Towards Combined Functional and Non-Functional Semantic Service Discovery

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Abstract. Service-orientation is increasingly adopted by application and service developers, leading to a plethora of services becoming increasingly available. To enable the construction of applications from such services, the respective description and discovery of services must be supported. Both functional and non-functional aspects should also be considered as they play a significant role in the service management lifecycle. The focus in state-of-the-art service discovery has been mainly on one aspect and not both of them. As such, this paper aims at investigating the issues involved in considering both functional and non-functional aspects in service discovery. In particular, it proposes different ways via which aspect-specific algorithms can be combined to generate a complete service discovery system. It also proposes a specific unified service discovery architecture. Finally, it evaluates the proposed algorithms with respect to their performance to give valuable insights to the reader.

Keywords: service, discovery, matchmaking, semantics, ontology, performance, evaluation, functional, non-functional, QoS, architecture

1 Introduction

Nowadays, modern applications and business processes adopt service-orientation due to the many advantages it delivers, including loose coupling, re-usability, increased performance and cost reduction. To construct such applications, the services from which they are built need to be described appropriately, discovered and finally composed. Concerning service discovery, the state-of-the-art can be split into approaches that either focus on functional or non-functional aspects.

Functional service discovery work [8] mainly focuses on matching the user's functional requirements by exploiting various types of techniques from information retrieval and the semantic web [9, 16]. Functional requirements and capabilities are mainly described via the service IO while some work [7, 18] focuses on covering behavioral aspects via service preconditions and effects which are however not available in real service advertisements. Most approaches nowadays exploit semantic techniques to exhibit better accuracy levels in conjunction with other techniques focusing on performance speedup. However, the approach accuracy is imperfect due to the non-consideration of behavioural aspects.

Non-functional service discovery work [10] can be split into three main categories. Ontology-based approaches [20] employ subsumption techniques to infer the matching between ontology-based non-functional service descriptions but are suitable for unary-constrained specifications. Constraint-based approaches [5] exploit n-ary specifications as models, including quality terms drawn from common vocabularies, and particular metrics which involve solving one or more constraint (combined) models to infer the matchmaking. Mixed approaches [10] combine the best of both worlds by exploiting ontology-based specifications to cover the non-functional semantics and align the quality terms involved as well as the metrics in the previous approach type to perform the service matchmaking.

While each aspect is more or less well covered in the literature, there are very few approaches [2, 6] dealing with both aspects concurrently. Such approaches, however, do not adopt the best possible algorithm for each aspect, do not capture the service semantics, and do not seem to have a suitable performance and accuracy level. Moreover, they do not seem to have explored the possible ways the two different types of matching can be best combined to infer the best possible one. In fact, most of these approaches employ a simplistic approach to account for non-functional user requirements and preferences which will never be adopted by respective practitioners.

As such, this paper first proposes a unified architecture explicating how different-aspect algorithms can be integrated to support a complete service discovery process by also accommodating for semantics capturing. Then, the paper proposes different combinations of aspect-specific algorithms attempting to accelerate the overall matching performance by not compromising discovery accuracy. Some combinations might be naturally applied and easily realised while others attempt to intelligently organise the service advertisement space to reduce the matchmaking time. These combined algorithms are finally evaluated by a semi-randomised framework according to their performance so as to provide particular insights on which is the preferred one in different circumstances.

We believe that apart from attempting to intelligently combine different aspect discovery algorithms, our work can be really beneficial to practitioners on how to investigate, select and realise the best possible combination of such algorithms to realise a respective service discovery system.

The rest of the paper is structured as follows. Section 2 reviews the related work. Section 3 presents the unified architecture. Section 4 analyses the proposed combined algorithms. Section 5 presents the performance evaluation results. Finally, Section 6 concludes the paper and draws directions for further research.

2 Related Work

As we focus on combined service discovery, we only consider combined approaches. For aspect-based discovery analysis, the reader can refer to [8] and [10].

QoS Ranking By reviewing related work, it seems that most approaches [12–14] first functionally match the service request and then rank the respective matches based on the user's non-functional preferences. Non-functional ranking usually relies on considering utility functions that depend on the respective quality term monotonicity while the overall rank is produced via a weighted sum of the application of the utility functions over the match's promised quality term values. Based on the above, it seems that all such approaches neglect the fact that a user may pose non-functional requirements which must be respected such that the functional matches are further filtered before they are ranked.

