Published in final edited form as:

Exp Brain Res. 2011 December ; 215(3-4): 247–255. doi:10.1007/s00221-011-2889-3.

Determining posture from physiological tremor

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Abstract

The measurement of body and limb posture is important to many clinical and research studies. Current approaches either directly measure posture (e.g., using optical or magnetic methods) or more indirectly measure it by integrating changes over time (e.g., using gyroscopes and/or accelerometers). Here, we introduce a way of estimating posture from movements without requiring integration over time and the resulting complications. We show how the almost imperceptible tremor of the hand is affected by posture in an intuitive way and therefore can be used to estimate the posture of the arm. We recorded postures and tremor of the arms of volunteers. By using only the minor axis in the covariance of hand tremor, we could estimate the angle of the forearm with a standard deviation of about 4° when the subject's elbow is resting on a table and about 10° when it is off the table. This technique can also be applied as a post hoc analysis on other hand-position data sets to extract posture. This new method allows the estimation of body posture from tremor, is complementary to other techniques, and so can become a useful tool for future research and clinical applications.

Keywords

Physiological tremor; Posture; Motion tracking

Introduction

The measurement of posture can be useful for a variety of research and clinical applications. Posture is important because it affects movement in virtually any task including reaching (Nishikawa et al. 1999; Rochat 1992; Scott and Kalaska 1995), grasping (Desmurget et al. 1995; Mason et al. 2001), force production (Kutch et al. 2008; Sergio and Kalaska 2003), and even complex tasks such as skiing (Watanabe and Ohtsuki 1978). The measure of posture is important both for electrophysiological research (e.g., Scott and Kalaska 1995) and for clinical diagnostics (e.g., Bhidayasiri 2005). In both research and clinical settings, new methods of measuring posture can therefore impact the research efforts of many neurophysiologists.

There are two standard approaches to motion tracking (Aggarwal and Cai 1999). Some methods allow experimenters to directly measure posture. Active electromagnetic systems (e.g., radio frequency or magnetic flux) can measure the position of markers that indicate posture, but are distorted by any nearby metal objects, and may require relatively expensive, specialized equipment (reviewed in Foxlin 2002; Rolland et al. 2001). Optical methods, including video camera-based techniques, also suffer from problems with surrounding objects when the line of sight is interrupted. Even the inexpensive camera-based techniques

require complex, error-prone algorithms and are thus an active area of research (Wang et al. 2003; Aggarwal and Cai 1999; Moeslund et al. 2006).

Other methods that allow experimenters to measure posture require temporal integration. Acceleration sensors and gyroscopes allow us to measure changes in linear velocity and angles, respectively. To estimate position from these sensors, their output thus needs to be integrated over time. Such integration generally accumulates errors and so these methods require a means of recalibration to avoid problems of drift (Miller et al. 2004; Gallagher et al. 2004; Vlasic et al. 2007). In this paper, we will explore how we can use accelerations without integrating over time to estimate posture.

Even at rest in healthy subjects, the body is in motion—small vibratory motions referred to as physiological tremor. These slight, often imperceptible movements are the result of a number of factors including respiratory motion, the cardioballistic impulse, fluctuating muscle activation during postural resistance to gravity, and resonant motion due to joint stiffness and limb inertia. Stiffness is a function of various factors including posture (Mussa-Ivaldi et al. 1985; Latash 1992; Kirsch et al. 1994; Flash and Mussa-Ivaldi 1990). The combination of these factors leads to vibrations at fast timescales (1–25 Hz) (Marsden 1984) which can vary in characteristic ways depending on the posture of the subject. Indeed, a recent paper has characterized a similar dependency of tremor, as measured by produced forces, as a function of hand configuration (Kutch et al. 2008). Tremor is clearly influenced by posture, but it is not known to what extent this influence can be used to measure posture from changes in tremor.

