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Classifying Knee Pathologies using Instantaneous Screws of the Six Degrees-of-Freedom Knee Motion

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***Abstract* – We address the problem of knee pathology assessment by using screw theory to describe the knee motion and by using the screw representation of the motion as an input to a machine learning classifier. The flexions of knees with different pathologies are tracked using an optical tracking system. The screw parameters which describe the transformation of the tibia with respect to the femur in each two successive observation are represented as the instantaneous screw axis of the motion given in its *Plücker* line coordinate, along with its corresponding pitch. The set of screw parameters associated with a particular knee with a given pathology is then identified and clustered in R^6 to form a "signature" of the motion for the given pathology. Bone model and two cadaver knees with different pathologies were tracked, and the resulting screws were used to train a classifier system. The system was then tested successfully with new, never trained before data. The classifier demonstrated a very high success rate in identifying the knee pathology.**

Index Terms - Knee Kinematic, Screw Axis, Pathology Classification, Support Vector Machines.

I. INTRODUCTION

Assessment of joint pathology is not always trivial and requires, in most cases, a combination of visualization data (i.e. CT, X-ray, MR) combined with physical subjective tests performed by the physician. Diagnosis is particularly complex for the knee joint due to its complex structure and six degrees of freedom (DOF) motion. For example, in order to asses anterior cruciate ligament (ACL) deficient knees, there are currently three main tests that are performed by physicians: Lachman test, pivot shift test and the anterior drawer test [1]. All of these tests are performed manually by the physician while manipulating the patient lower limb. In our study, we demonstrate a method in which kinematic measurements of the knee are used to automatically identify the knee pathology.

In order to describe both translation and rotation motion of the knee , i.e. a 6-DOF motion between the tibia and the femur, studies have used the helical axis method [2-9]. Helical motion, also known as screw motion was mathematically formulated by Sir. Ball in 1900 [10]. According to Ball, a screw is a straight line with which a definite linear magnitude termed the pitch is associated. In his book, Ball also states that any given displacement of a rigid body can be effected by a rotation about an axis combined with a translation parallel to that axis.

Instantaneous screw representation was previously used to describe knee motion. Soudan et.al [2] identified the instant axis, or screw axis as one of the widespread methods for investigating the mechanics of the human joints. Although not implemented, the researchers point out that the instantaneous axis of the joint changes in both place and direction during joint movement. Woltring [3] presented an analytical model to describe the effect of measurement errors from landmark position data on the definition of the finite centroid and the finite helical axis. Blankevoort et.al. [4] described the finite helical axes for a flexion motion and checked the repeatability of the results by placing markers on four human knees and tracking them. In a study by Jonsson [6] the authors used stereo-photogrammetric analysis to calculate the helical axis of the knee during flexion.

In our study not only do we use screw coordinates to represent knee motion, but we also use this representation to automatically classify knee pathologies using a machine learning classifier. The idea of classifying knee motion in order to identify knee deficiencies has been previously pursued. Andriacchi [11] studied the anterior posterior (AP) linear motion of the femur with respect to the tibia during gait cycle. The experimental data were presented by a one dimension curve correlating flexion angle to AP displacement. This curve was later used to assess the dynamic AP motion of the knee in patient with ACL-deficient pathology [12] that did not develop the neuromuscular adaptation. So far machine learning classifiers in biomechanics have been used to classify data that relates to a single quantitative measurement change (i.e. step width) and not data that represents the 6-DOF motion of the knee. For example in [13] the researcher used machine learning to classify changes in gait characteristics of elderly non-fallers. This research has particularly shown that some foot placement gait measures (e.g., step width and stride variability) displayed greater associations with fall prediction. In [14] the researchers used Support Vector Machines (SVM) classifier in order to form an automatic recognition of gait changes, due to ageing, using two types of gait measures: walking velocities and foot-ground reaction forces in the vertical and anterior–posterior directions. During the experiment, the gaits of 12 young and 12 elderly participants were recorded during normal walking. Altogether, 24 gait features describing the two types of gait characteristics were extracted for developing gait recognition models and later

testing of generalization performance. Test results indicated an overall accuracy of 91.7% by the SVM classifier in its ability to distinguish the two gait patterns.

