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ORIGINAL ARTICLE

Self-learning computers for surgical planning and prediction of postoperative alignment

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Abstract

Purpose In past decades, the role of sagittal alignment has been widely demonstrated in the setting of spinal conditions. As several parameters can be affected, identifying the driver of the deformity is the cornerstone of a successful treatment approach. Despite the importance of restoring sagittal alignment for optimizing outcome, this task remains challenging. Self-learning computers and optimized algorithms are of great interest in spine surgery as in that they facilitate better planning and prediction of postoperative alignment. Nowadays, computer-assisted tools are part of surgeons' daily practice; however, the use of such tools remains to be time-consuming.

Methods: Narrative review and results Computer-assisted methods for the prediction of postoperative alignment consist of a three step analysis: identification of anatomical landmark, definition of alignment objectives, and simulation of surgery. Recently, complex rules for the prediction of alignment have been proposed. Even though this kind of work leads to more personalized objectives, the number of parameters involved renders it difficult for clinical use, stressing the importance of developing computer-assisted tools. The evolution of our current technology, including machine learning and other types of advanced algorithms, will provide powerful tools that could be useful in improving surgical outcomes and alignment prediction. These tools can combine different types of advanced technologies, such as image recognition and shape modeling, and using this technique, computer-assisted methods are able to predict spinal shape. The development of powerful computer-assisted methods involves the integration of several sources of information such as radiographic parameters (X-rays, MRI, CT scan, etc.), demographic information, and unusual non-osseous parameters (muscle quality, proprioception, gait analysis data). In using a larger set of data, these methods will aim to mimic what is actually done by spine surgeons, leading to real tailor-made solutions.

Conclusion Integrating newer technology can change the current way of planning/simulating surgery. The use of powerful computer-assisted tools that are able to integrate several parameters and learn from experience can change the traditional way of selecting treatment pathways and counseling patients. However, there is still much work to be done to reach a desired level as noted in other orthopedic fields, such as hip surgery. Many of these tools already exist in non-medical fields and their adaptation to spine surgery is of considerable interest.

Keywords Self-learning computers · Machine learning · Surgical planning · Sagittal alignment · Spine surgery

Introduction: why should we plan?

In past decades, the role of sagittal alignment has been widely demonstrated in the setting of spinal conditions. It is now well-established that sagittal alignment correlates with health-related quality of life scores (HRQOL). In adult spinal deformity, numerous studies have stressed that postoperative sagittal malalignment results in lower HRQOL, higher revision rates and residual pain [1, 2]. In degenerative conditions, several studies have shown that correction of sagittal malalignment, quantified by the pelvic incidence-lumbar

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lordosis (PI-LL) mismatch, was a predictor of success following short-segment fusions. On the other hand, a greater postoperative PI-LL mismatch leads to a higher risk of adjacent segment disease and decreased HRQOL scores [3, 4]. Moreover, restoration of sagittal alignment has been demonstrated to have several other favorable effects, such as decreasing the rate of pseudarthrosis and rod fracture [5].

Several parameters can be affected by spinal conditions, in isolation or combined, and lead to sagittal malalignment. Identifying the driver of the deformity is the cornerstone of a successful treatment approach. When surgery is performed, the correction of the driver of the deformity will lead to a global relaxation of the spino-pelvic axis and induce spontaneous correction of compensatory mechanisms. On the contrary, correcting parameters involved in compensatory mechanisms without correcting the driver will lead to poor outcome, as the patient will not be able to compensate for the deformity anymore. Such errors in surgical planning are to be avoided by any possible means.

Despite the importance of restoring sagittal alignment for optimizing outcome, this remains challenging. It has been demonstrated that in adult spinal deformity patients, surgical correction generally restores sagittal alignment in only 50% of the cases [6]. Preoperative planning is therefore of key importance to avoid postoperative sub-optimal alignment. In other fields of orthopedic surgery, computed-assisted methods are already well-established and are proven to increase accuracy due to better planning and simulation [7]. Therefore, self-learning computers and optimized algorithms are of great interest in spine surgery, such that better plans and prediction of postoperative alignment can be employed.

Evolution of surgical planning

At the dawn of spine surgery, and as recently as the past several decades, little importance was given to sagittal alignment and therefore, no systematic approach existed for its correction. Sagittal parameters, such as thoracic kyphosis or lumbar lordosis, were poorly defined by mean normative values. The history of surgical planning is quite recent. In 1986, Camargo et al. published an article stating that "The greater the deformity the lower the level of the osteotomy" [8]. Despite the simplicity of this statement, that was the first time such considerations (planning the level of the osteotomy) were introduced in the literature. Later in the 2000s, geometric constructions for the planning of subtraction osteotomies appeared, but still without taking into account the whole spine and individual variability [9, 10].

