biases. Finally, it is presented that an affine velocity analysis could be able to classify between both trajectories showing a correlation with the surgical skills and a clear difference for people with some surgical training.

## 1. Introduction

Minimally Invasive Surgery (MIS) has definitively changed the surgical landscape. In recent years, MIS has become the recommended standard technique improving outcomes compared with traditional open surgery. For this reason, effective training and objective evaluation of surgeons using these techniques are a major concern in biomedical research around the world.

In medical gesture recognition field, a gesture is defined as a dynamic movement. In particular, complex movements involve wrist movements and changes in the hands position and orientation. The comparison obtained between these movements has become an important topic which tries to find the similarities and differences and classify between several trajectories in 3D space [1, 2]. In general, in human recognition field, most of developed algorithms focuses on simple variables (spatial and temporal) to get a better classification for different kind of trajectories [3, 4, 5]. These

researchers use specific attributes of geometric, kinematic or dynamic nature [6, 7] to do this task. One of the most interesting insights is that the Central Nervous System (CNS) associates representations for movements based on geometrical and kinematical features instead of motor execution or muscle activation [8]. Particularly, during drawing movements, humans decrease the instantaneous tangential velocity of their hands while motion curvature increases and in a similar way, the velocity increases when trajectories become straight [9, 10]. It was shown that an empirical power law called *two-third power law* can successfully describe the correlation between the geometric attributes and kinematics of hand motion in drawing trajectories into a plane [11, 12].

Although this power law adequately represents drawing movements in a plane, it does not describe well every human movement planned by the CNS [13]. However, it was demonstrated that some types of human trajectories follow this law. In addition, the smooth pursuit of eye motion, controlled by distinct neural motor structures and a particular set of muscles, was analysed using this approach [14]. Vieilledent *et. al.*, on the other hand, studied curved locomotor trajectories with the hypothesis that movements like these, also obey this relationship [15]. Motion perception and prediction were similarly analyzed using the two-third power law [16].

Affine velocity has been another important research topic. Some researchers demonstrated that there is a unique function that associates curvature with affine invariant velocity and it follows the two-third power law [17]. It demonstrates that hand writing trajectories also follow a constant affine velocity [12]. These results demonstrate that the power law and kinematic attributes of movement can be represented and analyzed with an affine space instead of the standard Euclidean space [18]. In addition, affine velocity concepts have been applied to deform robot trajectories and to analyze image motions [19].

However, it has been shown that the two-third power law does not adequately describe the spatial drawing movements in 3D space. Some authors have suggested that the movement at constant affine velocity is a fundamental principle and that the two-third power law is a special case. Consequently, a new power law called *one-sixth power law* was introduced to describe three-dimensional drawing movements [20, 21]. Experimental results suggest that for the particular case of three-dimensional scribbling movements, the one-sixth power law describes the trajectories better than the two-third power law. Specifically, in the medical movement recognition field, affine velocity and an empirical power law based on one-sixth power law, were successfully used to classify basic obstetrical movements [22].

In this paper, an analysis of the affine velocity on navigation movements, performed in a complete minimally invasive training system, is presented. Some modifications of the power law exponents across two different movements are described and constant affine velocity is used to discriminate between this kind of hand human movements. Experimental results show that if the average over all subjects and movements is calculated, the power law exponents are in concordance with constant spatial affine velocity. Additionally, a correlation between the surgical skills and the empirical power law is presented.

The following section presents the mathematical foundation of the approach developed in this work. Section 3 reports experimental set-up and the results obtained using this important feature. Finally, in section 4, a conclusion is made and future directions are given.

## 2. Mathematical Background

It was demonstrated that the empirical two-third power law describes the inverse relationship between the trajectory curvature  $\kappa$  and speed  $v$  for planar drawing trajectories (1).

$$v = \alpha \kappa^{-\frac{1}{3}} \quad (1)$$

Where  $\alpha$  is a gain factor which, as some researchers showed, is constant for simple elliptical trajectories and piecewise constant for more complex motion [23, 24, 20]. Speed  $v$  and curvature  $\kappa$  are defined by:

$$v = \sqrt{\dot{x}^2 + \dot{y}^2} \quad \kappa = \frac{|\dot{x}\ddot{y} - \ddot{x}y|}{(\dot{x}^2 + \dot{y}^2)^{\frac{3}{2}}} \quad (2)$$

Affine velocity  $v_a$  is defined by:

$$v_a = |\dot{x}\ddot{y} - \ddot{x}y|^{\frac{1}{3}} \quad (3)$$

for planar trajectories, where  $|\bullet|$  represents the magnitude.