As can be observed, most of these works try to classify data that relates to a single quantitative measurement, e.g, anterior posterior linear motion [11], step width and stride variability [13] etc. In our proposed method, the data incorporates all six degrees of freedom of the knee motion. We use the instantaneous screw parameters (also known as twist parameters) of the knee, which provide the 6-DOF transformation of the knee while in motion. In our experiment we track bone model (Sawbones®) as well as two cadaver knees during flexion using an optical tracking system. The information provided is composed of multiple observations of relative bone states. We then calculate the instantaneous screw parameters that describe the momentary transformation between each two successive frames that are acquired during motion. The screw parameters incorporate into a sextuple vector the pitch of the screw (i.e. the ratio between the rotation and translation components of the investigated motion) and the Plücker coordinate description of the screw axis (i.e. the axis in space about which the momentary motion occurs). The collection of all the instantaneous screws forms a set of continuous twists that describes the motion. Each screw within a set represents a point in R^6 since it is a sextuple. We show that a set of instantaneous screws that describes a motion of a given knee forms a variety of points or a cluster in R^6. Moreover, we show that knees with similar classes (e.g. healthy or ACL/PCL deficient) have similar clusters. Finally, we hypothesize that once a large data set of different knees with different pathologies is created and classified (using supervised learning techniques), the kinematics of an untrained knee can be associated with one or more of the clusters. Therefore, the knee pathology can be identified without using subjective tests.

In this report we describe the tools and experimental setup that were used to demonstrate our method. We further present the results obtained from experiments with a Sawbones model and two cadaver right knees.

II. METHOD

A. Representation of screw motion (twist)

Any given displacement of a rigid body can be effected by a rotation about an axis combined with a translation parallel to that axis [10]. This way of defining rigid body displacements is termed screw motion or twist. In the present work, we use the screw parameters to describe the instantaneous, finite motion of two successive observation of the tibia movement while in flexion. A finite screw displacement describes the relative location of two rigid bodies or two different locations of the same body in a global reference frame [15]. The motion of a free body undergoing a finite transformation can be described as a combination of a translation, d, parallel to a fixed axis A in space, and a rotation ϕ about the same axis. The ratio of the translation component to the rotation component is known as the *pitch* of the screw, p, and is given as:

$$p = \frac{d}{\phi} \tag{1}$$

This type of motion is also known as a helical motion, screw motion, or simply a twist with an axis A and a pitch p as is illustrated in Fig. 1. The six instantaneous parameters of the unit screw $\hat{\$}_i$ are given as:

$$\hat{\$} = \begin{bmatrix} s \\ s_0 \times s + ps \end{bmatrix} = \begin{bmatrix} L & M & N & P^* & Q^* & R^* \end{bmatrix}^T \tag{2}$$

Where, s, is a unit vector along the direction of the screw axis, s_o is a position vector of a point on the screw axis, and p is the pitch as defined in (1). Five independent quantities, four for the axis and one for the pitch, can uniquely specify a screw motion. Two extreme examples are pure rotation and pure translation. For a pure rotation motion i.e. $p = 0$ the screw is reduced to:

$$\hat{\$} = \begin{bmatrix} s \\ s_0 \times s \end{bmatrix} \tag{3}$$

For a pure translation motion i.e. $p = \infty$, the screw is reduced to:

$$\hat{\$} = \begin{bmatrix} 0 \\ s \end{bmatrix} \tag{4}$$

The description of the displacement of a rigid body can not be completely determined without the specification of the amplitude or intensity of the screw axis. Letting $\dot{q}$ be the intensity of a twist, the twist can be expressed as:

$$\$ = \dot{q}\hat{\$} \tag{5}$$

We refer the reader to [15-17] for a deeper discussion on screw motion and its use for representing motion of two rigid bodies.