Currently, computer-assisted tools are part of surgeons' daily practices. Every PACS system provides basic tools for analysis, such as angle and distance measurement. However, these tools have limited accuracy and should not be used for surgical planning [11]. Recently, the development of spine dedicated software has given surgeons several tools for both diagnosis and treatment. These new tools are accurate and can take into account a combination of several parameters, to predict postoperative changes in sagittal alignment. However, the use of such tools remains time-consuming, with analysis times ranging from a few minutes for simple 2D analysis and up to 20 min for complex 3D reconstructions [12, 13].

Prediction of postoperative alignment

Predicting changes in sagittal alignment is complex. Of note, Ailon et al. reported difficulties for surgeons to predict postoperative alignment: among 17 surgeons devoted to deformity surgery, actual postoperative radiographic parameters were accurately predicted in only 42% of the cases [14]. This study thus highlights the need for predictive formulas to improve surgeons' ability to predict postoperative alignment. Several authors attempted to develop formulas predicting postoperative radiographic parameters. These mathematical tools ranged from very simple formulas, such as Lumbar Lordosis > Thoracic Kyphosis +20°, to more complex ones taking a combination of several parameters into account. The more complex ones, by considering compensatory mechanisms, seem to provide more accuracy, but are probably less easy to use in daily practice. In 2012, Smith et al. compared five mathematical formulas for the prediction of postoperative sagittal alignment after pedicle subtraction osteotomy [15]. They found that the most accurate formula for the prediction of SVA was one developed by Lafage et al.: $SVA = -52.87 + 5.90(PI) - 5.13\,(LL_{max}) - 4.45\,(PT) - 2.09\,(TK_{max}) + 0.57\,(age)$ [16]. While this formula may be cumbersome to employ in daily practice, results were reported with 75% accuracy on SVA prediction. Nevertheless, the use of computer-assisted methods could probably help to improve the accuracy of prediction, as demonstrated by Langella et al [17]. In this retrospective study, the authors aimed to determine the accuracy of a spine dedicated software in predicting postoperative alignment of 40 patients undergoing surgery for sagittal malalignment. A failure of prediction was defined as an actual postoperative alignment including a pelvic tilt > 21° or an SVA > 50 mm. With computer-assisted methods, they reported a failure in prediction of less than 20% of the cases. By adding the prediction of changes in pelvic tilt into the surgical planning, the chance for postoperative unsatisfactory alignment dropped down to 12%. This supports the ability of computer-assisted methods to provide an accurate prediction of postoperative alignment (Fig. 1 and Table 1).

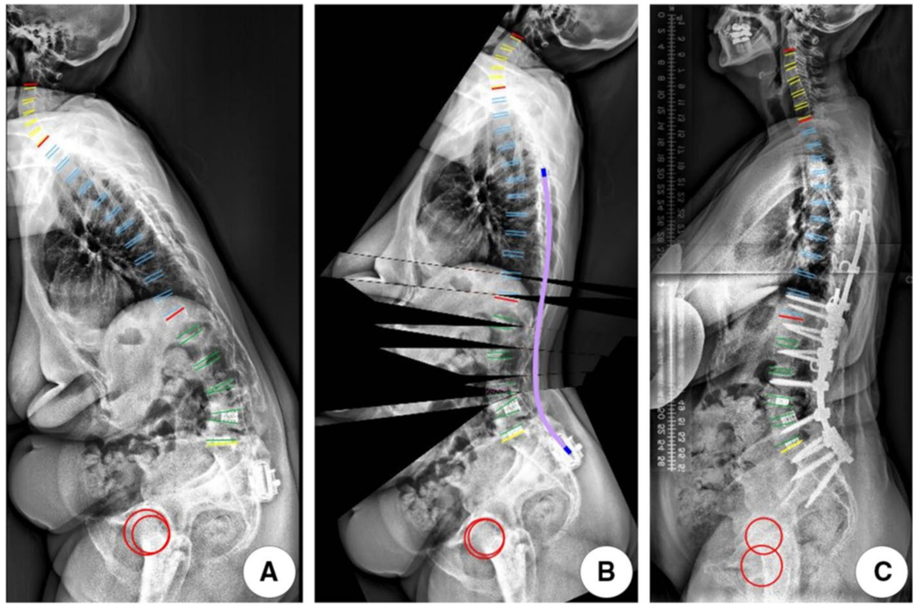

Fig. 1 Case example of a preoperative planning performed with a spine dedicated software. **a** Baseline. **b** Planning. **c** Postoperative. The planning consisted in the simulation of an L4 pedicle subtraction osteotomy, 3 Smith-Peterson osteotomies and a L3-L4 interbody cage. Sagittal parameters are presented in Table 1