Tremor occurs with characteristic frequencies. Each moving joint has a characteristic resonant frequency. As the moment of inertia increases (by increasing mass or size), the resonant frequency decreases—for example, the resonant frequencies for a few joints are 25 Hz for the fingers, 6–8 Hz for the wrist, 3–4 Hz for the elbow, and 0.5–2 Hz for the shoulder joint (Marsden 1984; Deuschl et al. 2001). This frequency can be modulated by a number of factors, including muscle stiffness—higher stiffness will increase the frequency. Additionally, there is a 8–12 Hz central component in most subjects (Hallett 1998) caused by the modulation of motor commands issues by the central nervous system. Tremor can increase depending upon fatigue, posture (e.g., outstretched arms), or medications (e.g., caffeine). In healthy subjects, physiological tremor is not visible as long as the accelerations are below approximately 70 mm/s^2 ($\sim 7 \text{ mg}$) (Wade et al. 1982); for reference, physiological tremor which is normally not perceptible can readily be observed in the movement of a laser pointer during a presentation.

In this paper, we analyze how the slight movements due to normal, physiological tremor can be used to determine the posture of the subject. This will demonstrate that high-precision sampling methods can be used to make inferences from data that may have simply been disregarded as noise. Specifically, the posture of the forearm can be determined through the small, vibratory movements of the hand. The direction of these tremors can determine both the orientation of the forearm and whether or not the arm is stabilized with the elbow on (supported) or off a table (unsupported). We present a simple, raw estimate of the arm posture by finding the direction of minimum motion. This initial estimate works exceptionally well in the supported condition, and an estimate using a two-parameter linear correction is presented which improves results for the unsupported case. The appropriate timescale for analysis using this technique will be shown to match the timescale of the resonant frequency of the elbow joint through an analysis of optimal sampling rate/frequency. We will demonstrate that what others may consider motor noise in motion capture is actually a useful signal that can enable inexpensive techniques for posture determination.

Methods

Experiment

Arm configurations of eight healthy subjects (3 M/5F, 34 ± 11 years) were recorded as they maintained a series of instructed postures. Subjects were initially seated so their elbows could rest comfortably on a table. We recorded their right arm positions by active optical markers at a sampling rate of 500 Hz using the 3D Investigator Position Sensor (Northern Digital Inc.; Waterloo, Ontario, Canada). Technical specifications include an accuracy of 0.4 mm and a resolution of 0.01 mm. The sensor array was placed on the subject's right side approximately 2.4 m from the position of their elbow. Wired position markers were placed in three locations on their arm—the wrist, elbow, and shoulder. These optical sensors thus allowed us to measure both posture as well as the small movements of the hand. We fixed the marker to the wrist approximately on the styloid process of the ulna, on the elbow at the humeral lateral epicondyle, and on the shoulder at the rightmost point on the scapula. All analyses were done based on the exact position of these markers.

On each trial, subjects were instructed to move their right forearms into a position to match a displayed azimuth and elevation. The posture instructions were uniformly distributed between 0° and 90° inclination and -45° to 45° azimuth with 0° azimuth indicating directly forward. For analysis, only the measured azimuth and elevation were used, as the instructed positions were not strictly enforced. After a brief delay, subjects maintained their posture for 20 s during recording and were compensated based on how still they kept their arm. Each subject completed 8 blocks with 10 trials per block. Subjects self-initiated each trial by pressing a key with their free arm and recording began after 3 s. Subjects were encouraged to rest between blocks to avoid fatigue. In each block, the trials were evenly and randomly split into two conditions—supported (elbow on) versus unsupported (elbow off). All subjects signed IRB approved consent forms prior to their inclusion in this study. Our protocol was performed according to national and international standards and was approved by the local ethics committee.

Data analysis

For each trial, instantaneous velocities were determined by subtracting the positions between successive time points. Accelerations were extracted by using the difference between successive velocities. The sampling rate for analysis was 10 Hz. To obtain raw estimates of the azimuth and orientation, we effectively fit a 3D Gaussian ellipse to the collection of acceleration vectors and chose the direction of minimum variance. Specifically, for each trial, the vectors representing the instantaneous accelerations were collected, a 3×3 covariance matrix of the acceleration vectors was computed, and the covariance matrix was factored by eigenvalue decomposition. The axis of smallest acceleration was specified by the eigenvector corresponding to the smallest eigenvalue, and the particular direction was chosen along that axis to always point forward/away from the subject. The azimuth and orientation were estimated from this direction vector using the expected trigonometric transforms shown in Eqs. 1 and 2. Here, x , y , and z correspond to rightward, upward, and forward components of the direction vector, respectively, for the subject.