Some researchers [20] use the cube root of the signed area generated by the parallelogram defined by the first and second position derivatives with respect to time. Speed or Euclidean velocity  $v$  can be expressed, after some algebraic manipulations by:

$$v = v_a \kappa^{-\frac{1}{3}} \quad (4)$$

Comparing (1) and (4), one can determine that the motion with constant affine velocity can be represented by using the two-third power law. Spatial expressions are obtained based on the same equations for 3D trajectories. Formally, the speed  $v$ , the curvature  $\kappa$ , and the torsion  $\tau$  are defined in the following equations:

$$v = \sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2} \quad (5)$$

$$\kappa = \frac{\sqrt{(\ddot{z}y - \ddot{y}z)^2 + (\ddot{x}z - \ddot{z}x)^2 + (\ddot{y}x - \ddot{x}y)^2}}{(\dot{x}^2 + \dot{y}^2 + \dot{z}^2)^{\frac{3}{2}}} \quad (6)$$

$$\tau = \frac{\ddot{x}(\dot{y}\ddot{z} - \ddot{y}\dot{z}) + \ddot{y}(\dot{x}\ddot{z} - \dot{x}\ddot{z}) + \ddot{z}(\dot{x}\dot{y} - \dot{x}\dot{y})}{(\dot{y}\ddot{z} - \ddot{y}\dot{z})^2 + (\dot{x}\ddot{z} - \dot{x}\ddot{z})^2 + (\dot{x}\dot{y} - \dot{x}\dot{y})^2} \quad (7)$$

In this case, the 3D affine velocity is defined by the volume of the parallelepiped generated by the first, second, and third-derivative [20] and is expressed by:

$$v_a = \left| \frac{dr}{dt}, \frac{d^2r}{dt^2}, \frac{d^3r}{dt^3} \right|^{\frac{1}{6}}, \quad (8)$$

where  $r = (x, y, z)$  and  $|r_1, r_2, r_3|$  denotes the scalar triple product of any vectors  $r_1, r_2, r_3$ . Using (5), (6), (7), and (8), the spatial motion with constant affine velocity can be described using the one-sixth power law defined by:

$$v = v_a (\kappa^2 |\tau|)^{-\frac{1}{6}} = v_a \kappa^{-\frac{1}{3}} |\tau|^{-\frac{1}{6}} \quad (9)$$

The analysis carried out in this paper includes an analysis of a particular power law that represents better the data acquired in the experiments. In [22], it was demonstrated that obstetrical

movements can be represented using a power law based on one-sixth power law using different exponents. In this case, the exponents of (9) were not taken as a fixed constant (10) and in order to calculate the best exponents that fit the surgical data, a logarithmic linearization of this equation is used:

$$v = v_a \kappa^\alpha |\tau|^\beta \quad (10)$$

$$\log(v) = \log(v_a \kappa^\alpha |\tau|^\beta) = \log(v_a) + \alpha \log(\kappa) + \beta \log(|\tau|). \quad (11)$$

which can be rewritten as  $z = \gamma + \alpha x + \beta y$ , where  $z = \log(v)$ ,  $x = \log(\kappa)$ ,  $y = \log(|\tau|)$ , and  $\gamma = \log(v_a)$ .

### 3. Experimental Results

#### 3.1. Set-up

An empirical study using an instrumented laparoscope was conducted. The position of the laparoscope end effector was obtained based on an arrangement of six cameras and the OptiTrack Motive Software <sup>®</sup>.

Each camera can capture at 120 frames per second a 1.3 M pixels image resulting in a 3D sampling rate of 30 samples per channel per second. The laparoscope was instrumented with reflective markers attached at the end of the rod and the tasks involved in these experiments were performed in a complete minimally invasive training system (Figure 1). This device did not require any video equipment and it was simple portable set up. Figure 2 shows the complete experimental set-up [25].