The interesting approach in [14] seems able to cater for ontology encoding and fast reasoning issues. This approach attempts to smartly organise the functional advertisement space by exploiting two advertisement relations that seem to map to well-known functional degrees of match. However, the second relation seems not to be suitable based on the formal notion of subsumption. After cleverly matching a request, the functional matches produced are just ranked based on their non-functional degree of match.

The sequential approach in [13] starts by discovering services that functionally match the request and have an appropriate distance from the user to minimise network latency. Then, the expected execution time of each matched service is computed based on performance ratings which is finally exploited to rank the matched services and select the top one for dynamic adaptation reasons.

QoS Threshold-Based Filtering A small improvement over the previous category comes via threshold-based filtering of functional matches [6, 15]. However, it is questionnable whether a simple threshold can be enough to respect the semantics of all the non-functional requirements posed. It rather seems as a trial-and-error approach towards attempting not to overwhelm users with irrelevant results that do not satisfy their non-functional requirements. What makes the approach in [6] more interesting with respect to the rest in this category is that it attempts to enable a unified semantic service description and considers various types of information to infer the ranking, including QoS, business policies and context.

Combined [2] proposes a sequential combined algorithm coupled with service ranking based on non-functional preferences. This algorithm actually resembles *SeqOnTheFly* (see Section 4) as it attempts to match on the fly each functional result with the user's non-functional requirements. However, this work is not assorted with specification validation mechanisms and does not employ specification alignment, thus relying on a common quality term vocabulary. It does not also check how sequential matching can be enhanced for better performance.

In [3], a three step discovery process is proposed. First, functional matching is performed by exploiting subsumption hierarchy and predicate-based inferencing. Second, functional matches are clustered based on QoS via the average linkage clustering and squared Euclidian distance metrics. Third, the best cluster's matches are ranked based on each match's distance from the cluster centroid. We consider this approach as a combined one as it performs a kind of filtering on the functional match space. However, it is questionnable whether such a filtering is suitable if we also consider performance aspects. In addition, semantics for QoS terms are neglected. Functional matching seems also to be wrongly performed.

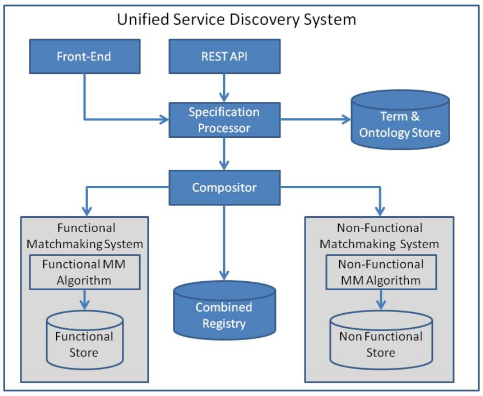


Fig. 1: The architecture of the unified service discovery system

3 Architecture

Figure 1 depicts the architecture of a complete and unified service discovery system by also showing the interactions between the respective components and their ordering in terms of basic discovery system operations. The architecture comprises 10 main components: 2 constitute entry points, 4 map to the main discovery logic and 4 relate to the respective individual and combined registries.

The first entry point is the *Front-end*, responsible for interacting with a human user, either a service provider or requester. This web-based UI component visualises information that can assist in the respective interaction, such as forms for specifying functional and non-functional requests or for enabling providers to upload, inspect and register or update service descriptions.

The *REST-API* is a service-based component enabling the programmatic interaction of the system with automated agents acting on behalf of users / organisations. This component exposes the functionality expected in a service discovery system, like registration, updating and matchmaking of service specifications. It also offers utilities that attempt to validate the specifications before being registered. Service provider-related functionalities are only available to registered users, while discovery ones are publicly available with however additional features only offered to registered users, like the ability to retrieve all matchmaking results and to provide customised algorithms for service selection.

Once one operation starts execution, the respective specifications are passed to the *Specification Processor* which loads and processes them to check their syntactic and semantic validity as well as to align them if they refer to equivalent but differently described terms. Non-functional specifications are also checked with respect to their constraint-based consistency. In case of a validation error, an error message is relayed to the user. Otherwise, the operation passes to the core discovery component named as *Compositor*. The alignment of the specification is performed by consulting a *Term and Ontology Repository* which includes a common set of basic terms via which alignment can be rapidly performed (see [10]) as well as the respective domain ontologies that have been encountered.