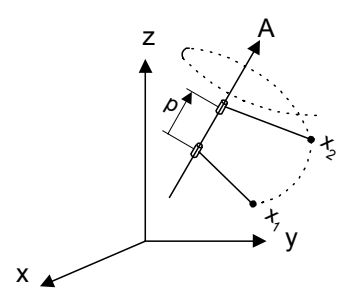

Fig. 1: Screw motion (Helical motion)

B. *Calculating the screw parameters of a finite motion*

Calculating the screw parameters of a rigid body undergoing a motion is not intuitive. Few methods have been presented in the literature regarding this issue. However, the final goal is the same: given two finite configuration of a rigid body, one needs to find the screw parameters that would result in this motion, i.e. the instantaneous screw axis parameters ($), and its corresponding pitch (p). Two works present formulations for such an algorithm [15, 18]. The main difference between the algorithms is the input which they require. In Davidson [15], the algorithm's input is a homogeneous transformation matrix from which the screw parameters are extracted. In Angeles [18] the algorithm's input is a set of three points on the rigid body, prior and post transformation (same points), from which the screw parameters that describe the motion are derived. Since the output of our experiments are homogeneous transformations between tracking systems we use the algorithm presented in Davidson [18]. We refer the reader to [18] for a full description of the algorithm.

C. *Cluster analysis of the screw parameters*

One of our research hypotheses is that different abnormalities would result in different paths that the knee follows when going through flexion, since it is likely that the abnormality affects the geometry or the mechanical constraints of the knee. These different paths result in different sets of screws that form different clusters in R^6 (Fig. 2). We exploit these properties to train a classification system (using supervised learning techniques) that learns the pattern of motion of different knee abnormalities. This system is later given a new set of screws from a new knee and is asked to identify which of the predefined clusters it belongs to (Fig. 3).

In this work we use the support vector machines (SVM) technique as described in [19, 20]. Generally speaking, the SVM algorithm creates a hyperplane that separates the data into two classes with the maximum margin. Given training examples labeled either "yes" or "no", a maximum margin hyperplane splits the "yes" and "no" training examples, such that the distance from the closest examples (the margin) to the hyperplane is maximized. For more precise explanation of SVM we refer the reader to [21].

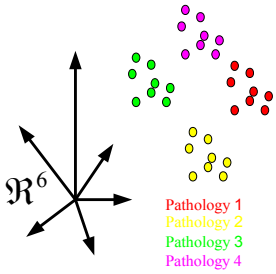

Fig. 2: Different clusters correlating to different path/set of screws

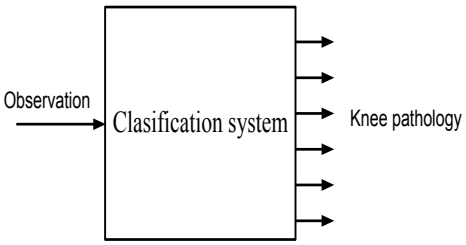

Fig. 3: AI system to identify knee pathology

III. Experimental Settings

A. *Sawbones experiment*

For our first experiment we used Sawbones model of the femur and tibia. The two bones were connected by four rubber tubes to simulate the lateral collateral ligament (LCL), medial collateral ligament (MCL), posterior cruciate ligament (PCL), and the anterior cruciate ligament (ACL). During the experiment, optical trackers were attached to both bones (Fig. 4), and were tracked using the Polaris® optical tracking system. In our experiment settings, the femur was rigidly fixed and used as the reference system, while the tibia was quasistatically manipulated from flexion to full extension by pulling the bone through a long wire connected as close as possible to the mechanical axis of the bone. As opposed to a physician manipulating the tibia while grasping it, the manipulation of the tibia by a long wire produces a minimally constrained motion, and may provide more information on the kinematics of the knee. During the experiment, an optical system recorded the location of the tibia, as it was subjected to a flexion motion (Fig. 5).

The data obtained were then used for classifying the different pathologies using the SVM technique. In the training process we trained the classifying system using five classes; one healthy knee model and four different pathologies: ruptured ACL, ruptured LCL, ruptured MCL, and a combination of a ruptured MCL and ruptured ACL. Thirty training runs, consisting of approximately 250 instantaneous screws for each of these pathologies were taken. Thirty additional runs were used for testing our classification method. In order to test our classification, for each testing run, each instantaneous screw was compared with the resulting classifier. The classifier then decided to which class this instantaneous screw belonged.

