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Impact of beam complexity on plan delivery accuracy verification of a transmission detector in volumetric modulated arc therapy

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ABSTRACT

Objective: To study the effect of beam complexity on VMAT delivery accuracy evaluated by means of a transmission detector, together with the possibility of scoring plan complexity.
Methods: 43 clinical VMAT plans delivered by a TrueBeam linear accelerator to both Delta^4 Discover and Delta^4 Phantom+ for patient-specific quality assurance were evaluated. Global Dose-γ analysis, MLC-γ analysis, percentage of leaves with a deviation between planned and measured leaf tip position lower than 1 mm (LD) were computed. Modulation complexity score (MCS_v), average leaf travel (LT), a multiplicative combination of LT and MCS_v (LTMCS), percentage of leaves with speed lower than 5 mm/s (LS), from 5 to 20 mm/s (MS), higher than 20 mm/s (HS) and the average value of leaf speed ($MLCS_{av}$) were evaluated by means of an home-made Matlab script.
Results: Dose-γ passing rate showed a moderate correlation with MCS_v, LT, $MLCS_{av}$, LS and HS, while a stronger positive correlation was found with LTMCS. A strong correlation was observed between LD and both LT and leaves speed, while a weak correlation was observed with MCS_v. A correlation between MLC-γ pass rate and plan complexity parameters was found except for MCS_v; a moderate correlation with LS was observed, while all other parameters showed weak correlations.
Conclusions: The study confirmed the possibility to establish correlations between plan complexity indices versus dose distribution and MLC parameters measured by a transmissive detector. Further investigation is necessary to define specific values of the complexity indices to evaluate whether a VMAT plan is deliverable as intended.

1. Introduction

Volumetric modulated arc therapy (VMAT), combining modulation of multileaf collimator (MLC) movements, gantry rotation speed and dose rate, ensures high dose conformity to the target and healthy tissue-sparing. The complexity of the VMAT plan might affect the deliverability of plan itself; in fact, the greater the plan modulation, the greater the uncertainty in delivery [1].

Linac mechanical limitations and the increase of the number of small or irregular fields result in differences in dose distributions between calculated and delivered plan. Therefore, a pre-treatment patient specific quality assurance (PSQA) for each VMAT plan is suggested [2,3] to check the accuracy of intensity modulated radiotherapy (IMRT) plan dose calculation and detects relevant errors in the radiation delivery. Several studies have shown that as the treatment plan becomes more complex the passing rate in VMAT quality assurance decreases [4,5,6].

On the other hand, some studies have introduced modulation indices of VMAT plans that could allow to predict in the planning phase the plan delivery accuracy [7,8]. The use of plan modulation indices makes it possible to optimize times and resources: eventual correlations between modulation indices and pre-treatment QA results could be used to introduce new strategies in treatment planning, optimization and verification [9]. By defining action and tolerance level specific for different types of treatment, it could be possible to avoid critical treatment plans, explain eventual anomalous conditions and differentiate the QA strategies.

The combined use of the diode array Delta^4 Phantom+ (ScandiDos, Uppsala, Sweden) [10] and the high-resolution diode based transmission detector (TRD) Delta^4 Discover (ScandiDos, Uppsala, Sweden) [11] allows the physicist to evaluate the plan delivery accuracy using

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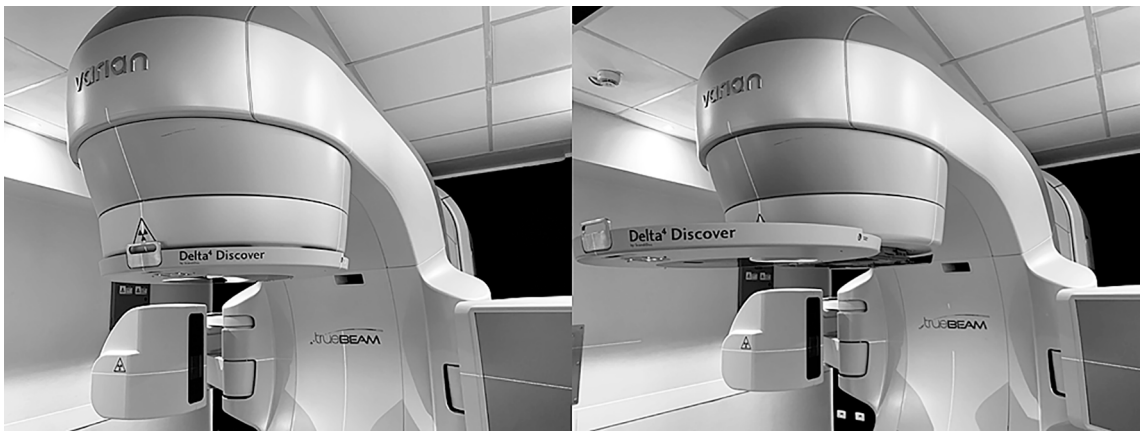

Fig. 1. Delta^4 Discover mounted on a Varian Truebeam Linac.

both the dose gamma index method [12] and the multileaf collimator position verification. The latter is performed by evaluating the MLC leaf edge deviations and the MLC gamma index, a new parameter introduced by the manufacturer for the analysis of the measurements on VMAT plans.

Based on the above considerations, the correlations between complexity plan indices based on the MLC movement patterns versus dose distribution and MLC parameters evaluated with measurements performed with Delta^4 Discover in conjunction with Delta^4 Phantom+ were investigated.

Additionally, the possibility of scoring complexity of VMAT plans was investigated for optimizing the workflow of plan creation, optimization and QA and for predicting the plan delivery accuracy with plan and MLC information. To the best of our knowledge, the currently published works describe the performances of the Delta^4 Discover system in pre-treatment and in-vivo verification [13,14,15]. This is the first attempt to study the detector behaviour as a function of treatment plan complexity.