**Fig. 1.** *Markers Location*

Two subjects with previous surgical experience and six subjects with no experience were involved in this experiment. Before performing the experiments, participants completed a questionnaire that included information about their age, dominant hand, and current training status (no experience or some surgical skills) (see Table 1). The participants performed two different navigation trajectories that involve depth perception skills. Both paths have variations in the difficulty level and in their position values as can be seen in their curvature trajectory (Figure 3). It is important to note that first trajectory has a more complex dynamic, reflected in the different peaks of the curvature values, compared to the second one. The aim was focused on avoiding collisions for

different navigation paths using the dominant hand (Figure 4). Particularly, Figure 4(b) shows the trajectories in black, the obstacles in gray, and the initial and final point in green. For this task, participants were instructed for each trajectory, they had 5 trials before recording the final 10 experiments. Motion started and finished approximately at the same point. Figures 5 and 6 shows an example of position values for each gesture associated to a participants with basic surgical skills and with no experience at all. In this figure, it is possible to note that participants who had no laparoscopic experience are less precise compared to the subjects that had some previous surgical experience.



**Fig. 2.** *Experimental Configuration.*

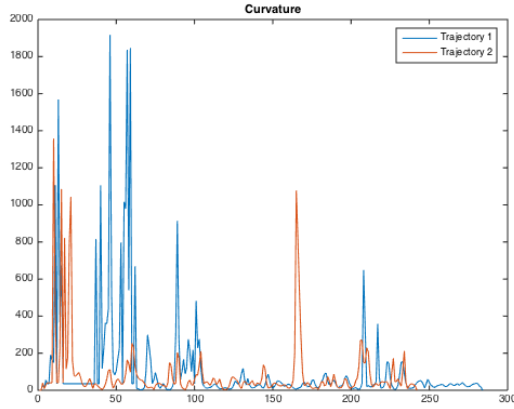
**Table 1** Participants Information.

	Age	Dominant hand	Training Status
Subject 1	20	Right	No experience
Subject 2	22	Right	Basic Surgical Skills
Subject 3	34	Right	No experience
Subject 4	27	Right	No experience
Subject 5	23	Right	No experience
Subject 6	30	Right	No experience
Subject 7	35	Right	Basic Surgical Skills
Subject 8	29	Right	No experience

### 3.2. *Data Analysis and Discussion*

The 3D trajectories  $(x, y, z)$ , acquired by the vision system, were first filtered using a 20th order low-pass FIR filter with a cutoff frequency of 5 Hz. The position data, for 160 trajectories, were interpolated using a cubic splines algorithm to calculate the analytical derivatives. Then, variables such as speed  $v$ , curvature  $\kappa$ , and torsion  $\tau$ , defined in 5, 6 and 7, were computed. In order to avoid uncertainties when the torsion is zero, a threshold (5% on the value of absolute torsion) was used in the different calculations.

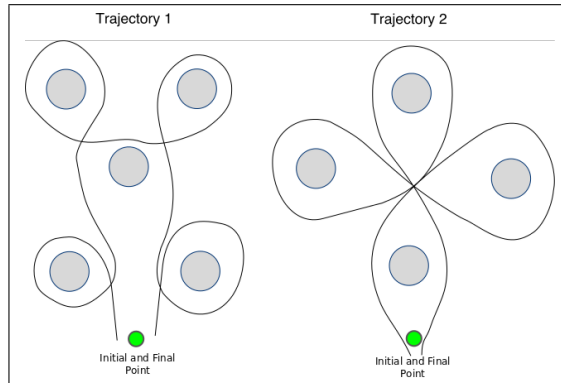
In order to determine the exponents for curvature  $\alpha$  and torsion  $\beta$  but also for the affine velocity  $v_a$ , described in (11), a multivariable linear regression was performed using a least square fitting technique [26].