The latter component realises the composition logic with respect to the individual aspect-specific algorithms exploited. In this sense, it guarantees the consistency of the information being registered in these algorithms. This is achieved via the *Combined Registry* which stores the mappings between functional and non-functional specifications of service providers. This integration approach allows the decoupling of the respective aspect-specific discovery functionality as well the independence from any service specification language. The adoption of a language is coupled with the selection of an aspect-specific algorithm. As such, we cater for the usage of either unified or aspect-specific service description languages. In case the latter type of languages is used, consistency is maintained via the entries of the *Combined Registry*. We mainly aim at semantic languages via which any kind of service profile is identified via a *URI*. This enables using only semantic algorithms but leads to an increased discovery accuracy in the end.

The *Compositor* implements the combined service matchmaking logic with respect to the main algorithms proposed in this paper (see Section 4). Moreover, the *Compositor* guarantees the transactionality of the service (de-)registration and update operations. This means that when an operation fails when executed via a specific aspect-specific sub-system, and was successful with respect to the other sub-system, then we have to roll-back to the previous state before the operation execution. The latter maps for example to de-registering a functional service specification if its non-functional counterpart fails to be registered. This type of transactionality is enabled by realistically assuming that each respective aspect-specific sub-system provides aspect-specific operations that return either boolean values indicating the operation outcome (e.g., non-registration as functional service specification already exists) or exceptions when errors occur. The respective suite of functionally-equivalent service operations is obviously already available in each aspect-specific system.

Each aspect-specific sub-system to be exploited should provide an entry point via which aspect-specific interactions can be performed (either a programmatic REST-API or a specific component). For the two main aspects, we name the respective components as *Functional Service Discovery* and *Non-Functional Service Discovery* and we do not unveil their respective structure as it can be specific to the respective sub-system selected. We just unveil that each sub-system logically has a respective (functional or non-functional) store in which the aspect-specific service specifications are stored.

Concerning implementation details, all system code has been realised in Java as it is the main implementation language for almost all available matchmakers. The implementation of the *Front-End* is on-going while the *REST-API* was realised via Jersey. The *Specification Processor* exploits different loading and validation techniques. The Pellet reasoner [17] is exploited for ontology-based loading and consistency checking while the Ibex[1] finite constraint and Choco[2]

[1] `www.ibex-lib.org`
[2] `http://www.choco-solver.org/`

constraint programming solvers are exploited for constraint-based consistency checking. The *Combined Registry* is currently a serialisable Java object which exposes different methods related to the manipulation of aspect-specific specifications (e.g., registering a functional and non-functional service URI pair or an additional non-functional profile for an existing service).

The *Alive Matchmaker* [4] was selected as a state-of-the-art functional matchmaking sub-system which exhibits high performance levels due to the application of smart structures via which the matching of semantic I/O concepts can be performed while also catering for domain ontology evolution. This matchmaker had some small accuracy problems which were solved by slightly altering the respective implementation. The *Unary* algorithm of the discovery system in [10] was selected for hybrid non-functional service matching as it is scalable, exhibits high performance levels and has perfect accuracy.

4 Algorithm Analysis

The combination of aspect-oriented matchmaking algorithms was explored under different criteria. The first one concerns the expected way to combine two separate functionalities. In this sense, two possible ways exist: (a) each functionality is performed in sequence or (b) both functionality are executed in parallel and their results are integrated.

Concerning (a), we chose to execute first the functional discovery algorithm as this more naturally depicts the process executed by humans who first seek to satisfy their functional requirements and then the non-functional ones. Functional service discovery can also be considered more restrictive than the non-functional one. This can be due to the fact that when performing non-functional matching, domain-independent metrics are usually considered leading to obtaining many functionally irrelevant results out of the scope of the respective domain. As such, when no results are discovered in the first discovery form, there is no reason to continue with the non-functional one spending unnecessary resources.

Solution (b), on the other hand, does not assume that one aspect-specific discovery can be faster than another but attempts to execute them in parallel to save time. Compared to the first approach, it may spend more resources but it will be surely faster, provided that when one aspect-based discovery ends earlier and has not result, we have the ability to stop the other one.

The second criterion explored the possibility to exploit different structures to smartly organise the service advertisement space so as to speed-up service matching. In particular, by relying on the approach in [10], we have considered combined subsumes relations between different service discovery offers (where a discovery offer maps to one functional and non-functional offer pair for one service) enabling us to not browse the whole advertisement space but stop at certain places without requiring to go down in respective subsumes branches. Figure 2 depicts the notion of a subsumes service advertisement hierarchy by showing a small forest of 4 offers. Offer O_1 subsumes offers O_{11} and O_{12} for different reasons. Offer O_{11} is subsumed due to its functional part while its non-