2. Methods and materials

2.1. Delta^4 discover transmission detector

The Delta^4 Discover transmission detector is a fluence measurement device designed to monitor dose and MLC position during every treatment fraction. The detector consists of 4040p-type diode detectors each with an active area of 1 mm diameter and separated by 2.5 mm and 5 mm along and perpendicular to the MLC motion direction respectively at the isocenter. The diode array can measure a maximum field size of $25 \times 19.5\ cm^2$ when projected to the isocenter level. The detector can be easily attached to the head of a TrueBeam Linac (Varian, a Siemens Healthineers Company, Palo Alto, CA, USA), extending 2.3 cm from its collimator [11] (Fig. 1). Diode reading is sampled every 150 μs with no pause between the samples. For each of these samples, the signal level is compared against a pre-set threshold level to determine if it contains useful informations or only noise [16]. The initial setup of the TRD consists in three steps. A relative calibration using a single photon energy is performed to check that all diodes operate correctly and eventually to switch off the detectors with strong deviating signal (near zero or saturation). Then a detector position calibration tool checks that the diode rows of the Delta^4 Discover matrix are correctly centered under the MLC leaves. If the calculated position is not as expected, fine adjustment of the TRD must be done. Finally, for each photon modality, using an IMRT plan supplied by the manufacturer, a leaf edge calibration is performed. During this measurement the exact position of the TRD matrix along the MLC leaf trajectory and the dosimetric leaf gap are determined; these values are saved and applied later during the determination of the MLC leaf edges position in plan verification. After a successfull calibration, more than 95 % of the deviations between the measured MLC edge and the nominal edge position should be within ± 1 mm. It seems reasonable that these procedures should be periodically performed in a dedicated QA program.

The Delta^4 Discover can be used in two different modes. In “Express Mode”, the detector, by means of the fluence measurement, can provide informations about the location of the MLC leaves and gantry and collimator angle. In “Synthesis Mode” the device, in conjunction with the Delta^4 Phantom+ creates a link between the signals from both the devices in order to convert fluence to dose. This preliminary synchronization allows to use the Delta^4 Discover by itself during daily treatments and to synthesize fluence measurements into a dose distribution in the Delta^4 Phantom+. In such a way, the Delta^4 Discover can be used to verify, by means of the gamma analysis implemented in the detector software, the dose distribution at each fraction of treatment delivery and the cumulative dose delivery as a function of control points (CP).

Additionally, for each leaf that can be tracked, the detector integrates the diodes signal typically over 25 ms and sends that integrated signal to the workstation. For each package the actual gantry angle is measured and the leaf edges are computed. The leaf edge detection algorithm fits a sigmoid to both penumbras and determines the point of sharpest gradient of each sigmoid. This position is then adjusted with the dosimetric leaf gap as obtained during the MLC calibration to retrieve the MLC leaf edge. The leaves deviations between measured and planned position are evaluated for each beam, leaves bank, control point and leaf.

The leaf edge detection algorithm may break down for extreme MLC apertures, when an isolated leaf pair is nearly closed and there are large openings adjacent to these leaves, or when MLC movements are very fast [17]. Therefore, in analogy with the dose deviation gamma index (Dose-γ), the Delta^4 Discover software calculates for VMAT plans an MLC gamma index (MLC-γ), by using the gamma formula with the measured difference in MLC leaf position corresponding to dose deviation and the difference in measured gantry angle corresponding to the spatial coordinate. The MLC gamma index calculation checks if the measured MLC leaf edge deviation intersects an ellipsoid representing the acceptance criteria for gantry angle and leaf position deviation.

The detector software enables the user to set pass or fail criteria that may be used to support the decision if a plan passes or fails the verification process. Pass/fail criteria can be set for the percentage of diodes with the Dose-γ index less than 1, percentage of MLC leaves in all control points with the MLC-γ index less than 1, deviation between planned and measured leaf tip.

Table 1
Distribution of anatomical sites and statistics of the VMAT plans. Head and neck, rectum, prostate and pelvis prostate cancer patients were treated with simultaneous integrated boost plans.

Patient class	#	Total PTV Volume (cm^3) (Mean ± 1 SD)	PTV Dose (Gy)	# of fractions	# of arcs	Mean total delivery time (min)
Lung	5	358 ± 50	60	30	2 partial	1.46
Esophagus	5	932 ± 368	41.4	23	2 full	2.85
Head & Neck	5	770 ± 103	70/63/58.1	35	2 full	3.06
Prostate	5	149 ± 30	70/63	28	2 partial	1.77
Brain	5	272 ± 53	60	30	2 partial	1.51
Male Pelvis	5	907 ± 172	70/63/53.2	28	2 full	3.08
Female Pelvis	5	991 ± 187	48.6	27	2 full	2.63
Rectum	5	1236 ± 140	50/45	25	2 full	2.83
Lung SBRT	3	19 ± 4	50	5	3 partial	8.04

2.2. VMAT plans

43 VMAT plans were created and optimized using the Varian treatment planning system (TPS) eclipse (Version 15.6) and delivered by a TrueBeam linear accelerator equipped with a standard millennium 120 multileaf collimator to both Delta^4 Discover and Delta^4 Phantom+. The clinically commissioned energies of 6 MV and 6 MV flattening filter free (FFF) were used. The maximum dose rates were 600 and 1400 MU/min. All plans were evaluated as clinically acceptable and deliverable by pre-treatment QA and had been previously used to treat patients in our institution.

In Table 1 the distribution of anatomical sites and the statistics of the VMAT plans are reported.

2.3. Plan complexity parameters

For each of 89 VMAT arcs and 178 leaf banks, the following parameters were calculated:

- MCS_v, a modified modulation complexity score for VMAT introduced by Masi et al. [18];
- LT, the average leaf travel over in-field moving leaves during each VMAT arc;
- LTMCS, a multiplicative combination of LT and MCS_v described by Masi et al. [18];
- the leaves speed.

The modulation complexity score (MCS) was originally described by McNiven et al. [19] for step-and-shoot IMRT static beams as a normalized sum over all segments of the product of the aperture area variability (AAV) and leaf sequence variability (LSV). Masi et al. [18] modified that index in order to apply it to VMAT plans by substituting CPs for IMRT segments. The MCS_v, as in the original definition, has values in the range from 0 to 1. MCS_v equal to 1 means no modulation and can be exemplified by an arc with a fixed rectangular aperture with no leaves moving during the arc. When modulation increases, MCS_v decreases.