**Fig. 3.** Curvature calculated for both gestures.



(a) Minimally Invasive Training System



(b) Trajectories shape

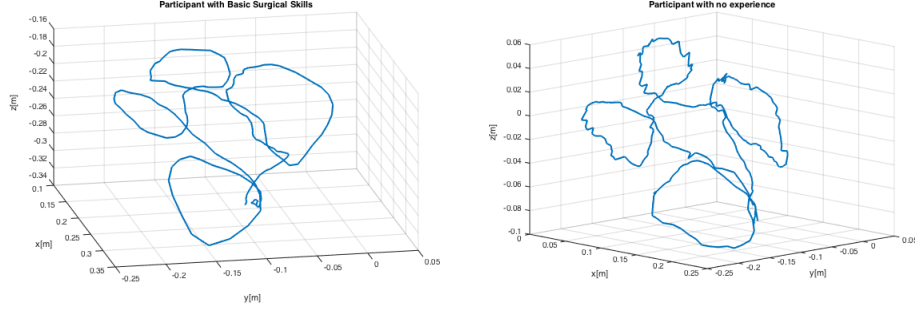
**Fig. 4.** Navigation trajectories involved in the experiments.

Linear least squares approach is used to fit the data with a model of the form:

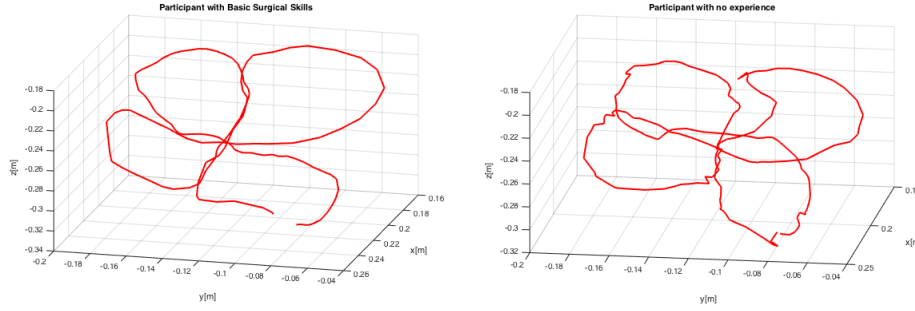
$$z \simeq \theta_0 + \theta_1 x + \theta_2 y \quad (12)$$

The residuals (defined as the differences between the observations and the model) are:

$$r_i = z_i - (\theta_0 + \theta_1 x_i + \theta_2 y_i), \quad i = 1, \dots, m, \quad (13)$$



**Fig. 5. Real Trajectory 1.**



**Fig. 6. Real Trajectory 2.**

where  $m$  is the number of samples. In order to make the residuals as small as possible, the sum of the squares of the residuals is minimized:

$$\|r\|^2 = \sum_1^m r_i^2 \quad (14)$$

In particular, the Moore-Penrose pseudoinverse is used to solve the linear least square problems, taking into account that this mathematical tool provides the minimization in this way:

$$\theta = w^+ z, \quad (15)$$

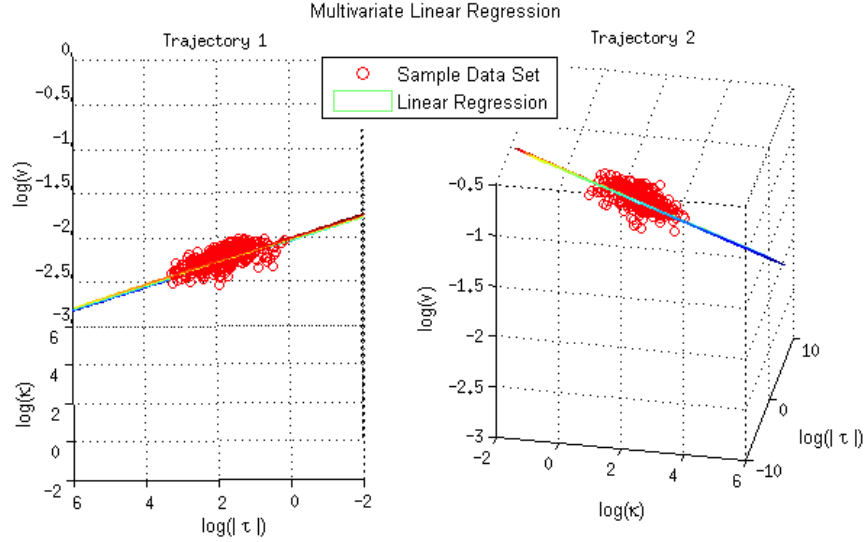
where  $w = [1 \ x \ y]$  and  $w^+$  is the pseudoinverse of  $w$ :