Fig. 4: Experimental setup with optical trackers attached (Sawbones)

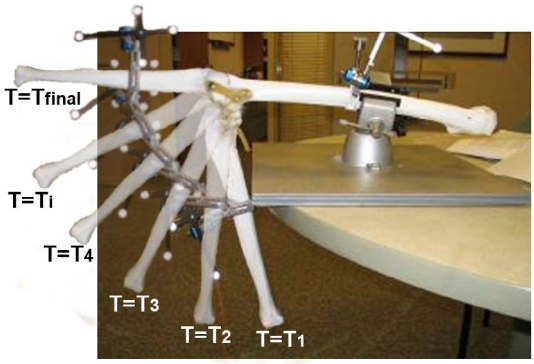

Fig. 5: Observation while flexing the knee (Sawbones)

B. *Cadaver experiment*

Following the Sawbones experiment, we ran a set of tests on two cadaver right knees (Fig. 6). The first knee was of an 81 year old male, who had Parkinson's disease, and the second knee was of a 68 year old male who had prostate cancer. Similar to the Sawbones experiment, the tibia tracker positions were recorded in the femur tracker reference frame. Focusing on the cruciate ligaments, three classes were recorded, i.e. healthy knee, ACL deficient knee, and a combined ACL, PCL deficient knee.

For each of the classes 20 runs (flexion to full extension) were recorded while quasistatically pulling the leg with a string attached to it. Next, we obtained the screw parameters that describe the finite motion between two successive observations. Half of the observations were used for training, whereas the other half were used for testing. Moreover, in order to confirm that our method is not sensitive to sampling frequency (i.e. number of points per unit of time) we created several testing sets of screws by sampling the screw parameters at different sampling frequencies. This aspect of the procedure is important since it is very hard to control and synchronize the sampling frequency of the data and velocity of the knee flexion per patient. The same SVM classifying technique was used as in the Sawbones experiment.

C. *Registration of anatomical reference frames*

Although the screw representation of a motion is invariant in the same reference frame, it is still dependent on the global reference system in which it is described. Therefore, it is crucial to establish a common (global) coordinate system between patients since the optical trackers, cameras, and anatomy, can be placed differently resulting in different reference systems. Without a proper definition of a global reference system between patients, the resulting screws will differ, though still describing the same motion. For this purpose we use the anatomical reference frame (ARF) of both tibia and femur as our global system among patients. We will further discuss this issue in section V.

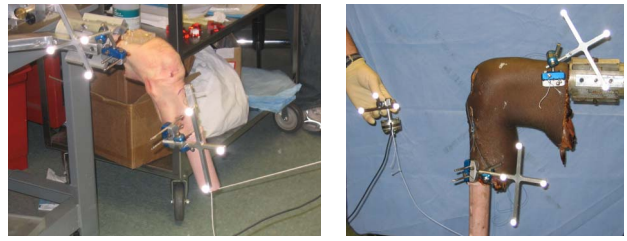

Fig. 6: Experimental setting; Male, 81 (left), Male, 68 (right)

IV. Results

A. *Sawbones experiment results*

As discussed earlier, each observation of the flexion of the knee can be represented as a set of screw parameters (a sextuple vector) which are decomposed into screw axis coordinates given in their *Plücker* representation associated with their corresponding pitch values. When the instantaneous screw axes are plotted sequentially, they form a 1-parameter rolled surface of lines [22]. The set of axes for the Sawbones model are shown in Fig. 7.

In order to make sure that the use of all six DOF is not redundant we conducted Principle Component Analysis (PCA) of the data and concluded that the six DOF have equal energy, thus are all valuable and should be used. Thirty sets of screw parameters were used for training the SVM classifier and different thirty sets were used for testing it. The results of this process are given in table I. The columns correspond to the different classes (e.g. healthy, ruptured ACL, etc.) and the rows present the average and standard deviation of the success rate in identifying the classes. Note that the average given in the table corresponds to the mean percentage of the screws per set that were associated with the correct class (averaged over all runs). Referring to table I, if we set the threshold for determining a pathology to 82% of the screws being classified to that pathology, we would get 100% success in identification.