To determine LT (mm), for each active leaf, the travel over the VMAT arc was computed and the average over all in-field moving leaves was evaluated.

As suggested by Masi et al. [18], the index LT_i as (1000 − LT)/1000 was calculated to obtain a value in the range from 0 to 1. LT_i values are higher for lower values of leaf travel. Then, the combined action of LT_i and MCS_v was also examined. LT_i was multiplied by MCS_v, creating an index (LTMCS) that takes into account both parameters and has values ranging from 0 to 1. This parameter goes to zero for increasing degrees of modulation and leaf motion.

Both MCS_v and LTMCS were focused on the assessment of movements and shapes of MLC.

Moreover, the speed of each leaf was calculated for each control point, with a method similar to that proposed by Park et al. [20]. Leaf position was extracted from the information contained in the DICOM RT Plan files for each control point while control point timing informations were extracted from the TPS. The analysis was limited to the active leaves, i.e. the leaves whose position has changed in at least one control point within the arc.

The leaf speed related to the k-th active leaf and the i-th control point was calculated according to the formula:

$$MLCS_{k,i} = \frac{|LP_{k,i+1} - LP_{k,i}|}{T_i}$$

where $LP_{k,i}$ is the position of the k-th active leaf in the i-th control point and T_i is the time difference between (i + 1)-th and i-th control point.

The frequency distribution of $MLCS_{k,i}$ was arbitrarily divided in three levels: percentage of $MLCS_{k,i}$ lower than 5 mm/s (Low Speed, LS), from 5 to 20 mm/s (Medium Speed, MS) and higher than 20 mm/s (High Speed, HS). Moreover, the average value of $MLCS_{k,i}$ ($MLCS_{av}$) of every bank was calculated for each VMAT arc.

The evaluation of these parameters was performed with an home-made Matlab (MathWorks, Natick, MA) script.

2.4. Delivery parameters

The pre-treatment verification was performed with the Delta^4 Discover and Delta^4 Phantom+. For each treatment arc or bank, the following parameters were computed and evaluated by Delta^4 Discover software:

- Dose-γ index;
- MLC-γ index;
- percentage of leaves over all CPs with a deviation between planned and measured leaf tip position lower than 1 mm (LD).

Global Dose-γ analyses were performed with gamma criteria of 2 % − 2 mm and a threshold of 10 % of maximum dose was set. MLC-γ pass rates with 1 mm − 0.5° criteria were computed. Based on the precision of the leaf edge calibration process (see Delta^4 Discover transmission detector section), a maximum leaf tip deviation of 1 mm was choosen.

2.5. Data analysis

Descriptive statistic was performed for the plan metrics (MCS_v, LT, LTMCS and $MLCS_{av}$, LS, MS, HS) and for the delivery parameters measured during pre-treatment verification (Dose-γ, MLC-γ and LD).

As a next step, to investigate the effect of plan complexity on the VMAT plan verification accuracy, correlations between plan complexity metrics and delivery parameters were executed with Spearman rank correlation coefficient (r_s). Correlation was considered very strong for $r_s \geq 0.80$, strong for $0.60 \leq r_s < 0.80$, moderate for $0.40 \leq r_s < 0.60$, weak for $0.20 \leq r_s < 0.40$ and very weak/no correlation for $r_s < 0.20$. Statistical significance was defined at $p < 0.05$.

3. Results

3.1. Plan complexity parameters

Descriptive statistics of plan complexity parameters over 43 VMAT

Table 2
Average value and standard deviation of MCS_v, LT, LTMCS and $MLCS_{k,i}$ related parameters reported for the different patient classes.

Patient class	$MCS_v \pm \sigma$	LT± σ (cm)	LTMCS± σ	$MLCS_{av}$± σ (mm/s)	LS± σ (%)	MS± σ (%)	HS± σ (%)
Lung	0.334 ± 0.066	30.0 ± 2.2	0.212 ± 0.089	9.5 ± 0.9	44.6 ± 5.0	30.0 ± 10.2	25.3 ± 9.0
Esophagus	0.270 ± 0.045	53.1 ± 6.1	0.127 ± 0.027	9.3 ± 1.3	46.2 ± 5.9	25.0 ± 2.4	28.7 ± 5.1
H&N	0.201 ± 0.018	59.1 ± 5.5	0.083 ± 0.016	9.9 ± 1.0	41.5 ± 4.8	30.0 ± 2.0	28.5 ± 3.7
Prostate	0.274 ± 0.038	28.2 ± 3.1	0.197 ± 0.033	7.1 ± 1.1	59.7 ± 4.0	21.5 ± 1.6	18.8 ± 3.3
Brain	0.324 ± 0.075	34.9 ± 8.4	0.211 ± 0.055	7.6 ± 1.9	56.9 ± 10.4	21.6 ± 4.2	21.5 ± 6.8
Male Pelvis	0.236 ± 0.020	63.6 ± 2.2	0.086 ± 0.011	10.6 ± 1.3	39.5 ± 5.8	27.8 ± 1.3	32.7 ± 5.0
Female Pelvis	0.293 ± 0.036	53.9 ± 5.1	0.135 ± 0.023	10.5 ± 1.1	40.5 ± 4.3	26.9 ± 1.0	32.6 ± 4.6
Rectum	0.332 ± 0.044	54.3 ± 9.7	0.155 ± 0.055	9.6 ± 0.8	44.5 ± 3.3	25.7 ± 0.7	29.8 ± 3.3
Lung SBRT	0.267 ± 0.042	20.1 ± 7.6	0.213 ± 0.039	6.4 ± 2.2	61.9 ± 11.9	21.3 ± 5.4	16.7 ± 6.7