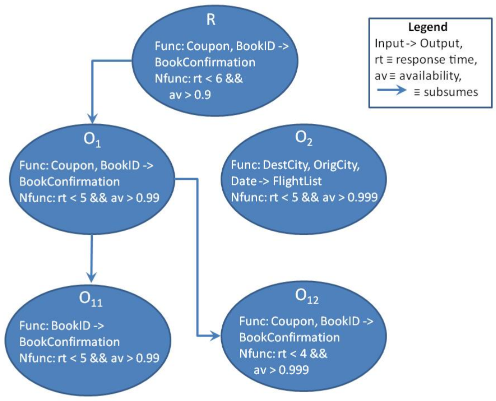


Fig. 2: The subsumption forest with request R subsuming a root tree node

functional part is equivalent while offer O_{12} is subsumed due to its non-functional part while its functional is equivalent. On the other hand, offer O_2 is not related to the tree's offers as its functional part is unrelated to the functional part of the tree offers. This also highlights the definition of the combined subsumes relation:

$$comb\_subsumes\,(S_1, S_2) \equiv func\_subsumes\,(S_1, S_2) \wedge nonfunc\_subsumes\,(S_1, S_2)$$

By exploiting this subsumption relation, we can speed up the service matching process. For example, assume that a request R is issued. We will first compare it with offer O_1. If R subsumes O_1, it will also subsume its descendants. As such, we do not have to go deeper into the respective tree. However, we might need to also check other trees in the forest which could be partially related to each other. There are actually two kinds of relations to be exploited: *subsumes* and the opposite one, *subsumedBy*. As recommended in [10], the first relation is more suited when usually more than 30 percent of the offers match a request. Otherwise, the second relation is more suitable. This recommendation was an outcome of an empirical evaluation over non-functional discovery algorithms. By combining functional and non-functional service matchmaking, we expect that the percentage of matched offers can be lowered with respect to the case of aspect-specific matching. In this way, it might be preferrable to exploit the *subsumedBy* relation in the end, especially for a highly populated service registry spanning multiple domains as each request is expected to be specific to just one domain and thus lead to matching of a quite low offer percentage.

In the sequel, we first provide a small section explicating the main symbols and assumptions that we make. Then, the next four subsections shortly analyse the main functionality of the proposed algorithms with respect to service registration and discovery by also providing a respective complexity analysis. Other operation types are not considered (e.g., deletion and updating) as they tend to map either to similar actions as in case of registration (i.e., deletion) or to either the same or almost double time (i.e., updating like insertion or like combination of deletion and insertion). Finally, the last section discusses our expectations for the performance of the proposed algorithms based on the complexity analysis.

4.1 Symbols & Assumptions

We assume that one functional and non-functional part comprise the service request. We also assume that S service offers have been registered. This means that around $\frac{S}{3}$ functional offers are to be registered in a functional matchmaker and S non-functional offers in the non-functional matchmaker. This is due to the fact that each functional offer is expected to be accompanied by 3 non-functional offers for the same service, mapping to gold, silver and bronze classes of customers. The pre-processing of a functional offer takes $O(1)$ time while for a non-functional offer takes $O(2M + M * T_z)$, where the first part maps to the offer's consistency checking and the second to its alignment and M represents the number of the offer's quality terms. The latter can be reduced to $O(M * T_z)$ constituting the total pre-processing time. Finally, we assume that each non-functional offer comprises at most $2M$ constraints mapping to the upper and lower bounds given to the respective quality terms (i.e., 2 constraints per term).

4.2 Sequential Algorithm

Analysis *Matchmaking.* We propose two main variations of this algorithm named as: *Sequential* and *SeqOnTheFly*. In the first version, we perform functional service discovery and once we have the respective results, we fetch the respective non-functional offers and we register them to the non-functional matchmaker. Then, we match them with the non-functional part of the request. In the end, we return back the respective results to the user and we clear the non-functional matchmaker. The second version differs with the first based on the fact that the non-functional offers mapping to the matched functional ones are checked on the fly if they are subsumed by the request's non-functional part. This maps to exploiting only the capability of a non-functional matchmaker to directly match two non-functional specifications. We expect that the first version is more suitable when the non-functional offers are great in number as the total registration time will be compensated by the fast matching that exploits the smart structures of the matchmaker. Otherwise, the second version should be preferred. The evaluation section will explore which is the amount of non-functional offers that represents the break point between choosing one over the other version.

Registration. Both algorithm versions follow the same registration process. This actually maps to registering the functional offer in the functional matchmaker and inserting the respective combined entry in the *Combined Registry.* There is no need for non-functional-based registration due to the way the non-functional matchmaker is exploited. We should note that the pre-requisite processing step for specifications controls their validity and transactionally rolls back the combined registration, if needed.