While testing these classes, we observed that the main distinction between the different cases occurred in the last third portion of the flexion-extension motion. This observation suggested that it is sufficient to use the last third portion for the training phase. As a result of this modification, success percentage in some of the classes increased (table II). The possibility of gaining increased accuracy by performing the identification and clustering on a subset of the experimental data should be further investigated.

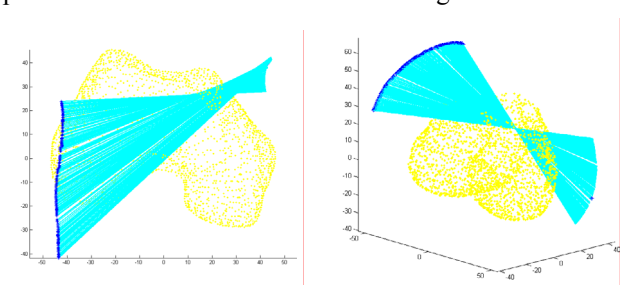

Fig. 7: Screw axis of all observations: coronal (left), 3D view (right)

TABLE I
SAWBONES EXPERIMENT: % OF SCREWS WITH CORRECT CLASSIFICATION

	Healthy Knee	Ruptured ACL	Ruptured LAT	Ruptured MED	Combination Ruptured MED+ACL
AVG	**82**	**99**	**93**	**92**	**87**
STD	**13.7**	**1.3**	**4.4**	**3.9**	**6.7**

TABLE II
SAWBONES EXPERIMENT: TESTING THE LAST 30% OF SCREWS PER RUN
(% OF SCREWS WITH CORRECT CLASSIFICATION)

	Healthy Knee	Ruptured ACL	Ruptured LAT	Ruptured MED	Combination Ruptured MED+ACL
AVG	**85**	**99**	**92**	**90**	**90**
STD	**11.5**	**0.7**	**7.0**	**5.3**	**11.7**

B. Cadaver experiment results

It is very difficult to distinguish the differences between the motion of the three knee classes (healthy knee motion, and ACL, ACL+PCL deficient knees) as presented in Fig. 8. However, looking at the instantaneous screw axes it is easier to distinguish the classes. A sample plot of the screw axes of the instantaneous screws for an ACL deficient knee is given in Fig. 9. The resulting plot is a 1-parameter rolled surface. Fig. 10 is similar to Fig. 9 except that all screw axes of the three classes of one knee are plotted in the same graph. Also plotted in Fig. 9 and Fig. 10 (marked with an arrow) is the striction curve of the rolled surface [22]. This curve can also serve as a mean of classifying kinematic pathologies, however, we do not use this extra data in this report.

The results of the SVM classifier are given in table III. As can be observed for all classes, the system was able to identify the class with high accuracy. The results of the classifier for a different sampling frequency, i.e. the knee was manipulated in a different speed resulting in a coarser sampling, are presented in table IV. Since the success rate for the classification process for both cadaver knees across all three pathologies did not decrease substantially with the change in sampling frequency, it appears that sampling frequency does not have to be maintained among experiments (patients).

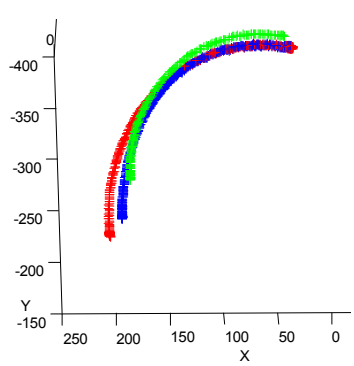

Fig. 8: Cadaver Experiment results: motion of tibia in three classes (Healthy, ACL and ACL+PCL deficient).

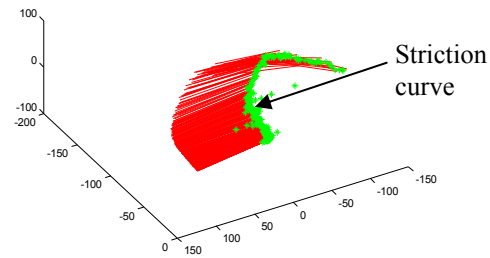

Fig. 9: Screw axes for ACL deficient knee (knee #2)