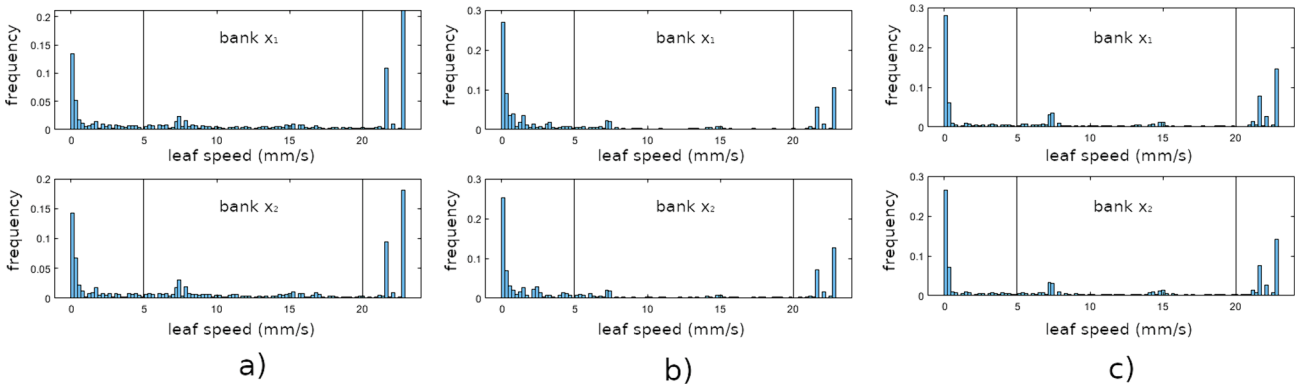

Fig. 2. Frequency of $MLCS_{k,i}$ in each leaf bank for H&N (a), Brain (b) and SBRT (c) plans.

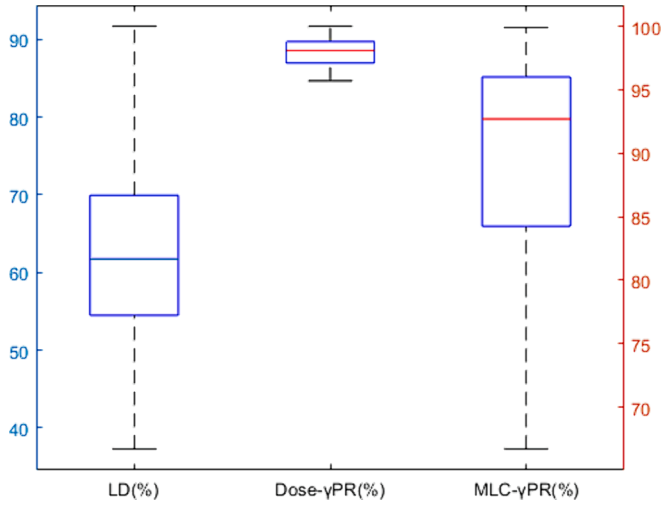

Fig. 3. Box plot of Dose-γ and MLC-γ passing rates (PR) (right scale) and LD (left scale) distribution for VMAT plans.

treatments are shown in Table 2. It can be observed that values of both MCS_v and LTMCS were higher in Brain and Lung plans than in H&N and Pelvis plans. Although MCS_v, by definition, can have values in the range from 0 to 1, we did not observe any value greater than 0.43. The highest values of MCS_v were obtained for low modulation plans characterized by a single Planning Target Volume (PTV) or by a distant OARs position with respect to the PTV or by unchallenging clinical dose constraints.

A wide range of LT values (11 cm – 68 cm) was obtained. Largest values were observed for Pelvis and H&N treatments, since these clinical sites have generally large treatment volumes. SBRT plans showed MCS_v values similar to those of Pelvis and H&N treatments due to the presence of small and irregular beam apertures, but they had shorter average leaf travel values due to the small size of the PTVs.

Table 3
Spearman rank correlation coefficients between Dose-γ passing rate, MLC-γ passing rate, LD and plan complexity parameters.

Metric	Dose-γ		LD		MLC-γ	
	r_s	p-value	r_s	p-value	r_s	p-value
MCS_v	0.47	0.01	0.21	0.04	0.16	0.14
LT	−0.54	<0.01	−0.60	<0.01	−0.39	<0.01
LTMCS	0.61	<0.01	0.52	<0.01	0.33	0.02
$MLCS_{av}$	−0.53	<0.01	−0.79	<0.01	−0.39	<0.01
LS	0.50	<0.01	0.79	<0.01	0.40	<0.01
MS	−0.31	0.04	−0.58	<0.01	−0.27	<0.01
HS	−0.60	<0.01	−0.71	<0.01	−0.37	<0.01

No values of MLC leaf speed higher than 24 mm/s were observed. To illustrate the differences in the patterns of $MLCS_{k,i}$ according to the plan complexity, histograms of $MLCS_{k,i}$ for H&N (low MCS_v, high $MLCS_{av}$), Brain (high MCS_v, low $MLCS_{av}$) and SBRT plans are shown in Fig. 2. As for leaf travel values, the highest percentage of low speed leaves was observed for SBRT plans due to the small size of PTVs.

3.2. Delivery parameters

Descriptive statistics for the delivery parameters, Dose-γ, MLC-γ passing rates and LD are summarized in Fig. 3.

The Dose-γ passing rate values are close to or greater than our department tolerance threshold of 95 %. 100 % of the measured arcs met the clinically established action level of 62 % for the MLC-γ pass rate. We observed a wide range of the percentage of leaves with a deviation lower than 1 mm, between 37 % and 92 %.

3.3. Correlation analysis

Results of Spearman correlation analysis between the delivery and plan parameters are illustrated in Table 3.

