# A Method for Segment Based Surface Reconstruction from Discrete Inclination Values 

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#### Abstract

Object orientation tracking in local reference frame can serve as a useful tool in fields such as surface shape recognition. Often measurement methods provide incomplete data about object orientation. In this paper a method is proposed for selection of surface segment direction when only inclination levels of each segment are known. Method is applicable in cases when some additional constraints can be applied to the surface, such as limited flexion and segment layout. During surface model approximation a specially adapted exhaustive search algorithm is used to find the most appropriate segment direction angle to satisfy physical constraints of the surface. This method proved to significantly increase approximation precision of non-trivial surfaces.


Index Terms-Reconstruction algorithms, shape measurement, sensor arrays, accelerometers, body sensor networks.

## I. Introduction

Object orientation tracking is used in a wide variety of applications covering such fields as robotics, health care, entertainment and many others. One of the fields benefiting from this kind of technology is human posture monitoring.

Depending on the usage requirements object orientation tracking can be done either with external or internal tracking technologies and either within global reference frame or local reference frame.

External tracking technologies (e.g. video analysis [1], [2]) allow the tracked object itself to be very simple and low cost, but they require complicated infrastructure in all locations where these technologies might be used. In contrast, internal tracking technologies (e.g. inertial positioning systems [3], [4]) can be used anywhere, but require complex sensor systems mounted on the object itself, introducing such problems as involved data acquisition and processing as well as limited battery life for mobile use.

The different reference frames used by the tracking systems depend on the final application of the data. Global reference frame is needed, if object location must be determined relative to other objects. This approach provides more data, but requires external reference system with which the tracking system needs to communicate in order to

[^0]locate itself (e.g. GPS satellites). On the other hand, some applications, such as posture monitoring, only require the use of local reference frame, in order to determine internal position states of the system. This approach does not require external technical support and is more suitable for mobile wearable applications.

A method using 3-axis accelerometer network for surface shape detection was proposed in [5]. This method is suitable for use in wearable shape recognizing fabrics applicable for human posture monitoring and treatment of spinal deformities via biofeedback. Surface shape is approximated from data obtained from an accelerometer network arranged in a regular grid formation. This approach contains only one type of small, low cost sensors reducing data fusion complexity and forming a scalable system suitable for integration in clothing. This is beneficial compared to other methods [6]-[9] using smaller amount or more complicated sensors.

In [5] accelerometers are used as inclination sensors allowing to obtain orientation of corresponding surface segments relative to gravity reference frame [10]. One plane $(x, y)$ of this reference frame is perpendicular to gravity vector, but the direction around vertical ( $z$ ) axis is not fixed. Because of this each sensor orientation around $z$-axis is unknown and is assumed to be a fixed value when surface model is constructed. This simplification allows basic shape approximation, but can introduce significant errors with more complicated surface shapes. This can be seen in Fig. 1 where method is used for human back model reconstruction. In positions with severe slouching, distances $d 1$ and $d 2$ are significantly different in reconstruction, although they are approximately equal in real life.


Fig. 1. Human back model approximation.

In this paper a method is proposed for minimization of segmented surface approximation error by selection of $z$ axis rotation angle for each segment if only inclination of each segment is known. The method itself is described in Section II followed by experimental evaluation set up in Section III and giving results in Section IV.

## II. METHOD

## A. Surface Parameters

A surface consisting of $I$ segments arranged in a $n \times m$ grid formation is assumed. This surface is continuous and bendable. It contains equal size segments arranged in an evenly spaced grid formation. The distance between segment rows and columns is denoted by $d$. Each segment in our model is represented as a cross-shaped object defined by four direction vectors: $\vec{N}=\left(\begin{array}{lll}0 & 0 & \frac{d}{2}\end{array}\right), \vec{E}=\left(\begin{array}{lll}\frac{d}{2} & 0 & 0\end{array}\right)$, $\vec{S}=\left(\begin{array}{lll}0 & 0 & -\frac{d}{2}\end{array}\right), \vec{W}=\left(\begin{array}{lll}-\frac{d}{2} & 0 & 0\end{array}\right)$ and center location vector $\vec{C}$ (Fig. 2). These segments are used to construct approximated surface model.