$$w^+ = (w^T w)^{-1} w^T \quad (16)$$

For this case, 11 corresponds to the equation of a plane in a 3D space  $(x, y, z)$  and parameters  $\theta_i$  correspond to the best coefficients that allow fitting the plane to the data. Regression results for both gestures, shown in Figure 7, shows the data and the plane identified suggesting that the movements, acquired in the experiments, follow the power law described in (10).

In Figure 8, the distributions for both exponents ( $\alpha$  and  $\beta$ ) are presented. The results show that both histograms can be fitted using normal distribution curves indicating a well-defined center of the distribution and the absence of a significant bias. In particular, Figure 8(a) shows the distribution of the derived values of curvature exponents. The mean value of  $\alpha$  is  $-0.2059 \approx -\frac{1}{5}$ , with a standard deviation of 0.1009. In turn, Figure 8(b) presents the distribution associated to torsion exponents, where mean value of  $\beta$  is  $-0.0990 \approx -\frac{1}{10}$  with a standard deviation of 0.065.





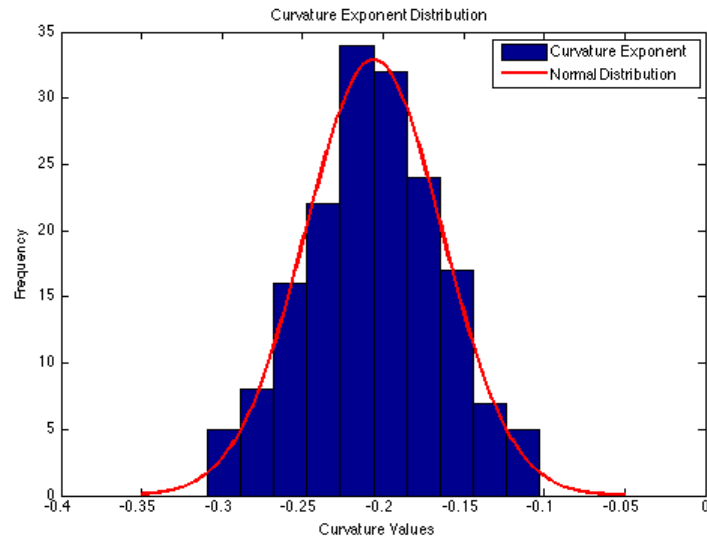
**Fig. 7.** Multivariable linear regression for one trial of each trajectory.

Based on the values of the constant  $\gamma$ , the affine velocity was calculated taking into account the relationship  $\gamma = \log(v_a)$ . Figure 9 presents the variability of affine velocity values for both trajectories performed by each participant involved in the experiments.

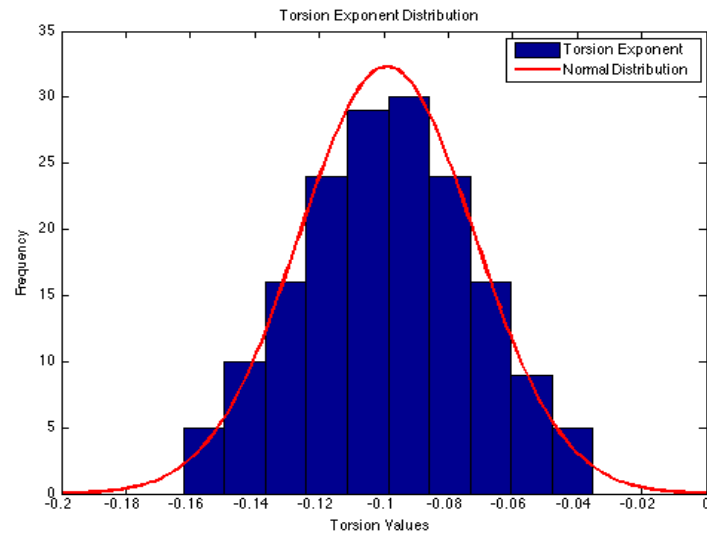
The data value distribution of Figure 9 shows that the affine velocity for the first trajectory, in every case, is higher than the values calculated for the second one. The results obtained for subject 2 and 7 (participants with previous surgical experience) are clustered in such a way that is possible to distinguish between both gestures. Data deviation, in particular, is smaller for these participants, facilitating the classification for their gestures. With this treath in mind, results show the biggest difference for the affine velocities of each gesture obtained from participants with previous surgical training (Dotted rectangle in Figure 9). It suggests that navigation skills in surgical training is highly correlated with the mathematical model that relates torsion, curvature, and speed.