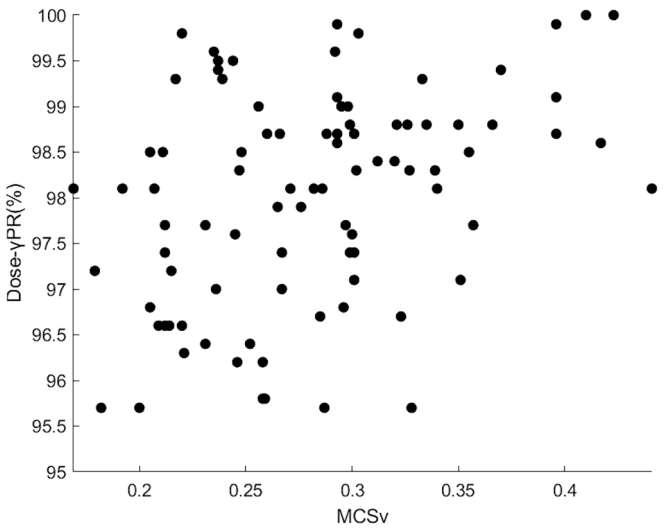

Fig. 4. Dose-γ passing rate (PR) against MCS_v.

3.3.1. *Dose-γ passing rates vs plan complexity parameters.*

A moderate positive correlation was observed between Dose-γ passing rate and MCS_v, as illustrated in Fig. 4. Higher passing rates were obtained for the patient classes with higher MCS_v.

Dose-γ pass-rate as a function of LT and LTMCS are plotted in Fig. 5 (a) and 5(b), respectively.

As expected, we observed a negative correlation with leaf travel, i.e. for higher LT values lower pass-rates (less accurate dosimetric results) were more frequent. As can be seen in Fig. 5(a), for plans having extremely high LT values (greater than 600 mm) most of the dosimetric verifications showed pass-rates below 98 %, while for leaf travel values lower than 300 mm all the Dose-γ pass- rate values were above 98 %. The behavior of Dose-γ passing rate as a function of LTMCS showed a positive correlation similar to that observed for MCS_v, but definitely stronger ($r_s = 0.61$).

A moderate correlation was observed between Dose-γ passing rate and $MLCS_{av}$, LS and HS as illustrated in Fig. 6. The r_s values of HS and LS as well as mean value of MLC speeds to global gamma passing rates with 2 %–2 mm were statistically significant (p-values < 0.01), except for MS.

The r_s values of LS had positive sign, while those of the other MLC speeds had negative one. Therefore, the values of global gamma passing rates increased as LS increased and decreased as MS and HS increased. Globally the slower the leaves, the better the dose gamma passing rate.

3.3.2. *LD vs plan complexity parameters*

The r_s and the corresponding p-values between LD and every plan parameters are shown in Table 3. The r_s values of LD were always statistically significant (p-values < 0.01). A weak correlation is observed between LD and MCS_v. Instead, for the 178 banks analyzed, a strong correlation is observed between LD and LT, as illustrated in Fig. 7.

The same strong correlation is obtained between LD and leaves speed, as shown in Fig. 8. The r_s value of LS had positive sign, while

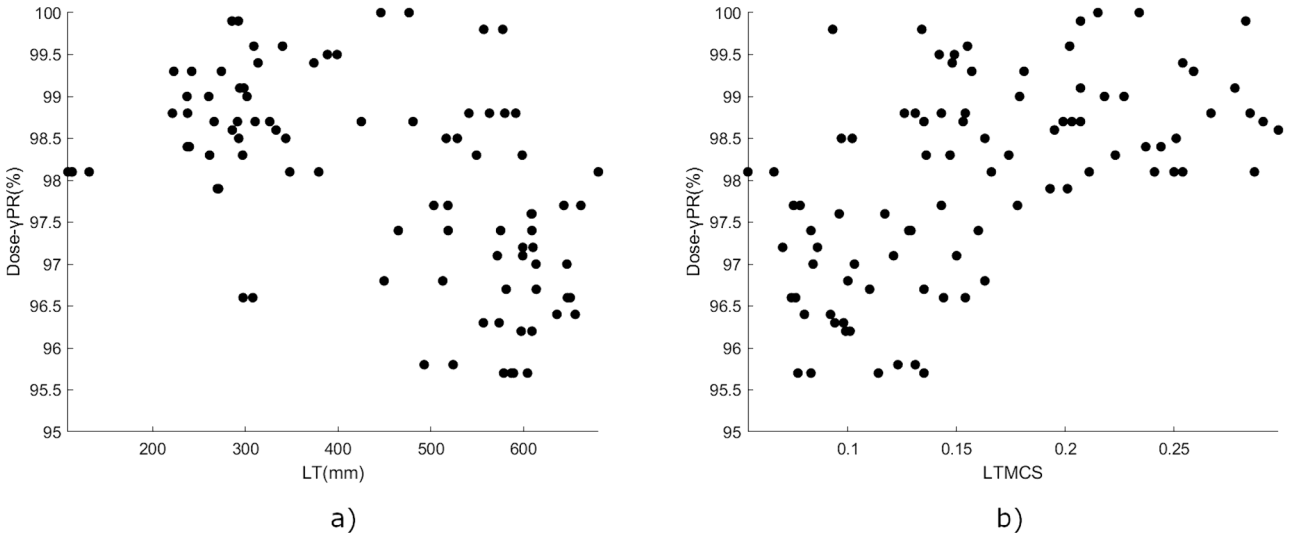

Fig. 5. Dose-γ passing rate (PR) against LT (a) and LTMCS (b).