Complexity analysis *Matchmaking.* We rely on the complexity analysis of the respective different matchmakers and on the fact that the validity of the request has to be checked. Pre-processing as already stated takes $O(M * T_Z)$.

The functional matching part [4] requires $O\left(R_O * \frac{S}{3} * R_{AO} + M_{FO} * I_S^{Mean}\right)$, where R_O, R_{AO} represent the number of input and acceptable inputs of the request, respectively, $\frac{S}{3}$ represents the number of functional service offers registered, M_{FO} the number of matched services based on their output and $I_{M_{FO}^{mean}}$ the mean number of inputs of each matched service. The latter can be reduced to $O(R_O * S * R_{AO})$ as $\frac{S}{3}$ is expected to be much bigger than M_{FO} and I_S^{Mean} could be at most 3. The non-functional matching part depends on the respective combined algorithm's version. For each version, we assume that $O(k * M_{FO})$ non-functional offers need to be matched, i.e., k non-functional offers for each functional match based on our core assumption about the mapping between functional and non-functional offers.

For normal non-functional matching, in the worst case, covering both registration and matching of non-functional offers, the time will be $O(M * (M_{FO} + 2 * log_{M_{FO}}))$. For on the fly non-functional matching, the time needed is $O(2M * M_{FO})$ as we must check each constraint of a non-functional offer with the request non-functional part's respective constraint.

Thus, in the end, the matchmaking time for *Sequential* will be

$$O(R_O * S * R_{AO} + (M * (M_{FO} + 2 * log_{M_{FO}})) + M * T_Z)$$

If we consider that M is small and cannot go beyond 10 quality terms and that S is much bigger than M_{FO}, the complexity formula can be reduced to:

$$O(R_O * S * R_{AO} + T_Z)$$

.

For *SeqOnTheFly*, the matchmaking time will be $O(R_O * S * R_{AO} + (2M * M_{FO}) + M * T_Z)$ which can be similarly reduced to $O(R_O * S * R_{AO} + T_Z)$. Thus, in the end, the matchmaking complexity for both algorithm versions coincides. *Registration.* We assume that one functional offer and its respective 3 non-functional offers are to be registered. Thus, we need to pre-process 4 specifications and then only register via the functional matchmaker the functional offer. Pre-processing will take again $O(M * T_Z)$ as in the matchmaking. The registration in the functional matchmaker takes $O(S_C)$ as in the worst case is dominated by the time needed to infer the subsumption hierarchy of the domain ontology mapping to the service I/O, where S_C represents this time for an ontology of C concepts. Thus, in the end, the registration time for both algorithm versions will be $O(T_Z + S_C)$.

4.3 Parallel Algorithm

Analysis Matchmaking is performed, after user request is pre-processed and aligned, by exploiting in parallel the functional and non-functional matchmakers and then concatenating their results. The exploitation of the *Combined Registry* to map functional matches to their non-functional counter-parts (which can be 3 times their number) guarantees the concatenation of the same type of objects.

For registration, we register the functional offer part in the functional matchmaker and the non-functional offer part to the non-functional matchmaker while the respective consistency is achieved by also informing the *Combined Registry*.

Time Complexity Analysis *Matchmaking.* Pre-processing as in the previous algorithm takes $O\left(M * T_Z\right)$. Functional matching, as already stated, takes $O\left(R_O * S * R_{AO}\right)$. Non-functional matching takes $O\left(M * \left(S + log_S\right)\right)$. Concatenating the different result types takes: $O\left(M_{FO}\right)$. In the end, the total matchmaking time will be: $O\left(\max\left(R_O * S * R_{AO}, M * \left(S + log_S\right)\right) + M_{FO} + M * T_Z\right)$ which can be further reduced to: $O\left(S + T_Z\right)$.

Registration. Functional registration takes $O\left(S_C\right)$ as indicated in the previous algorithm. Non-functional registration takes $O\left(M * log_S\right)$. Thus, total registration time will be $O\left(S_C + M * \left(log_S + T_Z\right)\right)$ which can be reduced to $O\left(S_C + log_S + T_Z\right)$.

4.4 Subsumes Algorithm

Analysis *Matchmaking.* Matchmaking is recursively performed (see [10]). The offer is matched with each root node. If it subsumes the node, it also subsumes its children. So we do not go down to the root node subsumption hierarchy but just consider both this node and its descendants as matches. Otherwise, we must descend this hierarchy recursively to find respective matching nodes. In the end, all the matching results for each root node search (including recursive calls) are collected to be returned to the user.