Fig. 2. Structure of segment representation.
Starting data $\overrightarrow{N_{l}}, \overrightarrow{E_{l}}, \overrightarrow{S_{l}}, \overrightarrow{W_{l}}$ for each of $i \in[1 . . I]$ segments is calculated by rotating vectors $\vec{N}, \vec{E}, \vec{S}, \vec{W}$ to the inclination values of the corresponding segment.

The actual segment $z$-axis rotation angle $\alpha_{i}$ and actual segment centre vector $\vec{C}_{i}$ will be calculated by applying the method described below.

## B. Optimization Algorithm

The optimization method itself is based on a simple exhaustive search over all the possible rotation angles around $z$-axis for each of the segments. The structure of the algorithm is shown in Fig. 3.
The regular grid is divided into $(n-1) \times(m-1)$ subproblems hereinafter referred to as work-sets. Each of these work-sets consist of four segments $A 1, A 2, A 3, A 4$ which are connected in such a way, that without any initial rotation they would form a square as seen in Fig. 4. Each of the segments is represented in work-sets at least once.

For the requirements of the algorithm a segment is considered processed when corresponding $\alpha_{i}$ and $\vec{C}_{i}$ have been found. Initially for one of the segments these values are manually defined to serve as a placement reference for the rest of the model.

The algorithm consists of these main steps:

1. Every work-set in the system is handled one at the time. The order of work-set selection is previously defined in such a way that every handled work-set contains at least one previously processed segment.


Fig. 3. Algorithm flow.


Fig. 4. Structure of a work-set.
2. While handling a work-set all the combinations of possible $\alpha_{i}$ values for non-processed segments within it are evaluated based on evaluation criteria explained in the next sub-section. The set of possible $\alpha_{i}$ values contains successive discrete angles from a certain interval. In this step $\vec{C}_{i}$ values are calculated from selected $\alpha_{i}$ values together with values from previously processed segments.
3. Those $\alpha_{i}$ and $\vec{C}_{i}$ values that match evaluation criteria
the best are stored as the resulting values for corresponding segments. This means, that all segments in the current work-set are processed and algorithm moves to the next work-set until no more are left.

## C. Evaluation Criteria Selection

To evaluate which of the combinations of possible $z$-axis rotation angles will improve the precision of the reconstructed model the most, constraints from the surface definition are applied during approximated model construction.

The surface is defined as continuous, and because of that the corresponding sides of the segments should be joined together. Ideally there should be such a combination of $\alpha_{i}$ rotations for each segment, such that all the segments can be connected as shown in Fig. 3 and their corresponding direction vector end points would coincide. Unfortunately this is not true because of the simplified grid model; however the algorithm looks for the closest solution to ideal model, by introducing a continuity criterion working as follows:

- Within a work-set three of four pairs of segments are assumed to be jointed in "U" shaped pattern ( $A 4$ to $A 1$, $A 1$ to $A 2$ and $A 2$ to $A 3$ ). Continuity criterion prefers solutions minimizing the distance $\Delta_{d}$ between the fourth pair of segments (A3 to A4);
- For each of four segments within a work-set and a given combination of $\alpha_{i}$ angles temporary endpoint vectors $\overrightarrow{N_{l}^{\prime}}, \overrightarrow{E_{l}^{\prime}}, \overrightarrow{S_{l}^{\prime}}, \overrightarrow{W_{l}^{\prime}}$ are calculated by rotating each of vectors $\overrightarrow{N_{l}}, \overrightarrow{E_{l}}, \overrightarrow{S_{l}}, \overrightarrow{W_{l}}$ by an angle $\alpha_{i}$ around $z$-axis;
- From these temporary points segment centres $\vec{C}_{i}$ are calculated. Because at least one of segments is already processed at most three of $\vec{C}_{i}$ are unknown and can be solved from equation system:

$$
\left\{\begin{array}{l}
\overrightarrow{C_{A 1}}+\overrightarrow{E_{A 1}^{\prime}}=\overrightarrow{C_{A 2}}+\overrightarrow{W_{A 2}^{\prime}}  \tag{1}\\
\overrightarrow{C_{A 1}}+\overrightarrow{N_{A 1}^{\prime}}=\overrightarrow{C_{A 4}}+\overrightarrow{S_{A 4}^{\prime}} \\
\overrightarrow{C_{A 2}}+\overrightarrow{N_{A 2}^{\prime}}=\overrightarrow{C_{A 3}}+\overrightarrow{S_{A 3}^{\prime}}
\end{array}\right.
$$