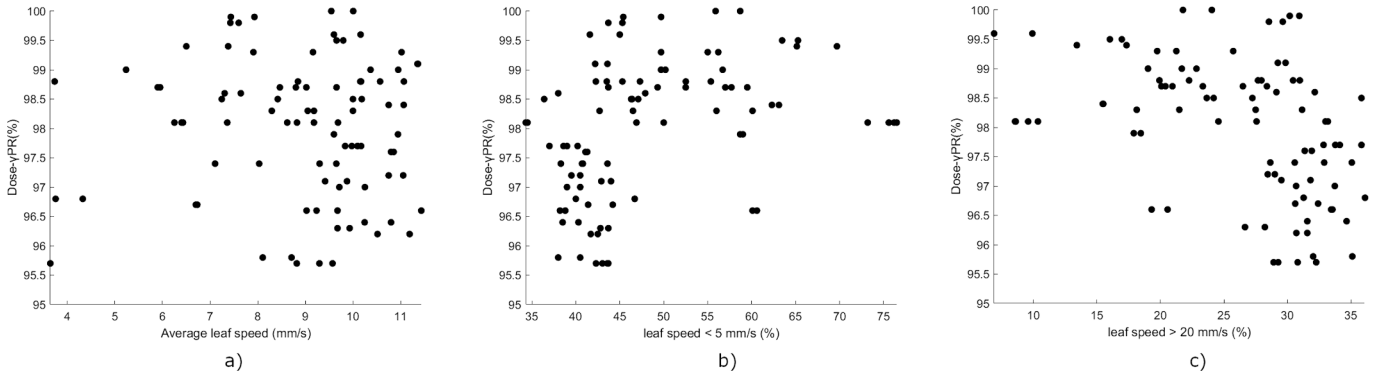

Fig. 6. Dose-γ passing rate (PR) against $MLCS_{av}$ (a), LS (b) and HS (c).

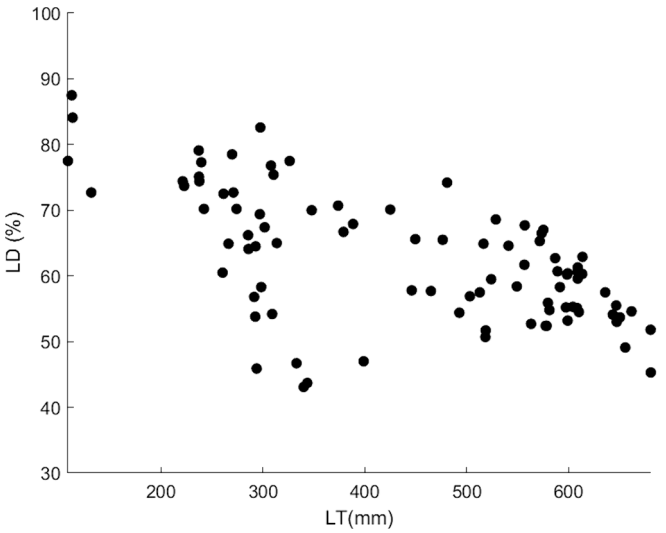

Fig. 7. Percentage of leaves with a deviation less than 1 mm *vs* LT.

those of the other MLC speed parameters always had negative signs.

3.3.3. *MLC-γ passing rates vs plan complexity parameters*

A correlation between MLC-γ pass rate and plan complexity parameters was found, except for MCS_v. A moderate correlation with LS (r_s = 0.40) was observed, while all other parameters showed weak correlations. The LS r_s value had positive sign, while $MLCS_{av}$, MS and HS showed a negative correlation, indicating that, when the leaf speeds increased, the MLC-γ passing rate decreased for most of the arcs (Fig. 9).

4. Discussion

PSQA consists in individualized measurements either before the first fraction (without patient) and/or during treatment (in vivo) and it is still considered as gold standard for treatment quality assessment [21,22,23]. The Delta^4 Discover, used in "Synthesis Mode", allows to verify the dose distribution and leaves positions at each fraction of treatment delivery.

Assuming that agreement between calculations and measurements decreases as plan modulation increases [4,5,6], it should be possible to predict PSQA results from complexity metrics. Correlation between PSQA results and complexity metrics is strongly impacted by many parameters: characteristics of detector, analysis method and criteria, linac and treatment technique, TPS and beam modelling. Therefore, the relationship between complexity metrics and PSQA results should be specifically established by each centre depending on PSQA process, machine settings and TPS modeling and optimizer.

To this aim, results of patient-specific quality assurance of 43 VMAT plans expressed as Dose-γ MLC-γ passing rates and LD were analyzed as a function of different plan complexity parameters: MCS_v, LT, LTMCS, and