Registration. Registration is also recursively performed [10]. First, each root node is checked with the offer to be matched. If the offer is equivalent to the node, it is entered into the node's represented offers and registration ends. If the offer subsumes the root node, it becomes its parent. If the root node subsumes the offer, we have to do the same checking recursively at the node's children. When we reach a position in the root node's subsumption hierarchy where the offer is subsumed by one node but does not subsume its children, then the offer is entered as a child of this parent node.

Complexity Analysis *Matchmaking.* Three cases are valid here [10]. In the worst case, we must perform subsumption checking for all forest nodes which involves functional and non-functional subsumption checking. Functional subsumption checking relies on expanding each output concept of the functional offer with respect to its ancestor concepts in $O\left(1\right)$ step and then checking if each output concept of the functional request is included in one of the expanded lists. This takes $O\left(R_O * S_O\right)$ for each functional offer. For non-functional subsumption checking, each offer's constraint is checked if it is more restrictive that the respective demand constraint. This takes $O\left(2 * M\right)$ time as for each offer constraint, we can immediately find the respective request counter part. So, individual subsumption checking takes $O\left(R_O * S_O + 2M\right)$. By visiting all S nodes and accounting processing time, in the end, the total matchmaking time is: $O\left(S * \left(R_O * S_O + 2M\right) + M * T_Z\right)$. As both R_O and R_O tend to be quite small and M is less than 10, this can be reduced to just $O\left(S + T_Z\right)$.

In the best case, only the sole root node is matched (forest reduced to a tree) which takes $O\left(S + T_Z\right)$. In the average case, we expect that the tree is more or less balanced, a percentage of P nodes is subsumed and there is always a pair of parent-child offers. In this case, total matching will taje: $O\left(S * \left(1 - \frac{P}{2}\right) + T_Z\right)$.

Registration. Three cases are considered based on the previous rationale. For all cases, we always need to do pre-processing but also account for ontology subsumption-based structure updating. This maps to a time of $O\left(S_C + T_Z\right)$.

In the best case, the first root node compared with the new offer is equivalent to it. This ends up doing two comparisons (one for node-to-offer subsumption and one for offer-to-node subsumption) and translates to $O\left(2 * \left(S * \left(R_O * S_O\right) + 2M\right)\right)$. Thus, in total, the time will be $O\left(S_C + T_Z\right)$.

In the worst case, we have a single tree and the offer has to be inserted in the rightmost leaf. This maps to performing twice the subsumption checking over all tree nodes which will map to $O\left(S + S_C + T_Z\right)$ in the end.

In the average case, we will have B balanced trees and the offer has to be inserted in the middle of the median tree. This will map to $\frac{S+B^2}{2B}$ subsumption checks which will then map in the end to a total time of: $O\left(\frac{S+B^2}{2B} + S_C + T_Z\right)$

4.5 SubsumedBy Algorithm

Analysis *subsumedBy* is an opposite relation with respect to *subsumes*. We organise the offer hierarchy in this way so as to cater for the case that a very small number of offers match a request which should be placed in the very leaves of the hierarchy (as subsumption translates to something more restricted or specific so less matches means more restricted matches).

Matchmaking. The matchmaking is performed by matching the request with the root nodes based on the *subsumes* relation. If there is no match, this means that there is no need to go down the root node's hierarchy (as either there is no relation at all or the request is *subsumedBy* the root node). Otherwise, we include the root node in the final matches and visit its children recursively. In the end, all matching results from each (recursive) root node search are collected and returned to the user.

Registration. Registration is similar and symmetric with respect to *Subsumes*. We check first the root nodes. An offer equivalent to a root node is included in the offers represented by this node and registration ends. If the offer is subsumed by this node, we make it the parent of this node. If it subsumes the node, we need to go recursively to the node's children. In the end, the offer will be placed either as a child of a root node's descendant or as a root of the forest (in case it is not related with any root node or is subsumed by one or more root nodes).

Complexity analysis *Matchmaking.* The best and worst cases map to the same time complexity as in the case of *Subsumes* with the sole exception being the conditions under which these cases hold. In the best case, we have one root node not subsumed by the request. In the worst case, all non-subsumed nodes by the request lie in the leaves of the forest and do not represent more than one offer. In the average case, the same assumptions hold as in *Subsumes* algorithm. This will, however, map to having to match the request with $O\left(S * \frac{P+1}{2}\right)$ nodes which in the end will map to the following total matchmaking time: $O\left(S * \frac{P+1}{2}\right) + T_Z$

Registration. This process is identical with that of *Subsumes* concerning the best and worst cases, so the respective time complexity is the same. The same holds for the conditions mapping to worst, best and average cases.