$$\text{azimuth}_{\text{raw}} = a \sin \left(x / \sqrt{(x^2 + y^2 + z^2)} \right) \quad (1)$$

$$\text{inclination}_{\text{raw}} = a \sin \left(z / \sqrt{(x^2 + y^2 + z^2)} \right) \quad (2)$$

We expect some bias in these estimates due to marker placement on the outside, as opposed to the center, of the arm, as will be discussed in the results. Also we expect tremor accelerations to be asymmetrically affected in the unsupported elbow condition due to motion of the arm and additional effects of resisting gravity. Because of this, a linear correction was used to better match the angles produced by Eqs. 1 and 2 to the azimuth and inclination determined by marker position. This was done using only a scaling factor and intercept, as shown in Eq. 3; from the data presented later (Fig. 3), we see that only a linear correction is necessary. The true azimuth and inclination were measured directly from the position sensors of the hand/wrist and elbow. For the purposes of the fits of Eq. 3, azimuths were not included in the analysis when the inclination was within 10° from vertical, as widely different values would result from slight deviations in hand position.

$$\text{angle}_{\text{corrected}} = m * \text{angle}_{\text{raw}} + b \quad (3)$$

We can obtain estimates for m and b from a regression between the raw estimates and the angles as measured by the markers. The estimates from the data presented below are given by Eq. 4 and result from a direct regression based on the data obtained from Eq. 2. The significance of these estimates is discussed in the results section.

$$\begin{aligned} \text{supported : azimuth}_{\text{corrected}} &= 0.97 * \text{azimuth}_{\text{raw}} && - 12.0 \\ \text{supported : inclination}_{\text{corrected}} &= 0.97 * \text{inclination}_{\text{raw}} && + 0.3 \\ \text{unsupported : azimuth}_{\text{corrected}} &= 1.19 * \text{azimuth}_{\text{raw}} && - 18.1 \\ \text{unsupported : inclination}_{\text{corrected}} &= 1.29 * \text{inclination}_{\text{raw}} && + 30 \end{aligned} \quad (4)$$

Model accuracy from Eq. 3 was evaluated by cross-validation. In the within-subject design, one of the 8 blocks was taken out and used as a test set while m and b were determined uniquely from the remaining set of 7 blocks. This was repeated for all blocks for each individual subject. To analyze how well the model applies across subjects, the model was also tested successively on each individual by subject-wise cross-validation, where the data from seven subjects were used to estimate the parameters in Eq. 3, and these parameters were used to obtain the estimates for the subject that was not used for the fit. The within-subject and between-subject accuracy of this technique was then evaluated by the standard errors of the produced estimates.

Results

Posture influences tremor

To characterize tremor, we sampled a series of postures by varying the subject's forearm posture over a range of approximately 90° in azimuth and inclination—40 trials with the elbow supported on the table and 40 trials without arm support. In some cases, the nature of the tremor can be easy to interpret. For example, when the elbow is resting on the table, wrist movement should be constrained to an arc pivoting on the elbow with little movement in the axial direction (see Fig. 1a). In such a situation, posture should have an expected effect on the statistics of tremor.

How does tremor change when posture is varied? Analyzing the distribution of such small movements in cases where the elbow is supported, we find that, as we should expect, the accelerations tend to be orthogonal to the forearm's orientation (Fig. 1b, c). The same effect is seen at various levels of inclination. Because tremor reliably varies with posture, it seems promising to use the minimum variance direction to estimate the angle of the forearm.

Unfortunately, not all posture estimation can be expected to occur with the arm supported on a table. To address this additional case, in half the trials, subjects were instructed to maintain a posture with their elbows slightly off the table. Intuitively, this will introduce significantly more motion that is not constrained to be angular from the elbow (Fig. 1d, e). Raw angle calculations will necessarily be less precise in the unsupported case as more motion is present in the direction of the forearm than when supported. However, trends in the distribution of micro-movements are visible even in the unsupported condition, and a linear regression can correct for biases due to elbow motion. We thus expect more estimation error in the unsupported condition, but still some predictive ability for posture determination.