- Then for this combination distance $\Delta_{d}$ is calculated

$$
\begin{equation*}
\Delta_{d}=\left\|\left(\overrightarrow{C_{A 3}}+\overrightarrow{W_{A 3}^{\prime}}\right)-\left(\overrightarrow{C_{A 4}}+\overrightarrow{E_{A 4}^{\prime}}\right)\right\| \tag{2}
\end{equation*}
$$

- $\quad \Delta_{d}$ represents the matching error between segments so the combination with the lowest $\Delta d$ is considered the best.
After applying continuity criterion still several valid solutions are possible because:
- Cases are possible with infinite number of solutions, for example, when two of the connection points between segments are both on a line parallel to $z$-axis;
- $\quad \alpha_{i}$ angles are changed by discrete step. Because of that continuity criterion must be loosened by stating that all combinations with $\Delta_{d}$ that differ from the best $\Delta_{d}$ by an experimentally determined step $\varepsilon_{d}$ are also considered as possible candidates for best solution.
Another criterion must be introduced to select the most probable continuous surface configuration of the possible candidates. It is assumed, that the starting configuration of the surface is a flat surface and all deformations require additional energy. For the purposes of this paper it is assumed that states which require less energy are more probable than those requiring more energy. Basically it means that the algorithm prefers flatter surfaces. This is provided by the second - flatness criterion, working as follows:
- For all the solution candidates after continuity criterion is applied the distance between segment centres is calculated as

$$
\begin{align*}
F=\left\|\overrightarrow{C_{A 1}}-\overrightarrow{C_{A 2}}\right\| & +\left\|\overrightarrow{C_{A 2}}-\overrightarrow{C_{A 3}}\right\|+\left\|\overrightarrow{C_{A 3}}-\overrightarrow{C_{A 4}}\right\|+ \\
& +\left\|\overrightarrow{C_{A 4}}-\overrightarrow{C_{A 1}}\right\| . \tag{3}
\end{align*}
$$

- The solution with the largest $F$ is selected as the most flat of all solution candidates.
These two criteria are sufficient to select the preferred solution.


Fig. 5. Test setup (a), reconstruction without and with the described method (b), (c).

## III. EXPERIMENTAL SETUP AND RESULTS

The algorithm proposed in this paper was tested on a
prototype accelerometer network consisting of $I=16$ ( $n=4$, $m=4$ ) sensor nodes and distance between sensors $d=80 \mathrm{~mm}$. This network is fixed to an elastic wearable harness in an
evenly spaced grid formation as described in [5].
Values $\overrightarrow{N_{l}}, \overrightarrow{E_{l}}, \overrightarrow{S_{l}}, \overrightarrow{W_{l}}$ for each of $i \in[1 . .16]$ segments are calculated using quaternion method described in [5]. Segments are rotated to their corresponding sensor orientation according to their inclination measurement data.

Physical system introduces other reasons for selection of $\varepsilon_{d}$, such as sensor production and mounting errors. This value was experimentally selected as $\varepsilon_{d}=0.5 \mathrm{~mm}$.

To quantify the results acquired from experimental setup a curved sample surface was selected. The shape of selected sample surface is a conical frustum with base radius of 273 mm , top radius of 236 mm and height of 333 mm . Sensor network was attached to this sample surface (Fig. 5(a)) and the surface was placed $18^{\circ}$ relative to ground.

In this setup surface was reconstructed from sensor data and compared to theoretical surface model. This comparison is described with average error value $\Delta e$ calculated from reconstructed segment centre values $C_{i}$ and theoretical segment centre values $C_{i}^{\prime}$ for all of $I=16$ segments as

$$
\begin{equation*}
\Delta e=\frac{\sum_{i=1}^{I}\left\|c_{i}-c_{i}^{\prime}\right\|}{I} \tag{4}
\end{equation*}
$$

Before using the corrected rotation values provided by this algorithm average error between reconstructed surface and theoretical surface was $\Delta e=79 \mathrm{~mm}$ (Fig. 5(b)). After the proposed method was used this average error was reduced to $\Delta e=12 \mathrm{~mm}$ (Fig. 5(c)) resulting in approximately $85 \%$ error reduction in surface reconstruction.