4.6 Discussion

Based on the time complexity analysis, it seems that in the worst case the *Parallel* algorithm is the best followed by *Sequential* and then the *subsumes*-based algorithms. However, in the average case, if there is some kind of subsumption hierarchy between the different nodes, it might be the case that the *subsumes*-based algorithms have the best possible performance and the best algorithm can depend on the percentage of offers being matched.

Concerning registration time, the performance order seems to be more clear as the *Sequential* algorithm should have the best performance followed by *Parallel* and then the *subsumes-based* algorithms. As such, there seems to be a performance trade-off between matchmaking and registration such that different algorithms are nominated as best depending on the respective operation.

5 Evaluation

The evaluation was performed by exploiting the experimental framework in [10], covering the non-functional aspect and being able to generate in a controlled manner both randomised and real non-functional service specifications, as well as the OWLSTC framework, covering the functional aspect with real or realistic functional service specifications along with ways to measure functional discovery accuracy. The main goal was to evaluate the algorithms' average matchmaking and registration performance. Accuracy is neglected due to the following reasons: (a) non-functional matchmakers have perfect accuracy [10]; (b) accuracy results will be identical to those of the functional matchmaker exploited that have already been reported. The target is to discover those circumstances that the selection of a specific algorithm from those proposed is recommended. We also consider the *AliveMM* functional matchmaker so that we are enabled to compare the overall matchmaking time with respect to the functional part and unveil the degree in which the latter influences the former.

In the sequel, we explicate the way the sole experiment was conducted based on the experimental framework and then discuss the experiment results.

5.1 Experiment Set-Up and Control

Unified Framework Features. By combining individual aspect-specific experimental frameworks, we generate an overall framework with the capabilities to create in a controlled manner both functional as well as non-functional specifications. Functional specifications can either rely on the OWLSTC collection if we desire to be as realistic as possible or can be produced randomly [11] via a domain ontology's concepts combined to produce the respective service I/O. Non-functional specification relies on the WS-Dream [19] and QWS [1] datasets or on the generation of randomised unary specifications which can include integer or real-valued metrics of different types and semantics. In the experiment conducted, we relied on the OWLSTC collection and the randomised generation of non-functional specifications. Our choice for the non-functional aspect relates to the fact that the WS-Dream dataset is big but quite limited in the number of metrics while QWS is smaller. However, we really desired to generate non-functional offers that are both greater in number and have an increased number of metrics such that respective requests can also match a particular percentage of the offers.

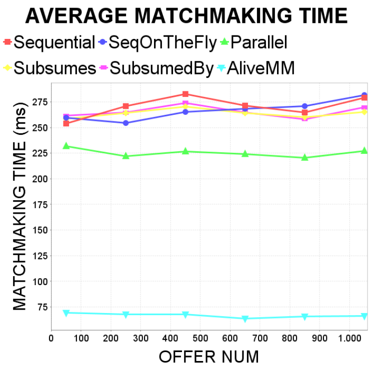
Offer Generation. For each functional service offer, three non-functional offers were generated in such a controlled manner. This resulted in generating around 3150 service offers (functional and non-functional pairs) provided that OWLSTC contains around 1050 functional service specifications. This also supports our main real-world assumption that each service can be associated to three non-functional offers catering for gold, silver and bronze customer classes. The amount of offers considered in each experiment step depended on a specific configuration parameter given as input to the specification generator. This means that if this number is 100, we randomly take 100 functional offers from OWLSTC and couple each of them with 3 non-functional offers randomly generated such that the next non-functional offer has an increased performance and price with respect to the previous one to map to the different customer classes.

Experiment Set-Up. The experiment was conducted in a Windows 7 SSD-based machine with 2GHz dual-core CPU and 6 GB of RAM. It included conducting a set of steps in which one configuration parameter varied (the offer number) according to a specific range (50 to 1050 with an increase step of 200 for the functional offers). Each step was executed 30 times to produce the respective average matchmaking and registration time values of the considered algorithms such that any possible interference at the OS level is diminished.

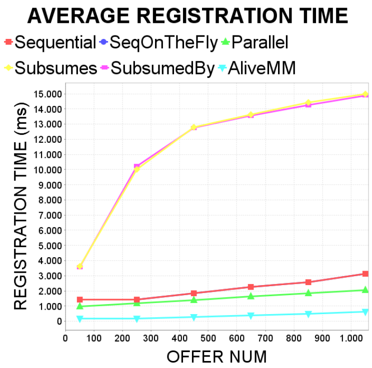
5.2 Experiment Results

Figures 3a and 3b depict the respective experiment results for matchmaking and registration time.