Determining if the arm is supported

Before we start estimating posture from tremor, we want to see if we can detect whether or not the elbow is supported. This might be important if in an experiment's arm support had not been recorded but may become necessary for subsequent data analysis. We tested two simple classification methods. The standard deviation of the hand position during the recording allows some rough classification but this is not very precise (Fig. 2a), mainly because drift over time significantly occurs in both support conditions. On the other hand, the mean standard deviation of the instantaneous acceleration permits a much more reliable classification. Using a threshold of 30 mm/s^2 ($\sim 3 \text{ mg}$) on average, we can correctly classify 93% of the trials as elbow raised or fixed. More advanced machine learning techniques can easily improve the recognition rate (data not shown) but this is beyond the scope of this paper. Even with a simple, one-parameter threshold on the standard deviation of acceleration, we can determine the support of the arm for healthy subjects, which will help in using the correct model for posture estimation.

Estimating the posture

The statistics of tremor are sufficient to directly predict the angles of the forearm when the elbow touches the table. We find that the direction of minimum acceleration allows us to predict the posture quite well (Fig. 3a, b, see methods for calculation details). Not surprisingly, the supported (elbow on) condition produces more precise estimates than the unsupported condition. In various cases, there is a systematic bias between the measured angle and the estimated angle. In the azimuth estimate (e.g., Fig. 3a), the bias of about 12.0° can be understood as an artifact stemming from the distance of the optical marker from the center of the joint. With the average forearm measurement of 24.6 cm, a 5-cm marker-to-elbow-joint distance would produce a roughly 12° bias. This demonstrates that the minimum variance technique may be more accurate (although clearly less precise) than the optical markers.

For the unsupported condition, we should expect less precise estimates (Fig. 3c, d). The addition of motion from the shoulder joint can bias the estimates. For example, there is a bias away from the forward-left azimuthal direction, which can come from more motion of the hand in the forward-left and backward-right direction (negative azimuthal directions). Movement of the elbow in that direction can be a result of the right arm pivoting around the shoulder. Moreover, there are biases toward horizontal. This is due to increased vertical tremor while supporting the arm against gravity. Large vertical elbow motion increases the vertical motion of the hand, causing a dramatic underestimation of the inclination. Both unsupported conditions produce expected, biased raw estimates, but because there is still a significant correlation in these raw estimates and the measured angles, it may be possible to correct this bias.

We attempt to correct for the small bias of the supported condition by regressing the raw estimates with the measured angles (Fig. 4a, d). To make sure that we are not overfitting the

data, we use cross-validation to assess quality of fit. To see how well we can construct subject-specific estimates, we cross-validate across trials from the same subject. The regression removed the bias, and the estimates have standard deviations of 4.1° and 4.2° for azimuth and inclination, respectively. To see how well we can construct subject invariant estimates, we cross-validate across subjects and still find low standard deviations of 4.3° and 4.7° , respectively. This indicates that the linear correction works even across subjects.

Corrections are clearly of particular importance for the unsupported condition (Fig. 4e–h). We find that the standard deviation within subjects was still relatively low at 9.5° and 11.8° , inclination and azimuth, respectively, while across subjects cross-validation showed a modest increase of 11.9° and 14.4° , respectively. Although these estimates have larger errors than the supported condition, we see that it is still possible to obtain corrected position estimates using linear regression. Even in the unsupported condition, relatively good estimates of posture are possible based on accelerations alone.

One of the most important factors in analyzing tremor and its relation to posture is measuring movements at the right timescale. The resonant frequency of the elbow joint is known to be near 3–4 Hz (Marsden 1984), so a reasonable choice for sampling in order to capture this frequency is 10 Hz (with a Nyquist limit of 5 Hz). At high frequencies, the instantaneous accelerations are likely to be from noise and can be discarded, whereas at low enough frequencies, the accelerations are more likely to be from drift or body sway than from the position of the forearm. To find the optimal sampling frequency, we performed block-wise cross-validation (as in Fig. 4a, b, e, f), but systematically changed the sampling rate (Fig. 5). Near 10 Hz, all the standard deviations are close to optimal, which justify the use of this particular timescale we used for analysis. Bandpass filtering was also used (data not shown) and produced similar results.

In this paper, we use a high-resolution method (differentiated optotrak signals) to measure acceleration. To consider the effect of sensor resolution, we estimated inclination and azimuth at different levels of quantization. Specifically, we performed block-wise cross-validation to obtain error estimates at different amounts of quantization. We can observe (Fig. 6) that with bin sizes of up to 10 mm/s^2 ($\sim 1 \text{ mg}$), we obtain a similar accuracy, but beyond 60 mm/s^2 ($\sim 6 \text{ mg}$), the estimates begin to degrade significantly. This is reasonable given that the maximum accelerations were only up to 100 mm/s^2 (Fig. 1). Because of this, measurements of these accelerations would require a minimum resolution of approximately 5 mg or better.