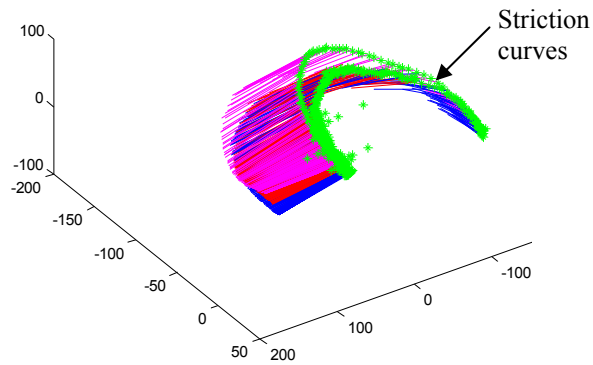

Fig. 10: Screw axes for all three pathologies (knee #2)

TABLE III
CADAVER EXPERIMENT: TESTING ALL SCREWS (2 KNEES)
(% OF SCREWS WITH CORRECT CLASSIFICATION)

	Healthy Knee	Ruptured ACL	Combination Ruptured ACL+PCL
AVG	**77**	**83**	**94**
STD	**4.9**	**4.7**	**1.9**

TABLE IV
CADAVER EXPERIMENT: SAMPLING HALF OF THE SCREWS (2 KNEES)
(% OF SCREWS WITH CORRECT CLASSIFICATION)

	Healthy Knee	Ruptured ACL	Combination Ruptured ACL+PCL
AVG	**78**	**74**	**96**
STD	**5.6**	**9.2**	**1.6**

V. DISCUSSION AND FUTURE WORK

In this paper we introduced a new method for identifying knee pathologies solely based on kinematics observations. During the experiment we computed the instantaneous screws that describe the knee flexion. These screws were later used for training a classifier to identify different pathologies. The results from both the Sawbones experiment and the two cadaver experiments indicate that it is possible to cluster a set of instantaneous screws which correlates to different knee pathologies. Moreover, when given a set of instantaneous screws of a knee which was never used during the training phase, the classifier was able to associate these screws to one of the clusters created in the learning phase, hence identify the pathology for which the new set of instantaneous screws

belonged to. The SVM classifier was able to classify the different pathologies with a high success percentage of 80 to 90 percent. We further demonstrate that the capability of the classifier to identify pathologies does not depend on the sampling frequency, i.e. sampling frequency and motion velocity do not have to be synchronized between patients.

In this report we used the SVM algorithm as our classifier. Although this tool has been reported as suitable for biomechanics and gait analysis studies [14], this method has at least one noticeable drawback which is the testing method of the classifier. In our SVM classification method, each screw is independently tested against the whole training set while disregarding its relative location in the flexion-extension motion. One possible improvement to explore is to use a different classifier such as the Hidden Markov Model method which will also take into account the sequence and relative location of each instantaneous screw within the set of screws which define the motion, i.e. the system's internal dynamics.

It is worth noting that for this report we used a registration procedure in order to define the anatomical reference system of both the tibia and the femur as our global reference systems among patients. More specifically, we calculated the position of the tibial anatomical reference system in the femoral global reference system. The instantaneous screws were then calculated in the femoral anatomical reference system. We are currently exploring two other options which may simplify the registration process which currently requires a CT scan and is performed in the CT reference system. One option to simplify this process is to use tracked ultrasound to identify anatomical landmarks which define the anatomical reference system [23]. The second approach that we are currently exploring is to use a parameterize striction curve (Fig. 9, Fig. 10). The striction curve of a rolled surface of lines can be approximated by the intersection points of the common normal between each two successive lines and the lines themselves [22]. Future work will also require further investigation of the use of non-invasive mounting of the optical trackers since this could introduce measurement errors due to soft tissue motion [24].

To conclude, in this paper we report the very first steps in the development process of an expert system which is capable of identifying knee pathologies based on kinematic observation of the knee while in flexion. The major advantage of the presented method is the use of instantaneous screws to represent the 6-DOF knee kinematics, combined with the use of the SVM classifier. Further investigation should be conducted in order to solidify the method; however, the initial results are very promising. It is worth noting that although we report our results for knee kinematics, the same concept can be applied to any other joint or mechanical system of moving rigid bodies.

ACKNOWLEDGEMENT

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