Table 1 Case example of a preoperative planning performed with a spine dedicated software

Parameters	Baseline	Planning	Postoperative
Pelvic tilt	39°	15°	15°
Thoracic kyphosis	16°	22°	24°
Lumbar lordosis	31°	− 38°	− 39°
PI-LL mismatch	74°	4°	6°
SVA	223 mm	32 mm	− 1.3 mm

Current state of the art

Computer-assisted methods for the prediction of postoperative alignment consist of a three step analysis: identification of anatomical landmark, definition of alignment objectives (and thus surgical objectives), and simulation of surgery. The prediction of final alignment is then based on geometric transformations. This process contains multiple sources of potential error. First, the identification of all anatomical landmarks is tedious work and can lead to errors of measurement [18]. Then, rules for the definition of surgical objectives are needed. The use of the SRS-Schwab classification can be an appropriate tool, as it provides a universal language to describe and categorize patients, with strong correlations between radiographic parameters and HRQOL [19]. It has the advantage of being easy to remember but could be more precise. More recently, more complex rules have been proposed, such as age-related alignment or the GAP system [20, 21]. However, the complexity of these tools requires the use of computers. For example, Lafage et al. reported 30 normative values for traditional radiographic parameters (6 age-related values for 5 parameters) (Table 2). Even though this kind of work leads to more personalized objectives and a better understanding of sagittal alignment, the number of parameters involved renders it difficult for clinical use, stressing the importance of developing computer-assisted tools. Finally, simulation of surgical procedure can be the source of several errors as well. Software will not delineate what is realistic from what is improbable or impossible. For example, a surgeon will be able to plan a 50°-PSO at a single level without being restrained by the software. The software does not offer feedback on what a surgeon can actually achieve.

Table 2 Age-ajusted normative values for sagittal parameters, from the work by Lafage et al

Age group	ODI	Pelvic tilt	PI-LL	LL-TK	SVA	T1-PA
< 35	9.49	11.1	− 11.3	29.2	− 29.1	4.4
35–44	11.77	15.5	− 6.2	21.9	− 4	10
45–54	15.43	18.9	− 1.7	16.4	16.5	14.5
55–64	20.87	22.1	3.3	11.1	37	18.8
65–74	24.62	25.2	7.5	6.1	55.6	22.8
> 74	32.54	28.8	13.7	0.2	79.9	27.8

What can be done to improve planning?

The evolution of our current technology will provide powerful tools that could be useful in improving surgical outcomes and alignment prediction. Machine learning and other types of advanced algorithms are part of these powerful tools. Machine learning is defined as an algorithm that is able to be learned by a computer and self-improves from experience. This type of solution is already used in many other fields: facial detection in picture analysis software, personalized website recommendation or advertising, etc. Machine learning can use a combination of different types of advanced technologies, such as image recognition and shape modeling [22]. Using this technique, computer-assisted methods are able to predict spinal shape. With only ten landmarks manually identified, software can accurately predict the position of more than 70 anatomical landmarks on standard radiographs with an error of < 5%, thus automatically drawing the shape of the spine (Fig. 2). Technology such as image recognition can also be developed to identify possible pathologic areas (i.e., driver of deformity) and compensatory mechanisms and then to propose adequate surgical solutions.

While current predictive models require working with restricted hypotheses, machine learning methods can integrate many more variables. Information can be prioritized and thus influence decisions at different levels. In this way, there is no need to discard any information and the process is much closer to the human decision process.

An interesting potential pathway for software development would be the creation of algorithms representative of individual surgeon's practice. Surgical objectives could be refined based on the usual correction that a particular surgeon is able to achieve or his postoperative outcomes. The same process can be achieved with complication prediction. Based on a surgeon's complication rate, HRQOL or radiographic outcomes, computer-assisted prediction tools could adapt the surgical strategy and provide realistic surgical objectives. These tools could also be used for educational purposes. Clinical research delivers ongoing information and guidance that can be difficult for surgeons to integrate in their practice. The development of computer-assisted tools will allow the integration of relevant research findings on an ongoing basis, making it easily available for users.