Discussion

Here, we have shown that by recording tremor of the hand, we are able to estimate the posture of the arm. We found that such estimation is possible based on the covariance matrix and can be precise to about 4° when the arm is supported and 10° when it is not supported. Also, we observed that the optimal sampling rate is one that captures the expected resonance frequency of the joint used to determine the posture; in this case, our method relies on tremor in the elbow. Uncorrected supported and corrected unsupported conditions can both be reliably estimated using a 10 Hz sampling rate. These results give us a better understanding of the viability of using physiological tremor to determine posture.

Physiological tremor may be disregarded as noise in many studies, but has been shown to be an informative signal about the state of the subject and may be worth measuring. When concerned only with endpoint positions, the small timescale and amplitude fluctuations are often too minor warrant consideration. Many such studies could simply subsample or smooth the data to remove this information. However, we have demonstrated that such

preprocessing steps prior to data collection can lead to a loss of valuable data. With the availability of high-precision endpoint measurements, this work justifies the collection of data with a relatively high precision and sampling rate. This would permit a post hoc analysis of subject posture without the use of any additional hardware. Clearly, physiological tremor is more than just noise, and so it may be useful in future experiments to consider sampling techniques which can capture it for later analysis.

For comparison, the current motion capture approach that is closest to what we presented here is based on kinematic measurements of joint angles and inertia. Inertial motion capture systems often use biomechanical models in combination with gyroscopes and accelerometers to measure rotational rates and linear motion. Gyroscopes measure angular velocity, while accelerometers measure linear acceleration—neither gives direct information about posture. By using integration over time and some introductory calculus, changes in angle and linear velocity can be tracked over time. With the proper calibration, the position over time can be calculated—but this integration is prone to drift. To recalibrate, these systems often use the earth's magnetic field or the downward acceleration by gravity. The tremor-based posture estimation technique we presented here could potentially be used to supplement inertial motion capture techniques by providing a signal that does not drift to recalibrate those that do.

Because this technique relies on accelerations, highly sensitive accelerometers could also be used to exploit these tremor signals. One advantage is that accelerometers are cheap and ubiquitous. Almost all smartphones, many digital cameras, and video game controllers have accelerometers which measure the tilt relative to gravity and the translational motion of the device. These sensors can be as small as a few cubic millimeters and cost only a few dollars to manufacture, and so have already found use in a number of studies measuring movement and general activity in adults (c.f. Murphy 2009; Pentland 2005; Sung et al. 2005). An additional benefit is the high portability due to the low power consumption and small size, permitting even wireless applications (Venkatraman et al. 2007). Accelerometers are cheap, highly portable, and easy to use, making any technique using them much more technically and economically attractive.

There are specific reasons why this technique may not be applied easily to accelerometer data. First, the presence of gravity provides a strong, reliable signal with which to measure inclination—likely more reliable than using tremor. Azimuth calculation does not benefit from a strong gravitational signal, but to use physiological tremor by accelerometry for the azimuth, a high degree of precision is required. Our results (Fig. 6) demonstrate that as you pass 50 mm/s^2 ($\sim 5 \text{ mg}$) quantization resolution, the minimum variance method degrades significantly. For comparison, accelerometer readings from many cell phones accelerometers are near 8-bit resolution (e.g., T-mobile G1—android OS), and to span -2 g to $+2 \text{ g}$, the maximum resolution is approximately 150 mm/s^2 ($\sim 15 \text{ mg}$). So we can conclude this technique can only be done well with a resolution significantly better than 50 mm/s^2 ($\sim 5 \text{ mg}$).

In this paper, we use acceleration signals from an external reference frame, which bypasses an additional difficulty in using accelerometers. With an accelerometer fixed to your arm, the reference frame of the accelerometer changes as the arm moves. This technique can provide the orientation of the forearm only in the reference frame of the acceleration signal. For this reason, this technique is most useful for analyzing tremor from endpoint position or acceleration signals from external reference frames, rather than accelerometers or other devices placed directly on the limb.