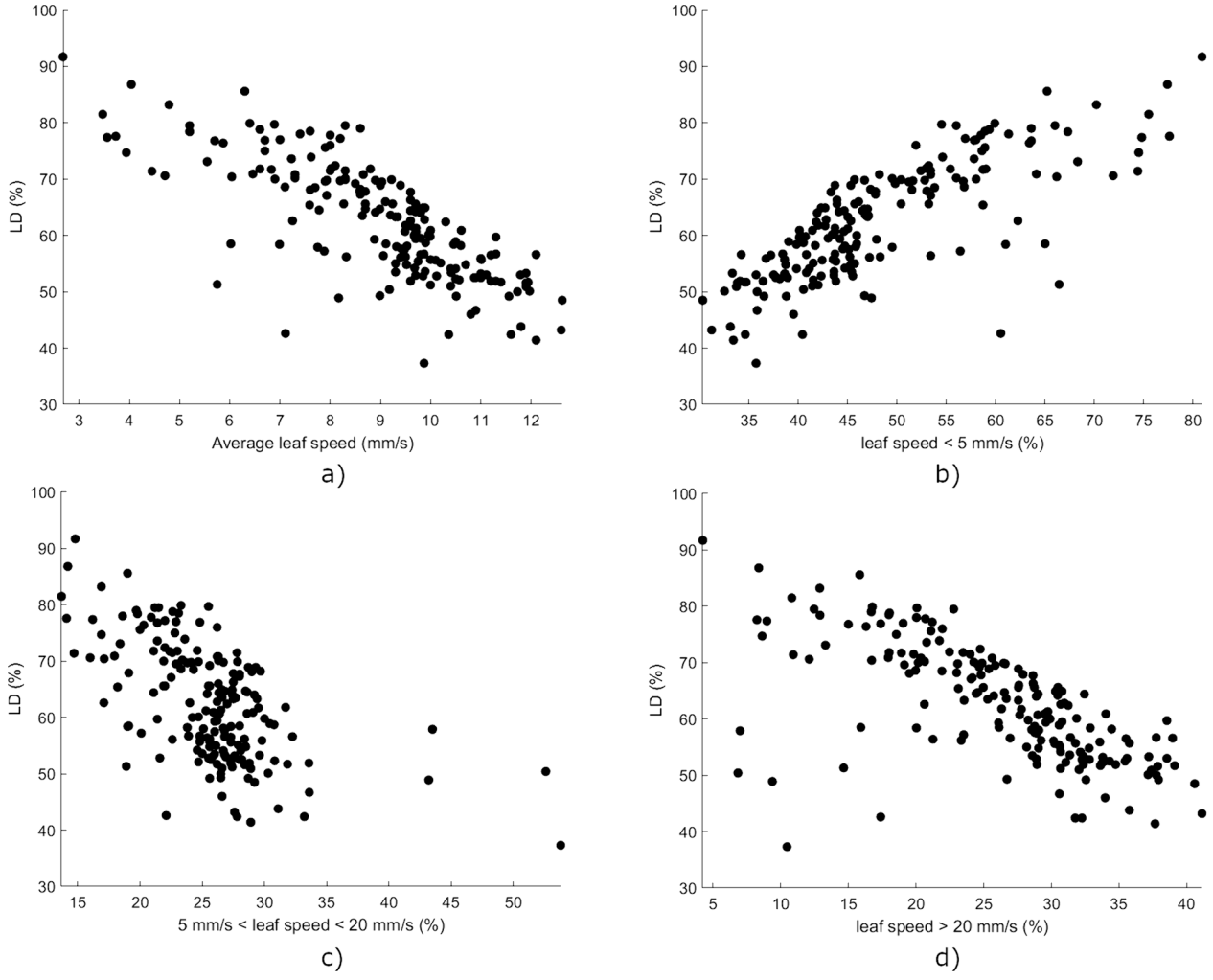

Fig. 8. LD against $MLCS_{av}$ (a), LS (b), MS (c) and HS (d).

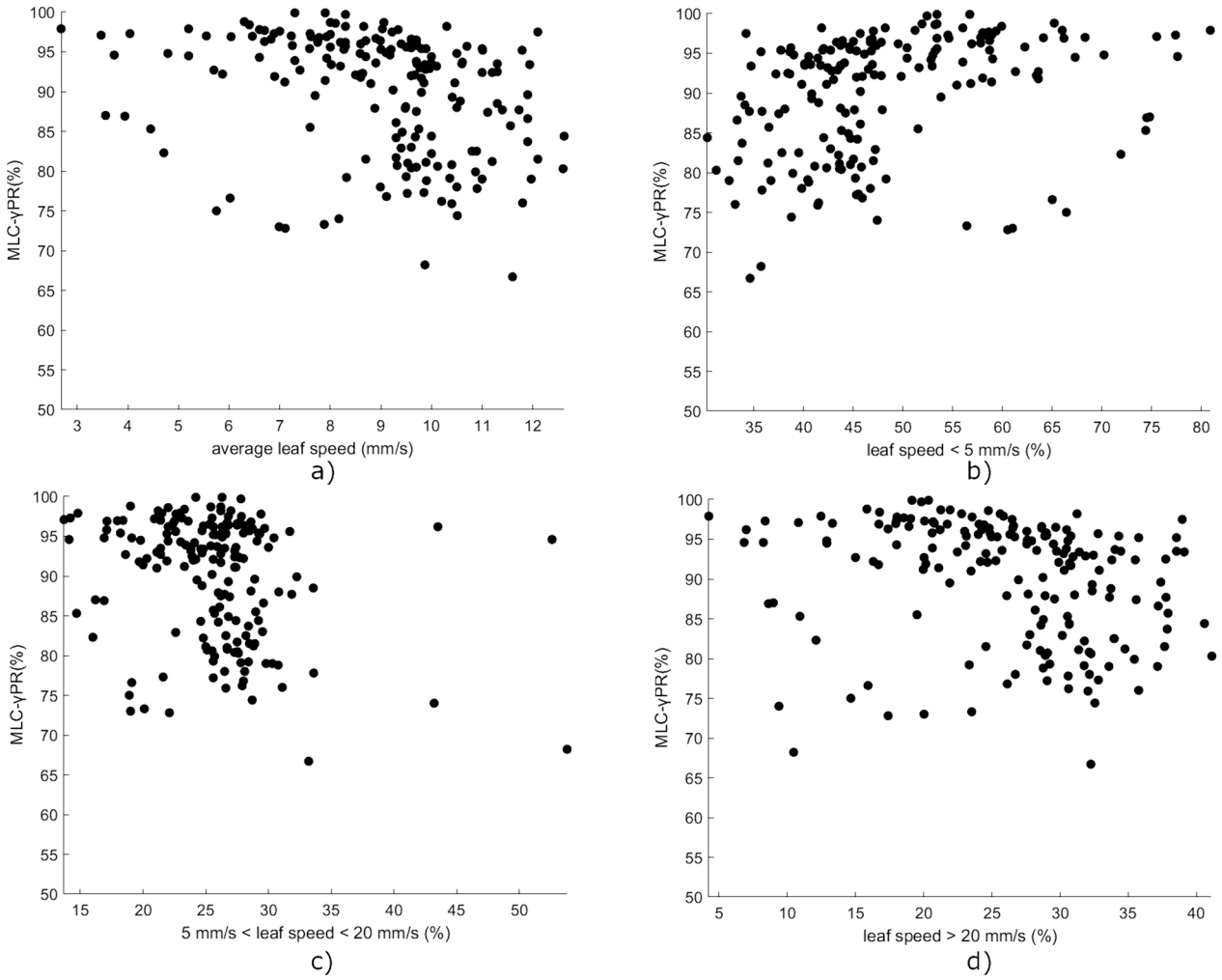

Fig. 9. MLC-γ passing rate (PR) against $MLCS_{av}$ (a), LS (b), MS (c) and HS (d).

leaves speed related parameters.

The distribution of the delivery parameters reported in Fig. 3 shows that the threshold values selected for each parameter were adequate since there were no saturation issues. Furthermore, the high LD range confirms that the 1 mm threshold makes LD quite sensitive to variations in leaves positioning.