Computer-assisted tools are emerging in spine surgery. Recently, the ISSG has reported accurate predictions of major complications following ASD surgery, with the use of patient-specific predictive models [23]. Prediction of alignment is following the same trend with promising results [24].

The development of powerful computer-assisted predictive models can involve the integration of several sources of information:

- Radiographic parameters from supine and standing X-rays, MRI, CT scan, etc.
- Demographic information such as age, sex and BMI.
- Unusual non-osseous parameters (muscle quality, proprioception, gait analysis data).

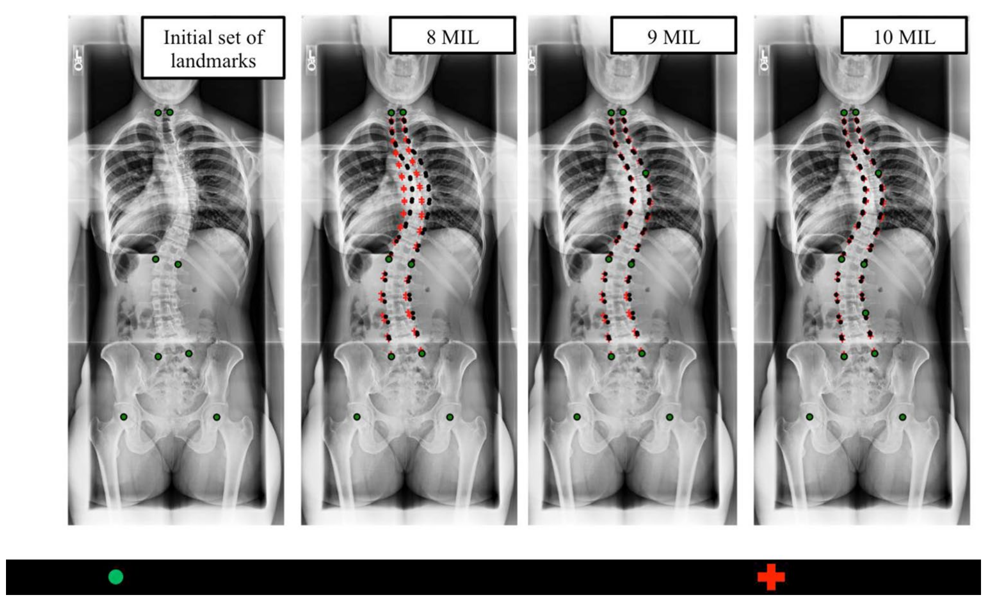

Fig. 2 Automated identification of radiographic landmarks (From Moal et al.). The computer was able to replace 60 landmarks based on the manual identification of ten landmarks

Using a larger set of data, these methods will aim to mimic what is actually done by spine surgeons. This way, objectives can be fine-tuned for each patient, based on personalized thresholds such as age-adjusted alignment, and thus lead to real tailor-made solutions.

Who could benefit from automated preoperative planning?

First and foremost, patients will be the clearest beneficiary from the development of automated planning. Better planning and prediction of outcome will influence a surgeon's decision making and lead to better postoperative outcomes. If these tools are efficient, one can expect a decrease in complications, and particularly in revisions due to mechanical failure. Moreover, being able to predict the complication rates associated with a procedure, based on different postoperative objectives, is of major interest for patient counseling and decision making. Improvement in surgical planning will also impact hospital costs, by decreasing operative time and reducing complication rates. Finally, industry will also benefit from this technology, by being able to develop patient-specific implant trays and decreasing the amount of surgical tools to be sterilized. By decreasing the number of unused implants or tools spent per surgery, the logistics/procurement costs can be reduced as well, which will have a meaningful impact on healthcare costs.

Conclusion

Preoperative planning is now well-recognized as a crucial step of surgical treatment, as it allows for decreasing unfavorable outcomes. Integrating newer technology can change the current way of planning/simulating surgery. The use of powerful computer-assisted tools, which are able to integrate several parameters and learn from experience, can change the traditional way of selecting treatment pathways and counseling patients. However, there is still much work to be done to reach a desired level as noted in other orthopedic fields, such as hip surgery. Many of these tools already exist in non-medical areas and their adaptation to spine surgery is of great interest.

Compliance with ethical standards

Conflict of interest None of the authors has any potential conflict of interest.

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