Concerning matchmaking time, we can clearly see that the best algorithm is *Parallel*. The order for the rest of the algorithms is not stable. In the beginning, the sequential algorithms are better than the subsumes ones but this is reversed when the number of functional offers is equal or above 650. This actually means that beyond a specific number of offers, the hierarchy of offers becomes more



(a) Service matchmaking results



(b) Service registration results

structured such that matchmaking time can be really saved via a subsumes-based approach. This matches exactly our expectations for the subsumes algorithms.

The partial order between the sequential algorithms is also unstable. Initially, as the number of non-functional offers to filter is small, *SeqOnTheFly* is slightly faster. However, beyond 650 functional offers, this is reversed as it becomes better to employ a non-functional matchmaker to register and match the non-functional offers rather than employ pair-wise non-functional filtering.

For the subsumes algorithms, we actually have equivalence apart from the initial step for which probably the number of matched offers is quite small thus favouring *SubsumedBy*. This is a point that requires further investigation as we need to discover those circumstances that one algorithm prevails over the other to assist practitioners in the respective selection.

Please note that the complexity analysis is actually validated from the results produced (especially with respect to the order of algorithms) due also to corresponding features of the OWLSTC collection. In particular, we see a more or less stable performance for the algorithms due to the small percentage of matched offers and the small number of output parameters per service. This leads to a more or less stable matchmaking performance for the functional matchmaker as also depicted in the results. Furthermore, while the number of non-functional offers to be matched is greater in each step, the scalable non-functional matchmaker used enabled to reach almost equivalent performance levels. Thus, the combination of these matchmakers also leads to a stable matchmaking performance.

Non-functional matchmaking time seems to take more with respect to functional one. This can be proven by comparing the performance between the functional matchmaker and the *Parallel* algorithm. This means that non-functional matching has still space for further optimisation. It also indicates that it is always proper for a sequential matchmaker to first filter based on the functional aspect and then based on the non-functional one. This is an interesting result that must be accounted by researchers and practitioners.

Concerning registration time, the best algorithm is again *Parallel* followed by the sequential ones. The difference between these algorithms is not big. However, the difference of the former algorithms with respect to the subsumes ones is big. This is also validated by the complexity analysis. This means that probably the subsumes algorithms should not be used in cases where a high number of offers is constantly registered or updated. However, it is also acceptable if in some cases the inclusion of an updated offer in matchmaking results is delayed. Thus, in the end, the use of these algorithms depends on the preferences and constraints of the registry provider especially with respect to the main requirements of its clients, being service providers and requesters.

No ordering between sequential and between subsumes algorithms can be inferred from the results. This is natural as the sequential algorithms rely on the same registration process. For the subsumes algorithms, by also relying on the matchmaking results, it seems that the structures produced are more or less similar, leading to almost the same registration time.

To conclude, we stress that the *Parallel* algorithm seems to be the best for both matchmaking and registration so it is undoubtly recommended as the ideal algorithm for service registry realisation. In case that a different algorithm is needed or preferred, then the recommendation will be towards the subsumes algorithms despite the fact that their behavior with respect to registration is the worst. However, for highly dynamic environments, it seems that the best choice will be the sequential algorithms as an alternative to *Parallel* due to their capability to also deal with the dynamicity in service updating.

6 Conclusions and Future Work

This paper has presented four algorithms which attempt to combine in a different way the facilities of functional and non-functional state-of-the-art service discovery algorithms. We believe that this investigation is genuine and really assists practitioners in choosing the algorithm that best matches their current situation. The respective algorithm evaluation has unveiled the circumstances in which each algorithm prevails based on performance aspects. Apart from these 4 novel algorithms proposed, we have also implemented an unified service discovery architecture covering both the functional and non-functional aspects. Such an architecture comprises components that not only perform core service discovery tasks but also specification validation and alignment. It also includes components that enable both a visual and a programmatic interaction with a human or software agents, respectively. The algorithm combination is performed such that transactionality of offer registration and updating is achieved.

Concerning future work, the following directions will be pursued. First, more thorough validation of the proposed algorithms to produce even more interesting performance insights. Second, completing the development of the service discovery architecture. Third, extending functional matching towards covering the service functional behaviour to further increase discovery accuracy in case respective formal service descriptions are in place. Finally, integrating the service discovery system in an existing service composition framework to enable a faster and more accurate service composition process.

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