A number of other methods could be used to map the distribution of endpoint accelerations to posture. Here, we only used the minor axis of the tremor covariance—one feature with a clear interpretation. Although additional features and regression methods would lead to marginally better performance, we believe the minimum variance method provides a good tradeoff between accuracy and ease of use.

The results that we presented are an example of how postural information can be extracted from hand vibration data that is typically disregarded and often filtered out as noise. This is a special case of a general finding in machine learning, that given a rich enough set of data, it is often possible to extract information that is important for the problem at hand. Engineers and other scientists have often been improving upon posture estimation using more sophisticated equipment. Here, we show that precise measurement of small-timescale acceleration can provide robust arm posture estimates. This work represents one of the many ways high-precision measurement devices (e.g., optical position sensory, high-precision accelerometers and gyroscopes, etc.) can exploit the natural physiological tremor in subjects to infer posture, which could be useful a variety of research and clinical settings.

Acknowledgments

We thank the National Institutes of Health (grants R01NS057814, 1R01NS063399 and 2P01NS044393) and the Chicago Community Trust for their financial support.

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Fig. 1.

The relationship between arm posture and tremor of the hand. **a** While a subject is holding a particular posture, the small vibrations of the hand are likely to be perpendicular to the forearm. **b** The small, instantaneous hand accelerations (tremor) over the course of three separate trials at various azimuths (-26° , -4.5° , 26°) at inclinations near horizontal are shown. The azimuthal movements shown here are projections on a horizontal plane. The *black bar* indicates the orientation of the forearm, with the hand represented as a *circle* at the end, as shown in part **a**. **c** Tremors with changes in inclination (9.3° , 41° , 81° above horizontal) with notations otherwise identical to **b**. As the forearm is raised, vibrations move from vertical to horizontal. The projection shown is on the sagittal plane. **d, e** Example tremors when the elbow no longer rests on the table with all notations as in **b, c**

Fig. 2.

Estimation of arm support using hand movement. **a** A histogram of the standard deviation of position over the course of a trial is shown. **b** A histogram of the standard deviation of instantaneous accelerations at a 10 Hz sampling rate is shown

Fig. 3.

Posture estimation using the direction of minimum variance. For each trial, azimuth and inclination were estimated using the direction of minimum variance for the acceleration vectors. **a** The relation of estimated and true azimuth is shown for the elbow on condition. **b** The relation of estimated and true inclination is shown for the elbow on condition. **c** The relation of estimated and true azimuth is shown for the elbow off condition. **d** The relation of estimated and true inclination is shown for the elbow off condition

Fig. 4.

Posture estimation using the minimum variance technique. Linearly corrected angle estimates are presented here as plots comparing the measured versus estimated angles. Azimuth (*left plots*) and inclination (*right plots*) are given for the condition with the elbow on the table (a–d) and elbow off the table (e–h). Cross-validation was used to estimate standard deviation. In **a, b, e, f**, the estimates were made within subjects using block-wise cross-validation. In **c, d, g, h**, the estimates were made between subjects by subject-wise cross-validation. Standard deviation of the estimates (*s*) and correlation (*r*) between estimated and measured angles are given for each plot

Fig. 5.

The influence of filtering timescale for posture estimation. Here, we find the sampling frequency most relevant for determining forearm posture from hand movements. Azimuth and inclination were estimated by block-wise cross-validation as shown in Fig. 4. The standard deviations of these estimates are plotted as a function of sampling frequency. The useful timescale for tremor of the hand is expected to be near the resonant frequency of the elbow joint (3–4 Hz), leading to an optimal sampling rate at least double that frequency due to Nyquist limits. The use of 10 Hz throughout the paper appears to be justified not only by this intuition, but also by the dip in error rates according to these cross-validation results

Fig. 6.

Effects of measurement resolution on posture estimation accuracy. Here, we measure the accuracy of the minimum variance estimation technique as we change the resolution of measurement. We quantize the continuous measurements and perform block-wise cross-validation to obtain a standard deviation of the estimate errors. The standard errors are limited by the standard deviation of the samples, as shown in the *horizontal dotted lines* ($\sigma_{\text{azimuth}} = 28.36^\circ$, $\sigma_{\text{inclination}} = 22.53^\circ$)