These results are a significant contribution to the gesture recognition field as it allows us to find an adequate classification using a simple algorithm based just on kinematic and geometric data.

Accordingly, some authors have shown that if the affine velocity is calculated instead of the euclidean velocity [13], trajectory determines movement dynamics. In this way, the particular two-third power law was the only one allowing a constant affine velocity, which suggests that it is this velocity which is perceived and controlled by the central nervous system. Based on this observation, affine velocity is proposed in order to characterize and classify surgical gestures. From the postulate that it is the constancy of the affine velocity rather than the two-third power law (which is perhaps not the only compatible law) that constitutes the invariant, it has experimentally identified a new law of power for medical gestures. This power law is also consistent with a constant affine velocity. The results show a good correlation of this new law with kinematic data. This result provides a rational explanation of the origin of the concrete value of the power law proposed by Viviani, which would be only one particular case found empirically among others.

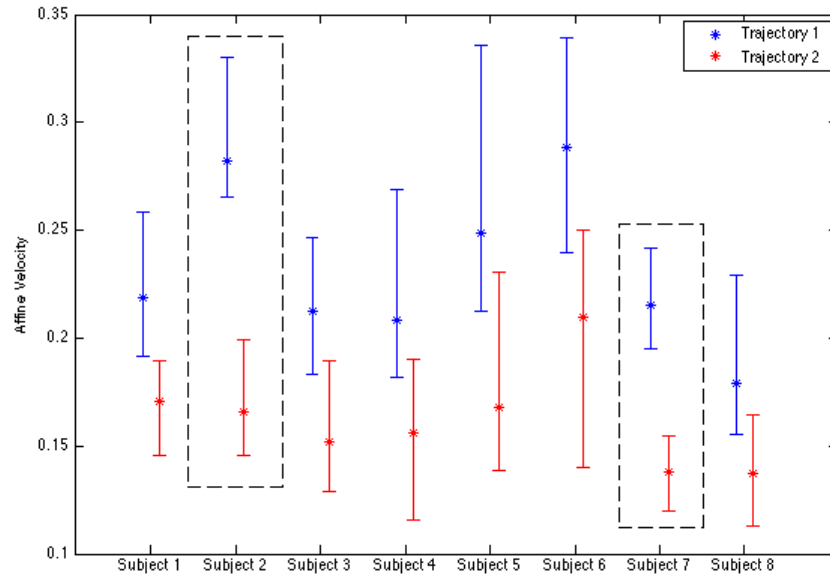


(a) Curvature Exponents Distribution



(b) Torsion Exponents Distribution

**Fig. 8.** Value Distribution for Curvature and Torsion Exponents.



**Fig. 9.** Affine Velocity for both gestures.

#### 4. Conclusion

Accurate classification and an adequate surgical skills recognition removes the subjectivity and variability from current expert-based evaluation methods used in surgical assessment. Different features, have been used for automatic evaluation in order to get an accurate outcomes, including position, speed, acceleration, forces, and torques. In this paper, an experimental relationship between speed, curvature, and torsion is used to compute a new suitable feature to classify surgical gestures: *the affine velocity*. The experiments carried out in this paper include two navigation gestures, that involve depth perception skills, acquired using an arrangement of six cameras, the OptiTrack Motive Software and a complete minimally invasive training system. The affine velocity calculations allow us to classify gestures and distinguish the surgical skills for the participants involved in these experiments. The results obtained present a new alternative to the analysis of surgical gestures from a traditional Euclidean analysis. Our ongoing research in this field is focused on segmenting medical movements using this feature in order to decompose surgical gesture into its basic components.

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