These calculations with a $10^{\circ}$ step for $\alpha_{i}$ angle values within range of $\alpha_{i} \in\left[-90^{\circ} . .90^{\circ}\right]$ took approximately 1 second on a modern personal computer.

## IV. CONCLUSIONS

The method proposed in this paper provides an algorithm for surface reconstruction from discrete inclination values. The use of segment grid pattern and constraints of physical surface can provide additional data that cannot be obtained directly from sensor measurements alone, such as segment direction angle around vertical axis. This makes it practical for use in scenarios where physical constraints such as continuity are applicable, for example in human posture monitoring where sensors can be attached to the surface of clothing.

This method provided measurable increase in surface shape reconstruction precision compared to the previously
described method in [5]. Even though, as is, the method requires too much computational power to be practical for real-time applications, it has aspects which can be adjusted to reduce the calculation time depending on the requirements of specific case. The size of the set of possible angle values can be reduced either by increasing the discrete step or by reducing the minimum and maximum angle boundaries, noticeably reducing algorithm execution time.

The precision of this method can be additionally adjusted by determining the best coefficient $\varepsilon_{d}$ and by selecting work-set order in such way that is most suitable for the specific scenario. Future work is required to determine more general rules for selecting these parameters. Additionally the algorithm itself could potentially be improved for precision and performance. More realistic and smoother surface reconstruction models could be achieved by applying data interpolation methods.

## References

[1] J. A. Zubairi, "Applications of computer-aided rasterstereog-raphy in spinal deformity detection", Image Vision Comput., vol. 20, no. 4, pp. 319-324, 2002. [Online]. Available: http://dx.doi.org/10.1016/ S0262-8856(02)00026-4
[2] Jing Tong, Jin Zhou, Ligang Liu, Zhigeng Pan, Hao Yan, "Scanning 3D full human bodies using kinects", IEEE Trans. Visualization and Computer Graphics, vol. 18, no. 4, pp. 643-650, Apr. 2012. [Online]. Available: http://dx.doi.org/10.1109/TVCG. 2012.56
[3] S. H. Stovall, Basic Inertial Navigation. Naval Air Warfare Center Weapons Division, China Lake, California, 1997.
[4] Qu Pingping, Fu Li, Zhao Xin, "Design of inertial navigation system based on micromechanical gyroscope and accelerometer", Control and Decision Conf. (CCDC 09), China, 2009, pp. 1351-1354.
[5] A. Hermanis, K. Nesenbergs, "Grid shaped accelerometer network for surface shape recognition", in 13th Biennial Baltic Electronics Conf. (BEC 2012), pp. 203-206, 2012. [Online]. Available: http://dx.doi.org/10.1109/BEC.2012.6376852
[6] D. Roetenberg, H. Luinge, P. Slycke Xsens MVN: Full 6DOF Human Motion Tracking Using Miniature Inertial Sensors, XSENS Technologies, Apr. 2009.
[7] H. J. Luinge, P. H. Veltink, "Inclination measurement of human movement using a 3-D accelerometer with autocalibration", IEEE Trans. Neural Systems and Rehabilitation Engineering, vol. 12, pp. 112-121, Mar. 2004. [Online]. Available: http://dx.doi.org/ 10.1109/TNSRE.2003.822759
[8] C. Goodvin, E. J. Park, K. Huang, K. Sakaki, "Development of a realtime three-dimensional spinal motion measurement system for clinical practice", Med Bio Eng Comput, pp. 1061-1075, Nov. 2006.
[9] W. Y. Wong, M. S. Wong, "Measurement of Postural Change in Trunk Movements Using Three Sensor Modules", IEEE Trans. instrumentation and Measurement, vol. 58, pp. 2737-2742, 2009. [Online]. Available: http://dx.doi.org/10.1109/TIM.2009.2016289
[10] AN3182 data sheet and application note. [Online]. Available: http://www.st.com/internet/com/technical_resources/technical_literatu re/application_note/cd00268887.pdf


[^0]:    Manuscript received April 22, 2013; accepted September 28, 2013.
    This research was funded by Latvian State research program, project "Innovative signal processing technologies for smart and effective electronic system development".