In analogy with what reported in literature [4,5], a correlation at least moderate is observed between Dose-γ passing rate and complexity indexes. With increasing complexity, whatever the index taken into consideration, there is a decrease in the outcome of PSQA results. Many authors [8,24] have found similar correlations (greater than 0.45) between Dose-γ passing rate 2 % − 2 mm and MCS using the Pearson correlation coefficient. McGarry et al. [25] found a correlation of about 0.5 between Dose-γ passing rate 3 % − 3 mm and MCS.

Correlation with Dose-γ passing rate was strong for LTMCS ($r_s >$ 0.60) which was proven to be a complete and exhaustive indicator in order to predict the accuracy of dosimetric delivery. Similar results were found by Masi et. al [18]. In their study measurements were performed with a Delta^4 phantom + and Pearson correlation coefficient was found equal to 0.60 for LTMCS, 0.54 for MCS and 0.62 for LT with the Dose-γ passing rate 2 % − 2 mm.

In this study, by correlation analysis, we demonstrated that leaves speed could affect the VMAT delivery accuracy. Mean MLC speed, LS and HS showed considerable correlations to the Dose-γ passing rates. As the MLC speed increased, VMAT delivery accuracy decreased. In more details, as the HS to LS ratio grows, global dose gamma passing rates become worse. The lowest correlation values were observed for MS ($r_s <$ 0.39), i.e. for medium complexity treatment plans.

This result is consistent with results reported by Park et al. [20]. In their study, the Spearman correlation coefficient between leaves speed collected from log files and Dose-γ passing rate, measured with a MapCheck detector (Sun Nuclear Corporation), was evaluated. The study highlights a correlation coefficient between average MLC speed and Dose-γ passing rate 2 % − 2 mm equal to −0.417, furthermore a correlation coefficient of 0.479 was found between Dose-γ passing rate 2 % −2 mm and the percentage of MLC leaves with a speed lower than 4 mm/s.

LD shows a weak correlation with MCS_v but a strong one with LT and a moderate one with LTMCS.

Leaves speed showed strong correlations with LD, similarly to what was found by Park et al. [20]. They showed that leaf speed is correlated with MLC performance for VMAT deliveries since a decrease of leaf speed improves positional accuracy of the MLC. In the study, based on log file analysis, a Spearman correlation coefficient between MLC position error and mean MLC speed and percentage of leaves with a speed lower than 4 mm/s was found equals 0.915 and −0.927, respectively.

LD exhibited the highest correlation with LS: plans with very slow leaves showed high LD values, while the correlation with HS, although good, was weaker. As a consequence, the best performances in determining leaves position are obtained for very slow leaves. The lack of synchronization between the control point of the RTplan file and delivery measurement rather than to a real issue in leaves positioning can explain the large amout of leaves with a deviation higher than 1 mm. Since the Delta^4 Discover integrates the diodes signal over 25 ms while

the leaves are constantly moving, the increase in uncertainty of leaf position detection for VMAT plans is likely due to synchronization mistakes in matching the leaves position for each control point, especially when the leaves are moving very fast. However, this consideration, though supported by the results of the quality controls on the MLC periodically performed in our center, would require a more in-depth study that is beyond the scope of this study.

Therefore, the MLC-γ index analysis was introduced by the manufacturer specifically for VMAT treatments as a solution to these issues, combining deviation in MLC leaf positioning and gantry angle. All the analyzed complexity parameters correlated with MLC-γ index.

The correlations between plan parameters and Dose-γ allow the user to predict the outcome of the dosimetric PSQA process. This objective can be achieved by setting specific Action and Tolerance limits for the different treatment sites considered, as suggested by TG 218 AAPM [26]; then, from the relationship between complexity and delivery, threshold values of the plan's complexity parameters could be defined in order to discriminate plans whose QA might not pass.

The results indicate MLCs speed parameters and LTMCS as the most suitable complexity metrics for scoring VMAT plans and for predicting plan dosimetric accuracy. Although MCS_v is a powerful metric to score VMAT plan complexity, due to the dynamic nature of VMAT delivery, it cannot be used as a single parameter.

LD, although intuitive and easily related to the performance of the linac, deserves careful evaluations, as well by means of log-files based analysis to differentiate measurement uncertainties from delivery ones. The MLC-γ overcomes the synchronization issues of LD and it is still able to intercept positoning errors, as reported by Petrucci et al. [15]. Its correlations with the plan parameters can be used to predict the outcome of the geometrical results of the PSQA process.

The awareness of the behavior and limitations of the measuring instruments and procedures used for PSQA allows for the correct assessment of anomalous situations in order to intercept critical or suboptimal treatment plans and to defines different QA strategies.

Issues associated to limitations of the measuring instrument can be solved using a log-files based PSQA, as widely discussed in literature [27,28]. However, this approach can not be considered a fully independent verification. Furthermore, the log-files do not make all the treatment parameters available to the user [29].

Although the results of this study are very promising, they did not allow us to define specific value of the complexity indices for predicting the plan delivery accuracy and consequently for optimizing the workflow of plan creation, optimization and QA. To this aim further investigation with a larger sample of VMAT plans for various tumor sites (also unacceptable plans due to excessive modulation), higher resolution of speed classes and plan complexity parameters related to the gantry speed modulation have to be considered. These items will be investigated in a future work.

5. Conclusions

The complexity of the VMAT plan might affect the deliverability of plan itself, the greater the plan modulation, the greater the uncertainty in delivery. The study confirmed the possibility to establish correlations between plan complexity indices versus dose distribution and MLC parameters measured by a transmissive detector. By defining plan complexity classes, these correlations could be used for predicting the plan delivery accuracy. In such a way critical or suboptimal treatment plans can be intercepted and different and more efficient QA strategies can be adopted.

Authors Contributions

Lorenzo Radici and Valeria Casanova Borca performed measurements and correlation analysis. Edoardo Petrucci made Matlab script for plan complexity evaluation and performed statistical analysis. Pasquino Massimo drafted the manuscript. Cristina Piva and Domenico Cante reviewed the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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